Intraday Public Information:

The French Evidence

Thesis presented to the Faculty of Economics and Social Sciences
at the University of Fribourg (Switzerland) to obtain the doctoral degree
in Economics and Social Sciences

by

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Accepted by the Faculty of Economics and Social Sciences
on 13th January 2004 on the recommendation of

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Fribourg (Switzerland)

2004

"Those who don't do anything never make a mistake"

Théodore de Banville

"The important thing is never to stop asking questions"

Albert Einstein

ACKNOWLEDGEMENTS

This thesis was started in 1999, when I was assistant to Prof. Jacques Pasquier-Dorthe, head of the Seminaire d'Economie d'Entreprise et de Gestion Financière (SEEGF) at the University of Fribourg, Switzerland. Prof. Pasquier-Dorthe is the first person to whom I would like to express my gratitude for having accepted to become my supervisor. His knowledge has been a constant fountain of inspiration and, what is equally important, he attaches great importance to the human relations within the SEEGF. His patience, his understanding, and his ability to grasp other people's problems are some of his merits which I shall never forget.

My thanks also go to Prof. M. Wallmeier for his willingness to act as second supervisory professor. He gave me useful advice and friendly encouragement. So did the other members of the Seminar, Sophie Gay Anger PhD, CFA, Michel Ruffa, Amos Poncini, Levon Babalyan and Florent Ledentu, all of whom I would like to thank for their support; in particular, Sophie Gay Anger, PhD, CFA made many helpful suggestions and provided constant encouragement. Of great assistance were my colleagues at the University and Dr. Curzio de Gottardi, who lent me moral and technical support, and who made it possible for me to work in a most pleasant environment. Dr Angelo Ranaldo, a former member of the SEEGF, merits particular acknowledgement. I can never thank him enough for the innumerable enlightening considerations, ideas, critical remarks, and for the time he spent on reading my thesis, always giving an objective judgment which allowed me to advance in my work, especially in view of his experience in the microstructure field.

In 2000, I had the chance to participate in a course on microeconomics, during which I became acquainted with Prof. B. Schmidt, Prof. J.J. Laffont, Prof. J.C. Rochet and Prof. M. Dewatripont who gave me a solid background in microeconomics. Another important source of information were the lectures given by Prof. Deschamps, who holds the Chair of Econometrics.

I am also extremely grateful to the Société de Bourse Française, in particular to Mr. B. Perrot, for giving me access to a great amount of useful data on the French Stock Exchange.

In this type of research work, the moral support plays an essential role, and this was perfectly assumed by my companion Cristiana. She gave me the strength and confidence to continue even at times when the difficulties seemed overwhelming. Likewise I shall never forget the many hours passed in discussing my thesis with my faithful friends Massimo, Dario and Gabriele, with my sister Claudia and her friend Federico, and with Graziano and Aurelia, the parents of my companion. Graziano in particular encouraged my efforts by pointing out the importance of empirical research. Today I feel that he pushed me into the right direction.

My very special thanks go to my father and mother who made it possible for me to continue the studies, and who lent me their continuing moral support. If I reach my goal, it is mainly due to that, and for this reason I would like to dedicate this doctoral thesis to them.

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LIST OF ABBREVIATIONS

AA: All Alerts news

AA-FR: All Alerts news France

ABSRET: Return in absolute terms

ADR: American Depositary Receipts

AIC: Akaike Information Criterion

AIM: Amsterdam Interprofessional Market

AMEX: American Stock Exchange

ARCH: Auto Regressive Conditional Heteroskedasticity

ARMA: Auto Regressive Moving Average

BAS: Bid-Ask spread

BBO: Best bid and offer

BDM: Base de Données de Marché

BNP: Banque Nationale de Paris

BVLP: Bolsa de Valores de Lisboa e Porto

CAC: Cotation Assistée en continu

CATS: Computer Aiding Trading System

CBOE: Chicago Board of Exchange

CET: Central European Time

CORES: Computer-assisted Order Routing and Execution System

CORP: Corporate news

CORP_FR: Corporate news France

CPI: Consumer Price Index

DF test: Dickey and Fueller Test

DSPR: Difference spread

DSPR_WAS: Difference spread from the weighted average spread file

ECN: Electronic Communication Network

ECO: Economic news

ECO_FR: Economic news France

EHS: Effective half spread

EMM: Euronext market model

EST: U.S. / Canadian Eastern Standard Time

EU: European Union

EUR: Euro

FR: Flow ratio

FX: Forex

GARCH: Generalized ARCH

IBIS: Integrated Stock Exchange Trading and Information System

INDU: Industrial news

INDU_FR: Industrial news France

IPO: Initial Public Offering

ITS: Intermarket Trading System

LIFFE: London International Financial Futures and Option Exchange

LOB: Limit Order Book

LR: Liquidity Ratio

LSB: Lin, Sanger and Booth (1995)

LSE: London Stock Exchange

MABSVIMB: Average traded volume imbalance in absolute terms

MARKET: Market news

MARKET_FR: Market news France

MEDVOL: Average traded volume

MID: Midquote

MRR: Madhavan, Richardson and Roomans (1997)

NASDAQ: National Association of Securities Dealers Automated Quotations

NBTR: Number of trades

NSC: Nouveau Système de Cotation

NYSE: New York Stock Exchange

OAT: Obligations Assimilables du Trésor

OTC: Over the counter

PAC: Partial Auto Correlation

PER: Price / earnings ratio

POSIT: Portfolio System for Institutional Trading

PP test: Phillips-Perron test

Prob(F-s): Probability related to the F-Statistic

PSE: Paris Stock Exchange

QHS: Quoted half spread

QHS_WAS: Quoted half spread from the weighted average spread file

RAA: ratio of AA

RAA_FR: ratio of AA_FR

RBB: Reuters Business Briefing

RCORP: Ratio of Corporate news

RCORP_FR: Ratio of Corporate news France

RDSPR: Ratio of DSPR

RECO: Ratio of Economic news

RECO_FR: Ratio of Economic news France

RET: Average return

RINDU: Ratio of Industrial news

RINDU_FR: Ratio of Industrial news

RMABSVIMB: Ratio of MABSVIMB

RMARKET: Ratio of Market news

RMARKET_FR: Ratio of Market news France

RNEWS: ratio of number of news announcements

RQHS_WAS: Ratio of QHS_WAS

RRET: Ratio of RET

RSUMVOL: Ratio of SUMVOL

RVARRET: Ratio of VARRET

RVOLA: ratio of VOLA

RWT: Ratio of WT

SABSVIMB: Cumulated traded volume imbalance in absolute terms

SBF: Société de Bourse Française

SEAQ – I: SEAQ International

SEAQ: Stock Exchange Automated Quotation System

SEATS: Stock Exchange Automated Trading System

SUMVOL: Cumulated traded volume

SWX: Swiss Stock Exchange

TARCH: Threshold ARCH

VAR: Value at-risk

VARRET: Volatility of returns

VIMB: Volume imbalance

VOLA: Volatility measured as log range

WAS: Weighted average spread

WT: Waiting Time between subsequent trades

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INTRODUCTION

0.1. The concept of microstructure

The process and outcome of exchanging assets under explicit trading rules is known as market microstructure (Garman 1976, O'Hara 1995, Easley and O'Hara 1995, Biais, Glosten and Spatt 2002). How a specific trading process affects trades, quotes and price formation, how actual markets and market intermediaries behave, and the consequences of market organization for price discovery and welfare are some of the most interesting topics in the field of the micro-finance. The mechanisms of trading involve specific intermediaries (specialists, Saitori, market makers, dealers); a specific location (centralized or fragmented markets) and a specific moment when the exchange takes place (fixing or continuous markets). Whatever the mechanism, buyers and sellers trade at a price. How this price is formed, and how price-setting rules evolve in markets, is fundamental in order to understand how services and goods are allocated in the economy. One has to investigate how different trading protocols affect trades, quotes and prices, and why prices exhibit particular time series properties. The goal is to understand the microstructure of financial markets and the process by which they become efficient.

One can say that, in a state of equilibrium, the price is determined by the intersection of supply and demand for a particular goods item. In the literature, we find two approaches: according to the first (O'Hara 1995), the equilibrium price is determined by simply looking for a market clearing price, but how exactly this market clearing price is achieved, is of no interest. The second, known as the Walrasian approach, is often used in economics. There, auctioneers, through a series of preliminary auctions, aggregate demand and supply in order to find a market-clearing price (quantity supplied equals quantity demanded). In this case, prices evolve naturally, the auctioneers remain passive, and there are no other factors influencing price behaviour. These two approaches can be related to the first Welfare theorem of the Arrow-Debreu model, namely that all economic agents have the same information or, at least, that all agents are equally uncertain.

In all these approaches, the trading mechanism practically plays no role for the resulting equilibrium. But, as Radner (1979) notes, "a more detailed specification of the trading mechanism is required than in the analysis of the general equilibrium, because, in the markets, traders have different information”. Thus, the analysis differs if I consider agents who are asymmetrically informed (the behaviour of agents may reveal information), or if, like in many markets where trading is not only matching supplies and demands in equilibrium, the behaviour of participants is not passive, so that the trading mechanism may have an importance of its own.

In this context, the study by Demsetz (1968) should be mentioned. He was one of the first to look into the determination of prices in security markets and the behaviour of traders. In his opinion trade may involve some implicit costs, because, unlike in the Walrasian auction, trading has a time dimension. Thus, at a particular moment, the number of traders wishing to sell without delay may not equal the number of those who want to buy immediately. This imbalance makes it impossible to find a market clearing price at a given time. However, it is possible, paying a price for immediacy, to overcome this lack of equilibrium. For example, there are two traders on the demand side (one who wants to transact immediately and one not) and two on the supply side (analogously). If a trader wants to buy (sell) now, he has to wait for a seller (buyer), or else offer a higher (lower) price to induce those waiting sellers (buyers) to transact now. Thus, in the equilibrium, there are two prices and not only one. The price depends on whether someone wants to buy or sell at a given moment.

The implication that a specific structure and organization of the market could affect the trading price is of equal importance. Other important aspects which can affect the trading price are the interaction between the market mechanism and trader behaviour. If the trading mechanism matters in setting prices, then it will also matter in affecting traders' order decisions.

In order to be able to study the microstructure of a particular market, one needs a broad understanding of the overall structure of the security market. This will be the topic of the first chapter.

0.2. Market structures

The most striking development in asset markets over the past two decades is the proliferation of new markets and the changes in the old one, due, above all, to the technological improvements and the European integration. Starting from the London Stock Exchange, a series of structural changes have affected financial markets in Europe, in North America and in the rest of the world. Furthermore, some electronic markets have evolved, such as Reuters' Instinet, Investment Technology Group's Posit, Globex and the Arizona Stock Exchange (O'Hara 1995).

In view of the higher competition, however, not all of these markets will survive. The question of which market design will, or even should prevail is rarely asked, let alone resolved.

The goals of a market depend, of course, on whose perspective is considered. For an exchange or automated clearing system, the underlying goal may be as straightforward as the maximization of trading commissions. From a trader's perspective, the ideal market may be one in which orders are accommodated with the least effect on price, or one that has the lowest overall trading cost. For a regulator, the best market may be the one with the greatest stability. For a society as a whole, however, it is clear that while each of these goals may be important, none captures all the ways in which markets affect welfare in the economy (O'Hara 1995).

The process of exchange occurs between buyers and sellers who can, for example, contact each other directly or communicate through a computer screen, or a single intermediary can arrange every trade, or there may be numerous individuals who meet to set prices. Whatever the setting, the organization of financial markets defines the rules of the game played by investors and liquidity suppliers. These rules affect the way in which prices are formed and trades determined. Many authors identify three dimensions in this trading game. First the time of playing, i.e. the moment when the exchange takes place. There exists two possibilities: at a specific moment, or continuously during a trading day. Second, who plays. The players may involve a wide range of market participants, although not all types of players are found in every mechanism. These players are: the customer (who submits buy and sell orders), the broker (who submits orders for the customer), the dealer (who trades for his own account) and the specialist or the market maker (who quotes prices for buying or selling assets). This list is not exhaustive. Finally, where one can play the game, i.e. the location of the exchange, which can be centralized (order flows transmitted to the same location) or fragmented (order flows can be routed through different channels).

The various microstructure models analyse different trading mechanisms and their impact on the price formation process and on the agents' behaviour. Starting with Demsetz (1968) to Roll (1984), Madhavan, Richardson and Roomans (1997) and Huang and Stoll (1997), the evolution of models is impressive. The majority of these studies are based on a price-driven market in the US. My study, instead, concentrates on an order-driven market. Furthermore, the low cost of tick-by-tick data collection has increased the capacity of models to better describe the process and outcome of assets exchange. More detailed description of these topics will be given in the first chapter.

0.3. The French Stock Exchange

While the models and applications may differ, each specific microstructure analysis classification requires some clarification of the underlying trading mechanism. Thus, the market design is an important feature in studying the price formation process and time series properties when an event occurs during the trading day. In contrast to the Walrasian auctioneer, the structure of the market does have an influence on the traders' decisions and on his behaviour.

The Paris Bourse nowadays is one of the most closely studied markets, because of its structure, transparency and low cost of data collection. Its structural changes occurred at three distinctive moments: First, the daily call auction before 1986. Second, the introduction of a computerized limit order market, in which trading occurs continuously, between 1986-2000. Finally, after September 22, 2000, when the stock exchanges of Amsterdam, Brussels and Paris merged under the holding company Euronext NV to form the first pan-European stock exchange. The Euronext trading system has the same characteristics as the Paris Bourse. It is an order-driven market (with a central order book), based on price / time priority.

One of the fundamental qualities the investor is looking for is the liquidity of a financial market, but the liquidity is also influenced by the mechanism of trading. Although the liquidity concept is ambiguous, I try to assess intraday market liquidity through commonly used measures and some new proxies, and I will check whether these available measures of liquidity provide the same degree of estimation of market liquidity. This is the objective of chapter 2.

0.4. Intraday public information pattern

The link between information and changes in asset prices is central to financial economics. As Admati and Pfleiderer (1988) argue, private information plays a dominant role in explaining the time patterns of trading volume and return volatility in security markets. Public information is relegated to a lesser role, that of an unspecified, exogenous factor. In spite of this hypothesis, I use a distinctive proxy of public information flow. This proxy, measured as the number of news released by the Reuters 2000 alert system terminal, can be considered as a good approximation of the information available to the market participants. I use the public information flow to document the patterns of information arrival, with an emphasis on the intraday flows. Information is central in market efficiency. Investors react to new information as it arrives, depending on its characteristics, revising their beliefs, depending on their expectations of risk and return. News patterns are a first step in order to achieve my goal of getting to know the impact of news on asset prices. My assessment of public information is not restricted to one category only (firm-specific or macroeconomic event), but is divided into different types, relevant and non-relevant for the French market, each one having a characteristic pattern and probably a different impact. The objective of the third chapter is to study these intraday news patterns.

0.5. The impact of public information on the Paris Bourse

Whether the amount of information that is publicly available to market participants affects the trading activity, has always been a field of great interest in financial economics. In general, whether current prices "fully reflect" all publicly available information, is known as "semi-strong form test" of efficient market models (Fama 1970). Information is considered the major source of heterogeneity in investor expectations, which, in turn, generate trading activity. News arrival on the market induces a revision in expectations and, depending on the level of consensus between investors, a rise in trading activity. Much of disagreement regarding the news market is due to the differing emphasis made in the various studies. The impact of public news arrival on prices has been studied extensively, both from the theoretical and empirical points of view. In particular, key macroeconomic news and their unexpected components have been examined. Also the overall flow of information, rather than specific news, has been explored. My objective is to develop a more general concept of information, which is not only limited to specific shock related announcement such as consumer price index or money supply. In fact, I will consider eight major categories of news that may have an impact on stocks that constitute the CAC40 index during the period studied (December 1999 – November 2000).

The analysis also concerns the public / private information controversy. Some investigations on microstructure deal with the effect of private information available to market participants on their strategic behaviour (Kyle 1985, Admati and Pfleiderer 1988), whereas others deal with this strategic behaviour of uninformed participants. I shall try to examine these aspects in more detail in chapter 4.

CHAPTER 1

MARKET STRUCTURES

1.1. Abstract

First I review the development of financial markets in last two decades, pointing out the main changes and taking into consideration the different types of stock markets. Each has its own "market architecture", i.e. a set of rules governing the trading process. These rules are based on choices concerning a variety of attributes, such as: (1) the degree of continuity (periodic vs. continuous systems), (2) dealer presence (auction or order-driven vs. dealer or quote driven), (3) location (centralized or fragmented), (4) price discovery (independent price discovery vs. prices determined in another market), (5) automation (floor trading vs. screen based electronic systems), (6) order forms (market, limit, stop, hidden, etc.), (7) protocols (program trading, minimum tick, circuit breaker, etc.), (8) pre- and post-trade transparency (quantity and quality of information provided to market participant), (9) information dissemination (extent and speed of information dissemination), (10) anonymity (hidden order, trader identity) and (11) off-market trading (off-exchange, after hours). The moment, the counterpart and the location are, however, the main characteristics of stock exchanges. Second, the most important microstructure models are presented, in which the bid-ask spread becomes the central axis of the microstructure theory (among others Kyle 1985, George, Kaul and Nimalendran 1993, Madhavan, Richardson and Roomans 1997, Huang and Stoll 1997). Finally, the importance and the meaning of tick-by-tick data as a source for developing new models are discussed.

1.2. Introduction

Nowadays, financial markets are similar in many operational aspects, even if there exist some microstructure differences. An exhaustive definition of market microstructure is given by Easley and O'Hara (1995): "market microstructure is the study of the process and outcome of exchanging assets under explicit trading rules". As stated in this definition, market microstructure pays attention to the interaction between a particular mechanism of trading and its outcome. Many authors who concentrate their research on microstructures offer important insights into the operation and behaviour of security markets. Although this is a vast research area, I shall focus my interest on the market behaviour in relation to different information environments. This chapter is organized as follows. First, I shall review the development of financial markets in the last twenty years. This will allow us to understand the actual market architecture, which is the basis of my analysis. I then describe and summarize the most important microstructure models in Section 4. Finally, the advantages of using tick-by-tick data in the empirical analysis will be evaluated.

1.3. Historical background of stock exchanges

Interest in market microstructure is driven by the rapid structural, technological and regulatory changes affecting the security industry worldwide. The causes of these transformations are complex. Here, I provide only a partial and not exhaustive review of them.

In the mid-1980s, the microstructure of the European equity market changed dramatically. The increasing competition among European stock markets, globalisation, pressure on trading costs and the development of alternative trading mechanism forced such changes (Pagano 1997).

Until 1985, each financial market in Europe operated without close contacts with other international stock exchanges. There were many barriers such as closed membership organization, high obstacles to potential entrants, national regulations, difficult capital mobility and high communication costs. The bourses had take measures in order to avoid this isolation. Thanks to the European integration, the situation has gradually improved since 1985. This progress combined with the technology evolution, led to increased capital mobility and a decrease in communication costs. Deregulation also allows a stronger influence to institutional investor. The benefits derived from the international diversification contribute to more intense trading across national borders.

The first European stock exchange which started modifying its rules was the London Stock Exchange (hereafter LSE). In the rest of the world, some revisions began at the end of 1970s. The Toronto Stock Exchange altered its trading organization in 1977, introducing a computerized execution system, whereas Tokyo, began its restructuring process in 1982. In 1986, the LSE decided to reform its equity market. It gave up old method based on trading through "jobbers" (dealers) [1], opening the dealership to banks and others financial institution. Similar to the U.S. NASDAQ system, it introduced a screen-based technique, called SEAQ. The latter concerned only British equities, whereas for international securities SEAQ-I was introduced. For each foreign stock, certain market makers provide bid and ask quotes. In order to increase the competitiveness of the LSE, stamp duty was abolished for foreign stocks, and halved for British equities. These reforms changed also the attitude of foreign investor who trade in the SEAQ-I, because now they can find more immediacy in trading through market makers, facility to trade very large blocks of stocks and absence of taxes. These are some of the reasons that have led U.S. institutional investors, above all, to diversify into European stock markets.

The other stock exchanges acted in response to this deregulation process. The Paris Bourse was the first one to react to the reforms implemented by the LSE. The danger of losing business to the SEAQ-I pushed the French Stock Exchange to introduce some innovations in its trading system. As Pagano (1997) points out, four major innovations were implemented one after the other: (a) introduction of screen-based trading, (b) replacement of publicly appointed brokers by

[1] Jobbers receive customer orders via single-capacity brokers (who act on account of the clientele or on their own account), and commissions are fixed by the members of the stock exchange.

corporate dual capacity brokers[2], (c) liberalization of commissions and (d) modification of the principle that trade should be concentrated in one market.

The Paris Stock Exchange was closely followed in its reforms by two other European markets: Madrid and Milan. Then, in the early 1990s, the German, Dutch, Israeli and, in the mid-1990s, Swiss markets reorganized their structure.

Madrid, in 1989, adopted an automated trading system, where "Sociedades de bolsa" replaced "agentes de cambio". The former can trade on their own account and can be held by domestic or foreign banks, insurance companies and securities firms.

This wave of reforms influenced other important trading places, such as Belgium, which adopted the French structure. In 1991, the Italian stock exchange moved from the open outcry call auction to an automated continuous auction managed by "Società di Intermediazione Mobiliare".

Germany's system of call auction is different from other European places. SEAQ-I pressure, first, and reforms in other European countries, forced Germany to modify its organization. Germany's response to SEAQ-I competition was the introduction of the IBIS, a screen-based trading system, run by the Frankfurt Stock Exchange. Other stock markets underwent minor transformations. Regional exchanges were maintained, but the IBIS system now runs the majority of trading transaction with Frankfurt. This gradual change will lead to the disappearance of regional exchanges and of "Kursmakler" [3]. During the same period, the German Stock Exchange was transformed into a joint-stock corporation, called Deutsche Börse AG [4].

Amsterdam is particularly influenced by the competition from SEAQ-I. It introduced some innovations in two steps. In the first, in 1987, the trading system run by "hoekmannen"(single capacity dealers) was joined to the AIM [5]. This new arrangement was programmed in such a way that it facilitates block-trading and meets the requirement of institutional investors and banks. In a second step, a continuous auction system was introduced.

According to the SWX (1996a and b), the Swiss Exchange began its changes in the nineties. In 1990, there were still seven stock exchanges, plus the option market SOFFEX (now called EUREX[6]). After the initial project, in 1992, the launch of the new electronic trading system started on August 2, 1996. Its structure is the first in the world that fully integrates the stock market trading system, covering the entire spectrum from trade order through to settlement (SWX 1996a and b).

Where stand the markets today ? What Pagano (1997) says in his paper about the possibility of increasing competition between trading systems, is even more true today. Some factors stimulate such competition. First, the EU Investment Services Directives facilitate cross-border access for

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[2] Act as agents (on account of the clientele) and as principals (on their own account).
[3] Officially appointed auctioneers who can take positions on their own account to avoid extreme price fluctuations.
[4] The main shareholders are: Deutsche Börse Beteiligungsgesellschaft (7.20%), Allianz (5.91%) and Bayerische Hypovereinsbank (4.69%).
[5] Amsterdam Interprofessional Market.
[6] Option Exchange born after the merger between the German Option Exchange and the Swiss Option Exchange (SOFFEX).

investment firms and cross-border branching by using the electronic networks of the European exchanges. French and German Bourses establish direct links to investors in London and in other major financial centers.

Pressure on trading costs, above all from institutional investors, is the second factor playing an important role in increasing competition among financial markets.

The recent introduction of the Euro, which eliminates the exchange rate risks within the European monetary union, allows increased cross-border trade volume. It will be important for some Bourses to be able to attract the majority of foreign investors, competing, in fact, with alternative trading systems for the same equity. Moreover, some trading networks are being set up by brokers in competition with official exchanges, which increases the competition also within the national boundaries, not only outside. These trading systems do not contribute to price discovery, but simply facilitate cross orders at a reference price drawn from an official exchange. The Arizona Stock Exchange is an example. It matches orders at NYSE closing prices. ISTINET, set up by Reuters, is another example, where the system allows traders to post anonymous bids and offers, and to negotiate electronically. As Madhavan (2000) points out, in the U.S., the structural shift affecting the security industry includes also competition between exchanges and ECNs[7], changes in the regulatory environment, and an increase in trading volume, new technological innovations, the growth of the Internet and the proliferation of new financial instruments.

Concentration and mergers between European stock markets are another factor which explains the increasing competitiveness amongst stock exchanges. Let's take Euronext as an example, which is the result of a merger between the Paris Bourse, and the Brussels and Amsterdam Stock Exchanges. Its objective is to become the first integrated European bourse. What the traders hope for is the reduction of transaction costs and an increase in liquidity needs. Transparency and efficiency of price discovery mechanism will be one of the attributes of the new Bourse.

Virt-x, on the other hand, is an innovative platform in London, where more than 600 European blue chips are traded [8]. Virt-x presents the lowest costs of production. Since its start this concentration on only one platform has been a guarantee for great liquidity.

As we have seen, the stock exchanges have made impressive progress during the last two decades, thanks to new technologies and competition. Technology will still progress in the coming years. At the same time competition and further economic integration in Europe will lead to the demise of some national stock exchanges. They will be replaced, maybe, by a single market for the European time zone.

Financial markets progress continuously. Nevertheless, we can make use of certain factors which allow us to look at the organization in a more differentiated manner. This is the objective of the next chapter.

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[7] Electronic communications network.

[8] All the Swiss blue chips are traded on this platform since 25th June 2001.

1.4. Organization of financial markets

In view of the remarkable diversity in trading mechanisms around the world and across assets, it is useful to begin with a taxonomy of market structures. As Madhavan (2000) and Venkataraman (2000) say, market architecture refers to the distinctive set of rules governing the trading process. These rules dictate when and how orders can be submitted, who can see or handle the orders, how orders are processed and how prices are set (O'Hara 1995). The rules of trading influence the profits derived from various trading strategies (Harris 1997), hence they affect trader behaviour, price formation and trading costs. The properties of asset prices depend, in some aspects, on the structure of the market on which they are quoted, and the markets differ in price evaluation, transmission, execution of orders and the role assumed by the intermediaries. Thus, all these variables are closely intertwined. Biais, Foucault and Hillion (1997) and Fleuriet and Simon (2000) define three criteria for distinguishing financial markets. The first one is the moment of the exchange, or, as Madhavan (2000) says, the degree of continuity. A distinction is made between fixing markets (which allow trading only at a specific point in time) and continuous markets (which allow trading at any point in time while the market is open). The second criterion refers to the exchange counterparts, or, as Madhavan (2000) calls it, the reliance on market makers. I shall distinguish between agency markets and dealer markets. Similarly, when describing the market typology through the price formation process, I shall distinguish price-driven markets (market makers take both sides in every transaction) and order-driven markets (without intervention by market makers). The third criterion is the location of the exchange, where we can in turn distinguish between centralized markets and fragmented markets.

1.4.1. The moment of the exchange

1.4.1.1. The fixing market

In the fixing market, orders are batched together for simultaneous execution in a single multilateral trade, once or twice during a working day and at a pre-specified time. All transactions get to the market at a single price, via a centralized mechanism, which best balances aggregated sales and aggregated purchase orders (Pagano and Röell 1992, Madhavan 1992, Madhavan 2000). The exchange volume is maximized. Purchases at this price and higher, and sales at this price and lower, generally are executed.

Biais, Foucault and Hillion (1997), and Economides and Schwartz (1995) distinguish four types of fixing markets:

1. The first type is called “price scan auction” by Economides and Schwartz (1995). All market participants are physically present in the same place. The auctioneer opens the market by calling the stock name and its starting price, and the participants respond with their wishes for purchases or sales. The auctioneer manages the call trading session, adjusting the price continuously until the value that best balances the buy and sell orders

is found: he raises the price if there is excess demand, and lowers the price if there is excess supply. This process continues until the discovery of the equilibrium price. If, because of discontinuities, there is no exact match between aggregated purchases and sales at a certain price, buy orders placed at the clearing price are not executed in full (if buys exceed sells), or sells are not executed in full (if sells exceed buys). Time priority (the orders placed first are executed first), or pro rata execution (an equal percentage of each order is executed) is commonly used to determine which orders to execute among those which had been placed at the lowest executable bid (if buys exceed sells) or at the highest executable ask (if sells exceed buys). Examples of this type of call auction include art auctions, tulip bulb auctions, the old call market system of the Paris Bourse (à la criée), the old trading system of the Milan Stock Exchange, the open outcry market, and the system currently used to open trading on the NYSE (Amihud, Mendelson and Murgia (1990), Madhavan (2000)).

2. An alternative to the first fixing type is the sealed bid / ask auction used by the U.S. Treasury Bonds. This method allows market participants to submit their bids, but these offers are not disclosed to the other participants until the fixing moment. This is a limitation. In fact, it hides orders that some participants might wish to expose and the others would like to see. When the auctioneer calls the fixing, orders are arrayed by price and cumulated from the highest bid to the lowest bid for buy orders and from the lowest ask to the highest ask for sell orders. The cumulated orders are matched against each other. After this, a clearing price is determined.

3. A crossing network method also batches orders (Economides and Schwartz (1995)), but instead of determining the price within the batching process, it uses a price that has been set elsewhere. For example, POSIT, Instinet, and the two NYSE crossing networks, all cross orders at prices that have been established in the primary market center. Instinet and the NYSE's after hours systems use closing prices, while POSIT uses current intraday prices.

4. The fourth approach is the open order book auction. It is the opening procedure used in most electronic continuous markets, such as Toronto's CATS, Tokyo's CORES, Paris' CAC and Australia's SEATS. Also the Arizona Stock Exchanges is an electronic call market. Aggregated quantities at each bid and ask prices are disclosed to market participants, as soon as the market receives them. All participants can watch the market as it is forming. Furthermore, the equilibrium price is continuously updated and displayed after each new order has been submitted.

1.4.1.2. The continuous market

In contrast to the fixing market, in a continuous market the trader can submit his orders at any time. Quotations and transactions are continuously updated, and orders are executed each time an opposite order with identical or better price is transmitted to the market. Moreover, a new price can be established after every transaction, instead of the fixing market where there is a single price for all transactions. Continuous trading increases the frequency of trading, thereby enabling immediate execution during the entire business day.

Brennan and Cao (1996) show that a move from periodic call auctions to continuous trading increases investors' welfare and asset values. Their model assumes an initial supply / demand shock, which is followed by information-motivated trading volume. Such an environment, allowing for more trading rounds, facilitates a better reaction to new information and improves risk sharing. The model predicts that a higher frequency of trading will result in a larger trading volume. Furthermore, the increase in volume should have a positive stock price response. However, continuous trading does not necessarily improve the investor welfare. If the supply and demand shocks are dispersed over the entire trading period, continuous trading may result in higher execution costs for liquidity traders. For example, in Kyle's (1985) model, allowing for more rounds of trade will increase the expected profits of the informed, thereby hurting the liquidity traders. As a result, continuous trading can lead to a reduction in trading volume, and, in the extreme, to a market breakdown (Madhavan (1992)). In such an environment, allowing for more rounds of the continuous trade can result in welfare reduction (Garbade and Silber (1979)).

1.4.2. The counterparts of the exchange

1.4.2.1. Price driven-market

Another way to distinguish a financial market consists in describing it by the price formation process. In a price-driven or quote-driven system, designated market makers supply liquidity to the market by quoting a purchase price (investor's ask price or market maker's bid price), an offer price (investor's bid price or market maker's ask price) and the number of shares at which they are willing to trade. The difference between the bid and the ask price is the market maker's spread. Demsetz (1968) argues that the market maker's spread, which is a measure of the value of the liquidity service provided by the dealer, is the appropriate return, under competition, in an organized exchange market. The priorities of the market maker is to provide liquidity to the market, to discover the price, to stabilize the price and to permit continuous trading by overcoming the asynchronous timing of investor orders. He adjusts the spread by buying and selling stocks in response to fluctuation in his own inventory in order to avoid imbalances between the offer and the supply sides. According to Smidt (1971), this is an active role assumed by the market maker, instead of the passive role Demsetz (1968) assigns to him. Demsetz (1968) argues that the market maker only regulates the bid-ask spread (hereafter BAS) in response to changing conditions. In reality, as Smidt (1971) suggests, the market maker actively adjusts the spread in response to fluctuations in his inventory levels. Although the primary function of the market maker remains that of a supplier of immediacy (Demsetz 1968), he also plays an active role in price setting, primarily with the objective of achieving a rapid turnover and not accumulating significant positions on one side of the market (Brockman and Chung 1999). This is a risky activity for the market maker, because he can expose himself to a considerable variation of prices. In fact, when he buys a stock for himself, it is not certain that he has the possibility to sell it immediately; thus, for example, if he is long, he will rarely purchase another security, but instead will quote a competitive ask price to lower his inventory levels (Madhavan 2000). A market maker offers the possibility to traders with privileged information to use their information to his detriment. Therefore he tries to protect himself from this possible loss, giving an ask price which is lower than a bid price (Ho and Stoll 1983). The market maker may be the monopolist for some assets and in some markets. In the NYSE, such a market maker monopolist, is called a "specialist". In many other cases market makers compete with one another. There exists, by now, a considerable literature on specialist behaviour. The rules of the NYSE require the specialist to maintain meaningful spreads at all times, keep price continuity, and trade in a stabilizing manner. Previous studies (Hasbrouck and Sofianos (1993), Madhavan and Sofianos (1998), and Kavacejz (1999)) show that the specialist's quotes anticipate future order imbalances and help to reduce transitory volatility. Madhavan and Panchapagesan (2000) maintain that the specialist's opening price is more efficient than the price which would prevail in an automated auction market using public orders only. These results suggest that the NYSE specialist can play a beneficial role in price formation. However, for heavily traded stocks, the role of a specialist is less clear due to his low participation rates.

According to Stoll (1985) and Madhavan (2000), market makers typically face competition from floor traders, competing dealers, limit orders and other exchanges. Models of competition among market makers were developed, for example, by Ho and Stoll (1983). Although the early literature argues that competition among market makers in the NASDAQ system would result in lower spreads than in a specialist system, the opposite seems to be the case, even after checking factors such as firm age, firm size, risk and price level (Madhavan 2000). Christie and Schultz (1994) and Christie, Harris and Schultz (1994), suggest that dealers on NASDAQ might have implicitly colluded to set spreads wider than those justified by competition. Theoretical studies by Kandel and Marx (1997) and Dutta and Madhavan (1997) provide some justifications for this opinion, always with reference to the NASDAQ.

The higher cost structure of a dealership market is reflected in the spread which dealers charge investors (Varnholt 1996). The transaction costs reduce the trading volume. Therefore, due to the relatively high transaction costs, dealership markets are primarily used for blue chip stocks or for government bonds. From an investor's point of view, dealership markets offer the advantage of immediacy in executing a trade.

1.4.2.2. Order-driven market

In a pure order-driven market, there is no designated market maker (Handa and Schwartz 1996). Thus, one defines an order-driven market as a trading system where incoming buy and sell orders are automatically and instantly matched with orders currently outstanding on the limit order book (hereafter LOB). Public limit orders spontaneously provide liquidity to the market and establish the bid-ask spread and the depth. There is only one intermediate: the broker, who submits the orders for his customers. Orders are accumulated in a limit order book (LOB). A limit order is registered in the LOB and executed each time an opposite order with identical or better price is transmitted to the market. The difference between the prices at the lowest sell limit order and the highest buy limit order defines the effective bid-ask spread (Brockman and Chung 1999). BAS is the investor's compensation for keeping an inventory, considering adverse selection risks, brokerage commissions, communication costs and clearing (Ranaldo 2001). Order-driven depth, on the other hand, is a function of the number of shares available at the highest bid and lowest ask, and is determined by the willingness of investors to provide immediacy through submission of limit orders (Brockman and Chung 1999).

In a pure order-driven market, buyers and sellers must decide between two types of orders, namely limit orders and market orders. A limit order specifies a particular price, and is a promise to trade at that price, but bears the risk of adverse selection and non-execution. Unexecuted limit orders enter the LOB, where they are stored until executed or cancelled. A market order is executed with certainty at the most attractive price posted by previous limit orders, but pays an implicit price for immediacy. The choice between limit orders and market orders depends on the market conditions and on the propensity of the investor to trade (his relative patience). Al-Suhaibani and Kryzanowski (2001) give a good survey of research works on the choice between limit orders and market orders. In particular, their paper focuses on the choice between limit order and market order by a trader, and the resultant profitability of such a choice.

Still concerning market orders, in the NYSE, in the Paris Bourse and in the Tokyo Stock Exchange, market orders can be stopped rather than immediately executed, either automatically like in Paris, or depending on the judgement of the Saitori in Tokyo or the specialist in New York. In the Paris Bourse, market orders which are stopped at the quotes, often attract liquidity from the other side of the market. For the NYSE, Harris and Hasbrouck (1996) find that market orders are often blocked by the specialist and executed within the quotes. Similarly for the Tokyo Stock Exchange, Hamao and Hasbrouck (1995) show that orders are often stopped by the Saitori.

These results suggest the existence of a potential liquidity supply, which is not available within the LOB. The following interpretation can be offered. For example, some agents who are willing to buy or sell do not place their orders in the book immediately, perhaps because they are afraid of adverse execution, or are reluctant to show their willingness to trade. Instead, they monitor the market, waiting for favourable opportunities to hit the quotes or place orders. Such opportunities arise when the spread is large or when market orders have been stopped (Biais, Hillion and Spatt 1995).

Studies by Rock (1988), Angel (1991), Kavacejz (1999), Harris and Hasbrouck (1996), Seppi (1997), Bias Hillion and Spatt (1995) and Foucault (1999), among others, help in advancing the knowledge of liquidity provision by studying the LOB.

Many of the world's major stock exchanges, such as the NYSE and Tokyo, rely at least partially on limit orders for the provision of liquidity. I found a variety of evidence showing how liquidity is supplied and consumed in the marketplace, and on the interaction of liquidity and priority considerations. The probability that investors place limit orders (rather than hitting the quotes) is greater when the BAS is larger, or when the order book is thin. On the contrary, investors tend to hit the quote when the spread is tight. Thus, the investors provide liquidity when it is valuable to the marketplace, and consume liquidity when it is plentiful. In order to obtain time priority under these circumstances, investors place limit orders relatively quickly when the liquidity has diminished.

Since the order book itself never assumes any positions, it needs no expensive risk management tools, similar to a market maker (Varnholt 1996). The use of electronic LOB, combined with an order-driven market making has been rapidly increasing in recent years, due to improvements in information technology and financial market deregulation. The practical importance of such a market structure is growing, as financial markets have adopted a computerized LOB, while others are evaluating the merits of introducing LOB into the market architecture. Recently the NYSE has debated the benefits of adopting elements of a consolidated LOB into its design (Hollifield, Miller and Sandås 2001).

Other important analyses of limit order markets were carried out by Rock (1990), Glosten (1994) and Bernhardt and Hughson (1993).

1.4.3. The location of the exchange

1.4.3.1 Centralized market

The third criterion that allows to distinguish financial markets is based on the trading space, which can be centralized or fragmented. A market is said to be centralized when the stock order flow is transmitted to the same location (same floor or same system), so that the market participants can observe all the quotes and trades and take them into account in their strategies. There is only one transaction price.

In centralized markets, trades are the outcome of multilateral negotiations, i.e. all the agents present in the market can participate in all trades. For example, in a floor or a pit, as soon as an agent quotes a price, other market participants can observe it and offer a better price. They can take this information into account in their own strategies. Examples of centralized markets are the stock and future exchanges (Biais 1993). In such open outcry markets, Ho and Stoll (1983) assumption that dealers can monitor their competitors' trades and quotes and interfere with their inventories, is realistic. This transparency also prevails in electronic agency markets.

1.4.3.2. Fragmented market

By contrast, in a fragmented market, the stock order flow can be routed through different markets. It is possible to have multiple prices for the same asset. Dealer markets, such as NASDAQ, SEAQ, the foreign exchange market and the Treasury bonds market, are fragmented. Deals are often the outcome of bilateral transactions negotiated on the phone, which the other market participants cannot observe. Fragmented markets are much less transparent. Trades and quotes are often displayed on screens, but this display is generally not instantaneous, nor is it sufficient. The extent to which screen quotes can be improved (in terms of price and quantity) is usually uncertain. They do not show the intensity with which agents want to sell or buy. In many over the counter (hereafter OTC) markets (interbank market, infrequently traded bonds or equities), company quotes can only be obtained by phone. Even if screen quotes are fixed (which is the case in the NASDAQ, in the French government bonds OAT market, or in SEAQ for alpha stocks), they can be irrelevant. Therefore, in fragmented markets, the agents can only assess quotes and positions of their competitors. In this respect, the agents who provide liquidity to the market are at a disadvantage, compared to the general public. Market order traders can ask market makers for quotes, in search of the best quotes. This is not possible for market makers. A given market maker would not show his best quotes, and hence his inventory position, to a competitor who asks him for a price on the telephone. Biais, Foucault and Hillion (1997) give three possible explanations for such fragmentation:

1. A security can be listed on more than one exchange (multiple quotations). For example, in the U.S. market it is possible that the NYSE stocks are also listed in regional stock exchanges (Boston, Chicago, Cincinnati, Pacific and Philadelphia) or in some private trading networks (Instinet).
2. Off-exchange transactions (outside the principal market). Some orders are handled differently from others. For instance, small orders are routed to immediate execution, whereas, large block trades are negotiated off-board in an upstairs market. These transactions are difficult to handle, because block trades provoke unfavourable price variations for two reasons: first, if the market is not liquid, and secondly, if transactions are perceived as a signal of the stock value.
   In many equity markets, including USA, there are two distinct trading mechanisms for large block transactions. Madhavan (2000) gives a good explanation of block trade mechanisms. First, a block can be sent directly to the downstairs or principal markets, such as the NYSE or NASDAQ. Second, a block trade can be directed to the upstairs market where a block broker facilitates the trading process by locating counterparties to the trade and then formally crossing the trade in accordance with the regulations of the

principal market[9]. One argument cited for the growth of upstairs markets in the U.S. is that the downstairs markets, in particular the NYSE, offer too much information about a trader's identity and motivations for trade. Madhavan (1995) and Seppi (1990) argue that big traders are afraid of having their strategies leaked, and prefer to use upstairs markets to accomplish large-block trades in one single step.

3. OTC markets. Intermediaries are not gathered into the same place where orders arrive. The market maker gives price quotations by telephone or by electronic terminals. Some price-driven markets are fragmented by nature, for example the NASDAQ, the SEAQ, and the interbank markets (Biais 1993).

Fragmentation causes some problems with respect to transparency. They concern information release about exchange conditions, and the possibility that the same security has two different prices in two different locations. Biais, Foucault and Hillion (1997) give two possible solutions to avoid such problems:

1. Even if transactions are decentralized, exchange conditions must be centralized. Block trades can be negotiated in the upstairs market, but must be recorded in the order book.
2. Try to connect different markets where the same stock is negotiated, so the broker is informed about different prices and can choose the best one. This system is used in the U.S. market for stocks that are handled on the NYSE and on the regional stock exchanges (for example the ITS trading system).

1.4.4. Other methods

There are other factors that allow to distinguish markets (Madhavan 2000, Biais, Foucault and Hillion 1997):

1. One important difference between trading systems is the quantity and the quality of the information available to the market participants at the time the price is formed. Pagano and Röell (1996), Madhavan (2002) and O'Hara (1995) define transparency as the extent to which market makers can observe the size and direction of the current order flow. Their notion is closer to that of Bias (1993), who defines transparency as the visibility of the limit orders or market maker quotes.

   Non transparent markets provide little in the way of indicated prices or quotes, while highly transparent markets often provide a great deal of relevant information before (quotes, depths, etc.) and after (actual prices, volumes, etc.) trade occurs. A useful way to think about transparency, which has many aspects, is to divide it into pre-trade and

[9] Reputation plays a critical role in upstairs markets, where it allows traders who are known not to trade on private information to obtain better prices than in an anonymous market. Liquidity providers, especially institutional traders, are reluctant to submit large limit orders, and thus offer free options to traders using market orders. This problem is especially significant in systems with open LOB and minimum price increments. Upstairs markets allow those traders to participate selectively, screened by block brokers, who avoid trades which may originate from traders with private information.

post-trade dimensions. Most continuous auction markets provide great pre-trade transparency, i.e. great visibility of the best price at which any incoming order can be executed. All deals are immediately publicized on-line. In electronic auction markets, brokers can scan the LOB and see exactly at what price an order would execute (except for hidden orders). In contrast, dealer markets, such as foreign exchange and corporate junk bond markets, NASDAQ and LSE, display only very limited information, namely quotes at which market maker must deal until they reach the posted size. Post-trade transparency, i.e., the public visibility of recent trading history, also tends to be lower in dealer markets (Madhavan 2002). This reflects both inherent technical factors and deliberate choices by exchange authorities. Technically, after a deal is negotiated over the telephone, it takes at least a few minutes to report it to the exchange and to publish it on the screen.

On the NYSE, until recently only the specialist could see the orders in the order book at every moment[10]. Only the bid-ask quotation is electronically disseminated to traders who are not specialists. In the Tokyo Stock Exchange, the Saitori can give some information about the order book, but only to the agents on the floor. In Tokyo, only the lead offices of the member can observe the orders, and they are required not to disseminate this information. The Toronto Stock Exchange and the Paris Bourse use an automated LOB system, which offers continuous trading with a high degree of transparency (i.e. public display of current and away limit orders) without relying on dealers. The Paris CAC and the SuperMontage[11] NASDAQ systems display for everybody five best bid and offer prices and the number of share offered at each of the five bid and ask quotes. Only the Société de Bourse France knows the totality of the order book.

Pagano and Röell (1996) investigated whether greater transparency enhances liquidity by reducing the opportunities for taking advantage of less informed or non-professional participants. They found that greater transparency generates lower trading costs for uninformed traders, although not necessarily for every size of trade.

2. It is possible to stabilize the stock prices if they exceed a maximal limit. This measure is adopted in order to avoid great variations. When the trading system stops the mechanism, the orders are accumulated. After the trading halt, a price that best balances the aggregate quantities is fixed. In a dealer market, this task is given to the market maker. The most organized markets also have formal procedures to halt trading in the event of large price movements (Circuit breaker).

[10] Now all traders can observe the book.

[11] SuperMontage, is a system that aggregates and displays the five best bids and offers for each stock in Nasdaq trades. Island Chief Technology Officer William Sterling says that SuperMontage will not allow its participants to maintain their anonymity throughout the lifecycle of a trade. If market makers enter a bid on SuperMontage as non-attributable, and if someone comes in and takes this bid, they will find out who it was as soon as the bid is executed. Thus SuperMontage offers pre-trade anonymity, but not post-trade anonymity.

3. The degree of exchange automation: floor versus screen-based electronic systems. Nowadays many markets are automated. Many aspects of the exchange process can be automated, for example orders, information release and order execution. Such automated mechanisms reduce the costs of transactions.

4. Decimalization and minimum tick. Decimalization refers to the quoting of stock prices in decimals rather than fractions, such as eighths or sixteenths[12]. The minimum tick is a separate issue, although in the literature it is often associated with decimalization, and concerns the smallest increment in which stock prices can be quoted. For example, a system may have decimal pricing but a minimum tick of 5 cents or 2 cents. From an economic perspective, what is relevant is the minimum tick, not the unit of measurement of stock prices (Madhavan 2002).

5. Price discovery: the extent to which the market provides independent price discovery, or uses prices determined in another market as the basis for transactions.

6. The allowed order form, i.e., market, limit, stop, hidden, upstairs crosses, baskets.

The following table gives a survey of the main characteristics of some of the world stock exchanges.

Table 1.4.1 Variation in Real-World Trading Systems

Architecture Elements	Typical ECN	NYSE Open Market	NYSE Intraday Trading	Paris Bourse	POSIT	Chicago Board of Trade	Foreign Exchange Market
Continuous trading	X		X	X		X	X
Dealer presence		X	X			X	
Price discovery	X	X	X	X		X	X
Automation	X			X	X		
Anonymity	X	X		X	X		
Pretrade quotes	X		X	X		X	
Posttrade quotes	X	X	X	X	X	X	

Source: Madhavan (2002)

SuperMontage integrates the functionality of Nasdaq's two incumbent systems: SuperSoes, the market's sole execution pipeline for all market-maker-addressed orders, and SelectNet, an order-routing vehicle, which Nasdaq participants use mainly to send orders to ECNs.

[12] Proponents of decimalization in the US markets noted that it would allow investors to compare prices more quickly than could be done when fractions were used, thereby facilitating competition. They often mistakenly estimated important cost savings for investors because quoted spreads were thought to fall dramatically.

1.4.5. Concluding remarks

At present, many different market structures are available, and there is an open discussion regarding which is the best one.

The current trend towards automation of auction trading mechanisms raises one important question: would a fully automated auction market provide better execution than a floor-based market structure ? Theoretical models on the competition between an automated and a hybrid LOB (with specialists) (e.g. Glosten (1994) and Seppi (1997)) suggest that neither structure is clearly superior. Domowitz and Steil (1999) discuss the benefits of an automated trading structure. They also survey the empirical literature on the issue and conclude that electronic trading generally yields considerable cost savings over traditional floor-based trading. In contrast, Benveniste, Marcus and Wilhelm (1992) argue that the professional relationship which evolves on the floor of an exchange, due to repeated trading between the specialists and floor brokers, results in information sharing on forthcoming order flows and the intrinsic value of the stock. This helps to reduce the information asymmetry and to increase the effective liquidity of a traditional floor-based system.

Theory suggests that a multilateral trading system (such as single-price call auctions) is an efficient mechanism for aggregating diverse information. Consequently, there is great interest in the way call auctions operate, and whether such a system can be used more widely for trading securities. Analyses of single price markets were made by Mendelson (1982) and Ho, Schwartz and Withcomb (1985). The information aggregation argument suggests that call auctions are valuable when there is wide spread uncertainty over fundamentals and market failure is possible. Empirical studies seem to support this aspect of the argument. Indeed, many continuous markets use single price auction mechanisms when there is much uncertainty, for examples at the time of opening, closing, or reopening after a trading halt.

Smidt (1979) discusses how differences between periodic and continuous systems might affect returns. Amihud and Mendelson (1987) compare and contrast return variances from open-to-open and close-to-close for NYSE stocks. Any differences are likely to result from diversities in the trading system. Their evidence seems to support the view that distinctions between continuous and batch systems can be observed in variables such as price and return volatility. Similarly, Amihud and Mendelson (1991), Stoll and Whaley (1990), and Forster and George (1996) also conclude that differences in market structures affect returns. Amihud, Mendelson and Lauterbach (1997) document large increases in asset values for stocks which moved to continuous trading on the Tel Aviv Stock Exchange.

Madhavan (1992) shows that a quote-driven system provides greater price efficiency than a continuous auction system. Both mechanisms reach the equilibrium when free entry into market making is possible.

Madahavan, Porter and Weaver (2002) found a decrease in liquidity associated with the display of the LOB on the Toronto Stock Exchange after checking for volume, volatility and price.

Biais (1993) compared centralized and fragmented markets, showing that although expected spreads are equal in both markets, centralized markets exhibit more volatile spreads than fragmented markets.

In theoretical studies, various conclusions were reached about the effects of transparency. According to some models (O'Hara 1995), transparency can reduce problems of adverse selection, and thus of spreads, by allowing dealers to screen out traders likely to have private information. Other models, such as Madhavan (1996), however, indicate that transparency can exacerbate price volatility. Intuitively disclosing information would allow investors to better estimate the extent of noise trading, thus increasing vulnerability of the market to asymmetric information effects. Contrary to popular belief, Madhavan (1996) showed that potentially adverse effects of transparency are likely to be greatest in thin markets.

Transparency is a complicated subject, but recent research provides revealing insights:

(1) Pre- and post-trade transparency can affect liquidity and price efficiency (O'Hara 1995, Madhavan 1996)

(2) Greater transparency is associated with more informative prices (O'Hara 1995, Bloomfield and O'Hara 2000)

(3) Complete transparency is not always beneficial. Much pre-trade transparency reduces liquidity, because traders are unwilling to reveal their intentions to trade (Madhavan, Porter and Weaver 2002). Too much post-trade transparency can induce fragmentation, as traders seek off-market venues for their trades.

(4) Changes in transparency are likely to benefit one group of traders at the expense of others (Madhavan 2002).

Consequently, no particular market structure will be equally preferred by all traders and dealers.

1.5. Microstructure models

Theoretically, every investor wants to maximize his utility, by buying a stock at the lowest price and selling it at the highest price within a certain investment horizon. In every market structure, the ask price, the price at which an investor can buy, is different from the bid price, the price at which it is possible to sell. Therefore, the realization of the investor's objective requires a full understanding of the price formation process. The aim of this chapter is to summarize theoretical and empirical works on some of the most important microstructure models in this field. Any survey must be selective, especially for the microstructure literature, which comprises literally thousands of research articles spanning over decades. The microstructure literature considers costs of transactions, fiscality and other frictions in the analysis of the price formation process of financial assets. Cohen, Hawawini, Maier, Schwartz and Whitcomb (1980), Biais (1989) and Peiers (1997) have analysed how some mechanisms of market exchange can influence price formation in the presence of such frictions. In particular Cohen, Hawawini, Maier, Schwartz and Whitcomb (1980) say in their paper that the literature on security market microstructure discusses the interplay between market participants, trading mechanisms and the dynamic behaviour of security prices in a regime where frictions impede the trading process. These frictions lead to a bid-ask spread and to a price settlement that is different from one stock to another. Many old models claim that the price formation is independent of transaction costs, behaviour of traders, organization of financial markets and revelation of information. However, these elements are important variables, which can influence the price formation process. Theoreticians have constructed many models in order to explain how the equilibrium price must consider investors' behaviour and security market structure. Recent studies on the microstructure of security markets draw attention to the role of the market organization in the determination of security prices. It is now increasingly recognized that institutional factors, such as the broker's handling of investor orders, the management of the limit order book or the existence of designated specialists with a firm obligation to maintain price continuity, affect the speed of price adjustment to changing conditions (Beja and Goldman 1980). The determinant of prices in a security market and its adjustment to new conditions is of great interest in the financial literature. Among the first investigations into the behaviour of stock prices were Bachelier (1900) and Kendall (1953). Kendall (1953), thanks to Bachelier's doctoral thesis, suggested the random walk hypothesis and developed the idea of market efficiency. After Kendall (1953), other authors such as Fama (1965) and Samuelson (1965), defined the concept of market efficiency, with three degrees of efficiency suggested later by Fama (1970). This theory is based on the random walk of price variation and considers the following hypothesis:

1. Homogeneity of investor expectations
2. Cost-free availability of information

Financial studies have considered other anomalies affecting stock prices (PER, week-end effect, January effect, etc), but all these hypotheses concerning efficiency theory were unable to explain the reality of the price formation process. Hypotheses such as homogeneity and cost-free availability of information, are unreal. Investor expectations are heterogeneous, because they differ with respect to richness level, beliefs, risk aversion and quality of information possessed. Heterogeneity in the price formation process is the basis for developing rational expectation models. These models consider that investors have much more information available, namely their own information and the information derived from prices which reveal totally or partially the private information of other market participants. Admati (1985) says that, if, in a speculative market, agents have diverse and asymmetric information, the equilibrium price will usually contain information beyond that held originally by each agent. This observation, together with the assumption that agents make statistically correct inferences based on all the information they possess, including current prices, leads to the notion of a rational expectation equilibrium, where equilibrium prices affect the behaviour of the agents (both by entering their budget constraints and by influencing their beliefs and predictions). Admati (1985) and Admati and Pfleiderer (1988) consider the heterogeneity expectations in their model of price formation.

Grossman (1976) shows that the price can resolve the asymmetric information problem which exists between informed[13] and uninformed agents. He shows that is possible to obtain a complete revealing equilibrium, where prices fully reflect the information (public and private).

Problems can occur when the information obtained by the informed has to be paid for. In fact, if equilibrium prices reveal all the available information, the informed traders couldn't obtain more profit than the uninformed one. Under these conditions, nobody has an interest to pay in order to be informed, and therefore equilibrium prices can not reveal any private information. Grossman and Stiglitz (1980) come to the conclusion that the price cannot be fully revealing. In order to solve this problem, the authors show the possibility of introducing a noise. This leads to the noisy rational expectation models (Grossman and Stiglitz (1980), Hellwig (1980), Admati (1985), Battacharya and Spiegel (1991)). The noise denotes investors with other objectives beside informational ones: liquidity traders.

Liquidity traders' reasons to exchange are liquidity needs, fiscal advantages or information they erroneously consider superior, for reasons that are not related directly to the future payoffs of financial assets[14]. A reasonable approach is to differentiate between discretionary liquidity traders and nondiscretionary liquidity traders (Admati and Pfleiderer 1988). Discretionary liquidity traders can be strategic and must operate over a given day, choosing when to trade during the day, subject to the constraint of trading only once during the time period, so as to minimize the (expected) cost of their transaction, i.e. they deal in the periods of lowest costs. Nondiscretionary liquidity traders must trade a particular number of shares at a particular time, regardless of costs.

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13 Informed traders trade in order to benefit from private information about the firm's value; they maximize their expected trading profit.

14 Included in this category are large traders, such as some financial institutions, whose trades reflect the liquidity needs of their clients or who trade for portfolio balancing reasons. Most models that involve liquidity (noise) trading assume that liquidity traders are executed by large institutional traders.

Noisy rational expectation models are not always sufficient to explain the price formation process, because these models use the hypothesis that investors have a negative utility function. Therefore, the richness level is not considered in the determination of the equilibrium price.

Noisy rational expectation models assume that agents know the models of the economists which they use for the description and the definition of prices. The behaviour of economic agents does not always follow economists' models (Shiller (1990)). The noise trading theory has a positive impact on the study of market microstructure because, it helps to develop models which consider the interaction among informed traders, liquidity traders and market makers for a better description of the bid-ask price formation. This theory is criticizable because of the difficulty to identify the noise trader. As a number of studies have documented (Kendall 1953, Fama 1965, 1970, Solnik 1973, Solnik and Bousquet 1990, Jain and Joh 1988, McInish and Wood 1990), the microstructure theory has a positive impact on studies regarding price formation of financial assets.

In the microstructure models, the existence of transaction costs involves some frictions in the price formation process. There exist two types of costs:

1. Direct costs: information costs, costs of market access
2 Implicit costs: the bid-ask spread, the difference between the lowest available quote to sell the security under consideration, and the highest available quote to buy the same security (Choi, Salandro and Shastri 1988). The BAS represents one component of the transaction costs faced by a trader who desires immediacy and actively seeks to establish position in a security (Demsetz 1968).

In particular, the BAS theory has continuously progressed since the seminal work of Demsetz (1968) and the first spread measurement model provided by Roll (1984). The bid-ask spread becomes the central axis of the microstructure theory15. The bid-ask spread is recognized and widely studied for the Anglo-Saxon markets, where price-driven markets are the dominant organization. In an order-driven market, the spread is also a reality. The different theories of financial markets define two typologies of bid-ask spread (Bessembinder and Kaufman (1997) and Stoll (1989)):

1. Quoted spread: it is the difference between the ask and the bid price quoted by the market maker. In an order-driven market, it is the difference between the two best limits of the limit order book on each side. It is directly observable and is related to characteristics such as the volume of trading stock price, the number of market makers, the risk of security and other factors (Stoll 1989).
2. Effective spread: it reflects the reduction in trading costs attributable to trades executed within the quotes (estimate of the percentage execution cost actually paid by a trader

[15] The pioneering analyses of BAS are: Stigler (1964), Demsetz (1968), West and Tinic (1971), Tinic (1972), Tinic and West (1972, 1974), Garman (1976), Beja and Hakansson (1977), Cohen, Maier, Schwartz and Withcomb (1978), Benston and Hagerman (1974), Hamilton (1976, 1978), Branch and Freed (1977), Stoll (1978), Ho and Stoll (1979, 1980), Newton and Quandt (1979), Schleef and Mildenstein (1979), Smidt (1979), Amihud and Mendelson (1980).

and of gross revenue to the supplier of immediacy). There are two components: price impact and realized half spread (Bessembinder and Kaufmann 1997). Price impact measures the average information content of the trade, which comprises market making costs in the form of losses to better informed trades. Realized half spread (price reversal after a trade) measures the effective gain (net of losses to better informed traders, but gross of inventory and order processing costs), of the service given by the market maker. The latter is the only one that has an economic meaning for the market maker. It is equal to the expected gain of the dealer through a round trip exchange. Realized half spread ought to be estimated. However, its estimation is difficult because of intermediation costs, defined as the difference between transaction price and equilibrium price. The equilibrium price is not observable. It is less than the spread quoted by a dealer (Stoll 1989).

Quoted and effective spreads are equal only under two conditions:

1. Absence of transaction costs
2. The execution of each order at the best bid and ask price.

Lee (1993) compares average quoted and effective BAS for trades executed off the NYSE to that executed on the NYSE within 10 minutes. Huang and Stoll (1994) estimate quoted and effective (realized) spreads by exchange, for a sample of large capitalization NYSE issues. Bessembinder and Kaufmann (1997) extend the analysis to include small and medium capitalization as well. They find that the effective BAS is only modestly larger for trades executed off the NYSE. However, the trades transacted off the NYSE contain less information, as measured by their impact on subsequent market prices, than trades executed on the NYSE. As a consequence, the realized BAS is lower by a factor of two to three for trades executed on the NYSE.

The observation that realized BAS is substantially greater for trades executed off the NYSE implies higher market making costs for the non-informed.

1.5.1. Determinants of the spread

Schwartz (1988) identifies four classes of variables as determinants of BAS: activity, risk, information and competition. Greater trading activity can lead to lower spreads, due to economies of scale in trading costs. Using trading cost arguments, previous researchers show that a number of activity variables are significant determinants of BAS, including:

1. The average number of shares traded (Tinic 1972)
2. The volume (Tinic and West 1972, Branch and Freed (1977), Stoll (1978))
3. The number of transactions (Benston and Hagerman (1974).

Copeland and Galai (1983) model the BAS as an option provided by the market maker, and show that the BAS is inversely related to the frequency of trading. They note that since less frequent trading usually means lower trading volume, the BAS is likely to be inversely related to measures of market activity. Inventory control models (Garman (1976) and Ho and Stoll (1980, 1981) show that uncertainty in the arrival of buy and sell orders forces dealers away from their optimal inventory position. Consequently, as in Amihud and Mendelson (1980), increasing order arrival variability would increase the BAS. Tinic (1972) and Hamilton (1978) hypothesize instead a direct relationship between the BAS and the intrinsic risk of holding a security. Several more recent studies relate information asymmetries between informed and liquidity traders to trading cost in security markets. Glosten and Milgrom (1985) and Hasbrouck (1988) think that as dealers' perceived exposure to private information rises, the BAS widens. Only few researchers (Hamilton, 1978), have focused on the intensity of competition among traders as a source of downward pressure on the spread.

In the literature, many researchers who studied the bid-ask spread components in order to explain transactions costs, have documented that the quoted spread must cover three types of costs incurred by providers of immediacy:

1. Order processing costs (Roll 1984).
2. Inventory holding costs (Stoll 1978, Ho and Stoll 1979, 1980, Amihud and Mendelson 1980). Under the inventory cost model, realized spread is less than quoted spread, because dealers lower both bid and ask prices after a dealer purchase and raise both after a sale, in order to induce transactions which will equilibrate the inventory.
3. Adverse information costs (Grossman and Stiglitz 1980, Copeland and Galai 1983, Glosten and Milgrom 1985, Kyle 1985 and Easley and O'Hara 1987). Under the adverse information cost model, bid and ask spread prices are changed in a similar way to reflect the information conveyed by transactions.

I shall try to analyse these three components in more detail.

1.5.1.1. Order processing costs

The order processing cost can be viewed as the compensation to the market maker for providing liquidity service. Copeland and Stoll (1990) argue that order costs represent clerical costs of carrying out a transaction, the cost of the dealer's time, and the cost of the physical communication and office equipment necessary to carry out the transaction. To a considerable degree, order costs are fixed with respect to any particular transaction. Because of these fixed costs, the average order processing cost per share should decrease as trade size increases.

Under the assumption that the market maker faces only order processing costs, Roll (1984), Glosten (1987), Niederhoffer and Osborne (1966) derive a simple measure of the spread based on the negative autocovariance of security returns.

1.5.1.2. Inventory holding costs

A. Theoretical approach

In the inventory models, the risk faced by a dealer during a transaction is an inventory risk: at the ask price proposed by a dealer for an asset, some traders may buy a certain amount of that asset, but there may be a much smaller (or much greater) amount of the asset offered at the bid price for the same time. During these periods, the dealer position is not hedged (Kast and Lapierd (1997)). Both authors say that the obligation of the market maker to be a counterpart can lead him to hold portfolios whose risk and diversification characteristics are not optimal. This is a cost for the market maker, which hit the customer in the form of a wide spread. The spread compensates market makers for bearing the risk of holding unwanted inventories.

Inventory models were developed by Stoll (1978), Amihud and Mendelson (1980), Ho and Stoll (1980, 1981), Biais (1993) and Kast and Lapierd (1997). They suggest models that explain the behaviour of a risk averse market maker (monopolist) who has to take a risky position in order to satisfy the liquidity needs of investors. Stoll's (1978) study shows that inventory holding costs are a function of:

1. Characteristics of the market maker: his risk aversion and his inventory position
2. The absolute value of the transaction
3. Characteristics of the title: return volatility and time holding period. Holding period depends on the transaction volume.

He finds that the stock spread is thin when the dealer has a more important position.

Ho and Stoll (1980, 1981) also show that uncertainty in the arrival of buy and sell orders forces dealers away from their optimal inventory position.

The main implications of such inventory models are:

1. If a dealer is long, he may be reluctant to take an additional inventory without dramatic temporary price reductions. Price effects become larger following a sequence of trades on one side of the market (institutions break up their block trades).
2. Transitory inventory effects affect market impact costs, which will be greater toward the end of the day, because market makers must be compensated for bearing overnight risks (Cushing and Madhavan 2001).
3. The degree to which dealers are capital constrained (larger inventory effects might be observed for dealers with less capital)
4. Market makers can be viewed as an institution to bring buyers and sellers together in time through the use of inventory. A buyer doesn't need to wait for a seller to arrive, but may simply buy from a dealer who depletes his or her inventory.

B. *Empirical studies*

Kast and Lapierd (1997) model the dealers' behaviour when the bid and ask prices are fixed. These prices reflect the risk aversion of the market makers. Benston and Hagerman (1974) suggest the width of the spread is an increasing function of the market maker risk aversion, and decreases with the number of market makers. If the market makers are risk averse, then inventory holding costs per unity increase with the risk of holding non optimal portfolios. Besides, the thinness of the spread can be associated with the existence of a large number of market makers, because the presence of other dealers on the market allows the other dealers to compensate the temporary imbalance of their inventory by doing inter-dealer exchanges.

Biais (1993) confirms Benston and Hagerman's (1974) results and suggests that the positive relation between inventory and spread is much more pronounced when the variance of the asset is important.

Mannaï (1995) tries to decompose the spread in the option market, where inventory holding costs are an increasing function of volatility.

Ho and Stoll (1983) develop a theoretical model in a multi-period context. This model considers market equilibrium, the behaviour of two market makers and the determinants of the bid-ask spread. Hansch, Naik and Viswanathan (1998) confirm, through an empirical study in the London market, the theoretical results of Ho and Stoll (1983):

1. The composition of the market spread depends on the position of the market maker. If he holds important risky assets, the dealer wouldn't buy other stocks in order to avoid increasing his positions on one side of the market. He would announce a favourable bid price. On the contrary, if his position is near zero or negative, the market maker would quote an interesting ask price.
2. The market spread is a function of expectation of the market makers on the positions of their competitors.

Cohen, Maier, Schwartz and Whitcomb (1981) and Hamon, Handa, Jacquillat and Schwartz (1994) study the inventory holding cost in a market structure without market makers, and where the spread is determined by the limit orders. There are two implications: first, the inventory effect causes quotations to change systematically as a function of order flow. After a buy (sell), the dealer stocks increase (decrease), and as a consequence his quotations decrease (increase). Secondly, these spread movements render much more likely the arrival of a sell order as a consequence of a buy order, and vice-versa. This means a negative order autocorrelation.

Choi, Salandro and Shastri's (1988) approach treats the BAS as a holding cost for the dealer. In this framework, BAS is directly related to the dealer's inventory costs which he incurs because the dealer cannot diversify his portfolio risk (Demsetz 1968, Ho and Stoll 1981). This approach has been criticized mainly because, in practice, dealers diversify operations across many securities, and practice risk sharing through partnership and pooling arrangements.

Bessembinder (1992) finds that spreads widen with proxies for inventory carrying costs. These proxies are: forecast of price risk, interest rate based measures of liquidity costs, and a non trading indicator. These findings can be contrasted with those of other studies conducted in equity markets (Hasbrouck (1991), George, Kaul and Nimalendran (1993) and Madhavan and Smidt (1991)) where inventory costs appear to have little effect if any on market maker quotes.

In the model of Amihud and Mendelson (1980), as the market maker approaches the desired inventory position, the BAS is reduced. Hence, if greater volumes of trading or larger trade sizes move a dealer away from the desired inventory position, spreads will increase. Ho and Macris (1984) show that the market maker adjusts his quotation in relation to his inventory position. He increases his quotations when his inventory level is below his optimal objective. Madhavan and Sofianos (1998) invalidate this result. They show that market makers check their inventories, participating actively in the market instead of only adjusting their quotations. Specialists can manage their positions by selectively trading rather than changing their bid and ask quotes. If specialists selectively time the magnitude and direction of their trades to control their inventory, they will participate more actively on the sell (buy) side when they are long (short).

Lee, Mucklow and Ready (1993), Hasbrouck and Sofianos (1993) and Madhavan and Smidt (1993) also find some evidence on the relation of BAS to dealer inventory control costs. They find that for a sample of NYSE stocks, BAS becomes wider in response to higher trading volume. Consequently, at the opening and closing of the market when volume tends to be higher, there would be greater order imbalance and, therefore, the BAS would be wider than during the rest of the day. Thus, for a specialist structure such as the NYSE, this type of model would predict a U-shaped BAS pattern, as a single market maker may be forced to accumulate unwanted inventories during peak trading volume, while in a system using competing market makers, such as the CBOE, he will be less likely to accumulate such positions.

Furthermore Chan, Chung and Johnson (1995) suggest that specialists and competing market makers may differ in their ability to manage imbalances by using their bid and ask quotes. In maintaining a fair and orderly market, specialists cannot execute orders only on one side of the spread, unlike competing market makers, who can set bid and ask quotes to attract trades on one side of the spread only.

Analysis of inventory based models suggests that specialists will widen spreads during periods of high volume, i.e., at the open, and the close. This theory does not explain the occurrence of high volume at these times; for this I shall turn to information models.

1.5.1.3. Adverse information cost (asymmetric information models)

A. Theoretical approach

The presence of investors with private information modifies the behaviour of the market makers and affect the bid-ask spread (Bagehot 1971). In the asymmetric information models (Copeland and Galai (1983), Glosten and Milgrom (1985) and Easley and O'Hara (1987)), the spread is considered as an indemnity of potential losses which the market maker incurs in the presence of better informed investors (adverse selection component).

Informed investors are defined as investors having superior information with respect to the market maker. If the dealer isn't able to identify these investors, he has to increase his spread in order to compensate his possible losses to informed investors.

Bagehot (1971), Copeland and Galai (1983) and Glosten and Milgrom (1985) assume the existence, in a continuous market, of informed and non-informed investors and risk neutral market makers. Giving this situation, the dealer includes in his prices a cost that compensates him for the expected losses to informed investors when activity is disguised through noise traders. Kyle (1985) underlines this disguise behaviour and gives the following interpretation: in the equilibrium, informed investors, in order not to reveal themselves, have to exchange the same quantity as the non-informed ones. In this way, the informed ones, who imitate the behaviour of the liquidity traders, reduce the capacity of the dealers to distinguish between their orders and the ones executed by the non-informed. Since they cannot distinguish the trading of the insider from the trading of noise traders, the noise traders in effect provide camouflage, which enables the insiders to make profits at the expense of market makers.

In fact, if the insider exchanges a different quantity with respect to non-informed agents, he is immediately revealed to the market. Thus, there is a gradual incorporation of information into prices. Easley and O'Hara (1995) consider the case where the non-informed can exchange small and big quantities. They show that, in this case, there exists equilibrium where the informed agents exchange only big quantities. This leads to a different spread for big and small orders. They also suggest that, when the number of transactions is thin until a certain moment, it is less probable that there is an informed agent in the market. This means that the spread decreases during the time when the frequency of transaction is thin and the exchange volume is low.

B. *General empirical evidence*

Copeland and Galai (1983) pay attention to the effect of information in the spread. In the presence of informed and non-informed investors, the market maker is likely to offer an option out of the money for a certain number of stocks at a certain moment. The exercise price of this option determines the spread. Copeland and Galai (1983) show that the ask and bid prices are the result of an arbitrage between eventual losses and expected gains from liquidity providers. Nevertheless, according to Glosten and Milgrom (1985), the mean value of the spread depends on the distribution manner of the arrival of the informed and non-informed investors, the elasticity of supply and demand of the non-informed, and the information quality of the informed during the period of transaction. Concerning the impact of the number of investors on the spread, Glosten and Milgrom (1985) confirm the result of Copeland and Galai (1983). According to them, the increasing number of informed leads to a wider spread. In the Glosten and Milgrom (1985) model, the adverse selection spread component is equal to the revision of the expectation of the market makers after the submission of an order. When someone submits an order to buy (sell) stocks, the uninformed market maker, knowing that the order might be information motivated, revises his expectations of the future stock value upward (downward).

Since the revision in expectations, conditional on the type of order received, can be anticipated, the rational market maker incorporates it into his bid and asks prices.

For Hasbrouck (1991), trades are a signal of private information. In his article, he proposes two new measures of trade informativeness. Many other microstructure models decompose prices into efficient ones and a disturbance term that comprises various microstructure imperfections. The variance of efficient price changes can be decomposed into trade-correlated and uncorrelated components. The trade correlated component has a natural interpretation as an absolute measure of trade informativeness (efficient price variance attributable to trade). The ratio of this component to the total variance is a relative measure (i.e. a proportion normalized with respect to the total public information). For a sample of NYSE listed companies, trades are found to be more informative for lower capitalization in both absolute and relative terms. From an analysis of intraday patterns, it appears that trades at the beginning of trading are more informative in absolute terms, but slightly less informative in relative terms (Hasbrouck 1991).

Trading on private information creates inefficiencies, because there is a less than optimal risk sharing (Glosten 1989). This occurs because the response of market makers to the existence of traders with private information is likely to reduce market liquidity. In fact, if the adverse selection is too extreme, each market maker will expect to lose money on trade. The consequence is that the market shuts down until enough public information arrives to relieve the adverse selection problem. The institution of a monopolist specialist may ease this inefficiency. A monopolist specialist may even close the market in such a situation, but he doesn't have to. The specialist may get some information from the informed by keeping the market open, thus reducing the adverse selection problem and making subsequent trades more profitable. The result is that both the liquidity traders and the informed traders will be better off than in a competing market maker system. While competing market makers are forced to set price schedules that lead to a conditional expected profit of zero (conditioned by the quantity traded), the monopolist specialist maximizes expected profits whatever the quantities (Glosten and Milgrom 1985, Glosten 1989). Neuberger and Hansch (1996) address the question whether dealers on the LSE act strategically, while a large part of the microstructure literature assumes that dealers are forced to make zero expected profits on each trade (Glosten and Milgrom 1985). They argue that, if dealers can get valuable information from order flows, one might expect them to act strategically in order to make money on their own account and avoid revealing their knowledge through price setting. They deliberately accept losses on some trades in order to make superior profits on others. Dealers normally do have information, which is not publicly available. In many dealership markets (most OTC), trade publication is neither on time nor comprehensive. Dealers tend to have better information than the other market participants about trades and prices. Even when trade prices and quantities are published promptly, there is much information available to the dealer, which is not made public. Thus, if dealers know more than other investors, how do they make use of that information ? They may not always be able to use the information to make money, but in many markets it is possible for a dealer to trade on his information. If he can trade on his information, he is also able to act strategically. This is what the authors also find.

Easley and O'Hara (1987), Kyle (1985) and Glosten (1987) have developed theoretical models suggesting that asymmetric information components should increase with the quantity traded. Lin, Sanger and Booth (1995), Huang and Stoll (1994), Lin (1992), Stoll (1989) Koshi and Michaely (2000)16 have found empirically that this assumption is correct. Jones, Kaul and Lipson (1994) suggest to make a distinction between competitive and strategic models. In competitive models with asymmetric information, the size of trades is positively related to the quality (or precision) of the information possessed by informed traders. Therefore, trade size introduces an adverse selection problem into security trading, because informed traders prefer to trade large amounts at any given price (Pfleiderer (1984), Easley and O'Hara (1987), Grundy and McNichols (1989), Holthausen and Verrecchia (1990), Kim and Verrecchia (1991)). Consequently, as Pfleiderer (1984) and Kim and Verrecchia (1991) explicitly show, there is a positive relation between absolute price changes and volume, where volume is measured as the aggregate demand of all investors.

In strategic models, asymmetric information also leads to trading, but an informed monopolist trader may camouflage his trading activity by making several small size trades rather than one large trade (Kyle (1985), Admati and Pfleiderer (1988) and Foster and Viswanathan (1990)). Such strategic behaviour may attenuate the positive relation between the size of transactions and the informed (monopolist) trader's information. Therefore, in both competitive and strategic models, the size of trades or volume of the informed agents is positively related to the quality of their information, thus resulting in a positive relation between volume and absolute price changes.

Why does the effective spread increase with trade size ? The conjecture that the increase is due to adverse information is based primarily on Easley and O'Hara (1987). The results of Lin, Sanger and Booth (1995) are also consistent with the model of Easley and O'Hara (1987) and supportive of their conjecture.

Lin, Sanger and Booth's (1995) measured the adverse information as a permanent component of the spread, but this might be biased for several reasons, especially in large trades: continuity requirements and the presence of limit orders may prevent the specialist from immediately adjusting quotes to a new equilibrium level. Another potential problem with their estimate of the adverse information component of the spread is that it does not use information contained in previous trades or quotes.

Chung, McInish, Wood and Whyhowski (1995) suggest that market makers deduce the extent of the adverse selection problem associated with a stock, and set up the BAS accordingly, by observing how many financial analysts are following the stock. Market makers do this based on the belief that more financial analysts would follow a stock with a greater extent of information. Similarly, financial analysts deduce the profit potential of a stock from the size of the spread set up by the market makers (based on the expectation that market makers would set up a greater spread for a stock with a greater information asymmetry).

[16] Koshi and Michaely (2000) investigated the effect of asymmetric information on prices and liquidity by analyzing trades, quotes, spreads and depths. Their finding are consistent with the hypothesis that large trades contain more information. Results are stronger for purchases than sales. Quoted prices are better measures of information effects than transaction prices, because they check for bid-ask bounces.

Benston and Hagerman (1974) use the unsystematic risk of a security as an empirical proxy for the degree of the market makers' exposure to informed traders. They hypothesize that the more frequent occurrence of firm-specific events leads to a greater unsystematic risk and, consequently, a greater opportunity for informed traders to trade against market makers. They predict a positive correlation between spreads and unsystematic risks. Stoll (1978) suggests that market makers' losses to informed traders will be greater for stocks with a greater trading volume. Chiang and Venkatesh (1988) use insider ownership and institutional holdings as proxies for the degree of information asymmetry faced by market makers.

Noronha, Sarin and Saudagaran (1996) estimate the changes in the degree of asymmetric information after international listings. They use three different tests, developed by Hasbrouck (1991), Madhavan and Smidt (1991) and George et al. (1991), and arrive at the same conclusions as Freedman (1992) namely that dual listing attracts informed traders, because it increases their opportunity to trade on their inside information. Similar results are obtained for the Toronto Stock Exchange on the basis of the Hasbrouck (1991) VAR approach.

Foster and Viswanathan (1996) analyze a multi-period model of trading with differently informed traders, liquidity traders and market makers. Generalizing Kyle’s (1985) informed monopolist trader model, Foster and Viswanathan (1996) assume that informed traders have disparate (heterogeneous) information and estimate the value of an asset not only from their own private information, but also using any information revealed by other traders during trading. Kyle (1985), Michener and Tighe (1991), Holden and Subrahmanyam (1992) and Foster and Viswanathan (1993) show that with identical information, informed traders compete very aggressively, and most of the information is impounded in prices within a few trading periods (rat race).

On the other hand, with heterogeneous information, each trader has some degree of monopoly power, because part of his information is known only to him. This reduces the degree of competition between traders, which provides an incentive to trade less aggressively. In addition, the correlation between the signals of the informed traders falls considerably as more trading occurs.

C. *Empirical evidence of the impact of public information on the asymmetric components*

Kim and Verrecchia (1991) model the effects of information asymmetry prior to the release of public information. One implication of their research is that if market makers anticipate an increased probability of facing an informed trader before public information is released, the adverse selection component of the BAS will increase. Lee, Mucklow and Ready (1993) and Krinsky and Lee (1996) found empirical evidence that information asymmetry affects the BAS around the time of publication of earnings, and Koshi and Michaely (2000) found evidence of increased trade around the time of dividend announcements.

Information asymmetry might increase following the release of public information, if market participants differ in their ability to interpret the information. Kim and Verrecchia (1994) model an environment with superior information processors, who trade profitably after public information events. Peiers (1997) and Ito, Lyons and Melvin (1998) found empirical evidence that domestic currency dealers hold an informational advantage over foreign dealers with regard to economic conditions within their country. Although it is unlikely that Treasury market participants are aware of economic news before it is released, it is still possible that certain traders are better to estimate the impact of economic news on bond prices, so that their trades may reveal information to other market participants after a certain announcement.

Research on currency markets also highlights other types of information asymmetry that may be influenced by the release of public information. Lyons (1995) and Cao and Lyons (1999) model the foreign exchange market and suggest that the access of FX dealers to the customer order flow provides them with useful private information about short-term price movements. Evans and Lyons (2001) found empirically that a high portion of daily exchange rate movements can be explained by the order flow. Fleming (2001) found that order flow explains price changes in the US Treasury market as well, which suggests that Treasury dealers with sizeable customer order flows may possess an informational advantage in inter-dealer trading.

Koshi and Michaely (2000) analyze the price and liquidity impact of trades of different sizes in three distinct periods: when dividends are announced, during regular periods and after the dividends are paid. It is likely that a trade during an announcement period will contain more information than a similar size trade on a regular day. A trade around the ex dividend day is least likely to contain information, since much of the ex-day trading is tax- rather than information motivated. They also examine a fourth extreme case in which market participants know a priori that trades have no information content. Theory predicts that such trades have no information-based impact on either prices or liquidity.

Regarding liquidity, average spreads are higher, and depth is lower, during announcement periods than during regular or ex dividend periods. Thus, the impact of an individual trade on spreads is most pronounced during periods when the amount of information asymmetry is highest.

How can one isolate the asymmetric information component of the spread ? The simplest solution suggests that every variation of the quoted spread is caused by asymmetric information. Morse and Ushman (1983) were interested in the evolution of the asymmetric component during the period when the earnings of 25 stocks quoted on the Paris Bourse were announced. They applied the event study to the spread on the basis of daily incoming data. However, they found no spread modification during the quarterly earnings announcements.

Based on Beaver's (1968) approach, Gajewski (1996) conducted a similar study, but with intraday data. He showed that the spread widens significantly after earnings announcements. The revisions of the spread around earnings announcements reflect the mean change in the expectations of the agents. On the other hand, the volume conveys the heterogeneity of expectation revisions by the agents. Chiang and Venkatesh (1986) suggest that in order to isolate the asymmetric information component, one can limit the study to periods where the presence of informed investors is much more evident (during earnings announcements, stocks buy back programmes, IPO). They perform a regression of the quoted spread, with variables similar as in Stoll's (1978) study. For 75 stocks quoted on the NYSE, they observe a spread increase in cases where earnings and dividend announcements are dissociated. A similar method is used by Franz Rao and Tripothy (1995) with different variables (transaction volume, volatility, PER). A decreasing spread following earnings announcements confirms the hypothesis of a reduction of asymmetric information.

Chiang and Venkatesh (1988) use the percentage of ownership by corporate insiders as a proxy for the degree of information asymmetry faced by the dealer. A positive correlation between spreads (net of holding costs and firm size effects) and insider holdings would imply that dealers perceive a positive relationship between holdings and information asymmetry. The authors use Stoll's (1978) theory and the empirical work as a starting point.

They also advance the hypothesis that information asymmetry is likely to be higher before earnings and dividend announcements, and use time series data on spreads to ascertain whether spreads have increased during those pre-announcement periods.

1.5.2. Empirical studies on the three components of transaction costs

Ranaldo (2001) analyses the BAS components in an electronic limit order market. He uses three models: the Lin, Sanger and Booth (1995) (hereafter LSB) model, the Madhavan, Richardson and Roomans (1997) (hereafter MRR) model, and the AR(1) model, which is an extension of the MRR and considers also the price discreteness and the protracted effects of price and order dynamics, like Hasbrouck (1991). The three models are based on different assumptions, and their comparative analysis provides insights into the fundamental role of structural models. The spread components are examined also in relation to market liquidity, trade size and the entire trading day. Ranaldo (2001) finds that adverse selection and order persistence components increase with stock liquidity, and they characterize the afternoon trading. The adverse selection component (order processing being the main transaction component) increases (decreases) with trade size.

His conclusions are: first, in all three models, the order processing cost appears to be the widest component. Second, the LSB model seems to overestimate (underestimate) the adverse selection costs (order processing), and the MRR (1997) show somewhat inconsistent results especially in terms of adverse selection estimates. Third, in the LSB (1995) model, greater severe asymmetric information costs are associated with more liquid stock, whereas in the MRR (1997) and in the AR(1) model, the less liquid a stock is, the more severe is the adverse selection. Fourth, large volume sizes convey a higher degree of private information, while order processing costs decrease with order size. The three models provide yet more discordant results. Finally, the intraday patterns of spread components show that the asymmetric information affects the afternoon trading, in contrast to the US markets. Order processing is much more evident in the earlier part of the Swiss Stock Exchange trading.

The models of Madhavan, Richardson and Roomans (1997) and Huang and Stoll (1997) are closely related. The latter decompose the non-information part of the spread into inventory and order processing components. By contrast, the MRR (1997) model gives a better explanation on the effect of information flows on stock prices over the day, and comes to interesting conclusions:

1. Both information flows and trading frictions are important factors in explaining intraday price volatility in individual stocks.
2. Information asymmetry decreases steadily throughout the day, which is consistent with theoretical models (Handa and Schwartz 1991 and Madhavan 1992), where market makers learn from the order flow, as well as with evidence from experimental markets (Bloomfield 1996, Bloomfield and O'Hara 1996). However, dealer costs increase over the day (possibly reflecting the costs of carrying inventory overnight), so that the BAS exhibits the U-shaped pattern already noted in previous research work.
3. Execution costs can be estimated by taking into account the possibility that orders may be executed within the BAS, as well as information and inventory effects. The transaction costs are significantly lower than the BAS, once the probability of executing within the quotes is considered. In contrast to the BAS, the execution costs increase over the day. This result correlates with concentrated trading at the opening by discretionary liquidity traders who can selectively time their trades.

Since my work concerns the microstructure of an order-driven market with a limit order book, my most important reference will be the model developed by Glosten (1994).

1.6. Tick-by-tick data

The development of high frequency data bases, which provide the spreads (bid and ask), prices, trade volumes and time of each entry, allows for empirical investigations on a wide range of issues in the financial market. Goodhart and O'Hara (1997) offer a good summary, setting out some of the many important issues concerning the use, analysis and application of high frequency data sets and shedding new light on estimation models and on econometric methods of market microstructure.

Nowadays, many stock markets operate during opening hours, on a continuous, high frequency basis. Market microstructure studies depend on access to this data. Second-by-second data allows the virtually continuous observation of prices, volumes, trade size and depths. The ability to access and analyse high frequency data bases provides an enormous potential for a better understanding of financial markets.

One reason why data sets traditionally were low frequency and discrete, was the cost of collection and analysis. The advent of electronic technology has brought a dramatic fall in the cost of gathering data, and has decreased the cost of simultaneous transmission of "news" to physically dispersed viewers. These structural changes in trading have important implications for both the availability and interpretation of high frequency data. While each market differs, there are features in common. All centralized exchange data providing bids and asks, price and volume of any trade is usually available with a great degree of accuracy. In decentralized markets, there is no such quasi-automatic mechanism for providing information on quotes or trades at all.

Most automated exchanges collect data on price, quantity, time, trader identity, order type and depths. However, dissemination of this information to traders and outside observers, such as researchers, can be problematic in some markets, for example where the LOB is not displayed even to market participants. In recent years, much progress has been made with respect to the information available to market participants. Nowadays they can observe the five best orders, on each side of the book, in many important stock exchanges (for example in France, Switzerland and in the NASDAQ SuperMontage system).

The different process of price formation in an automated market, as compared to other systems, has been a subject of many studies. Glosten (1994) highlights the advantages of an electronic exchange, in particular compared to a market maker system but provides a useful overview of alternative systems. Domowitz and Wang (1994) analyse two computerized market designs with respect to pricing and their relative efficiency properties. Bollersev and Domowitz (1992) consider the effect of alternative trade algorithms in electronic clearing systems on volatility. Biais et al. (1995) analyse the behaviour of the Paris limit order bourse. In their view high frequency is fundamental for understanding the market behaviour. However, the availability of continuous time data sets presents the problem of dealing with a process which is itself time varying.

Traditional studies had relied on price observations drawn at fixed time intervals, considering that prices probably don't vary significantly over short time intervals. With the rise of microstructure research, the complexity of the process by which prices evolve through time has become more evident. A fundamental property of high frequency data is that observations can occur at varying time intervals, and trades are not equally spaced throughout the day. The sporadic nature of trading makes measurements, for example of returns and volatility, problematic. Researchers have dealt with these problems in a number of ways. Goodhart and O'Hara (1997) provide a useful review, and I shall survey the main publications in which high frequency data were used.

First, in studies on the statistical characteristics of continuous financial market processes, which examine for example time-varying volatility. The best known fact about intraday statistical characteristics is that many indicators broadly follow a U-shaped, or a reverse J-shaped pattern, namely: the volume of trades (Admati and Pfleiderer 1988, Foster and Viswanathan 1996, Jain and Joh 1988 Brock and Kleidon 1992); the volatility (Kim and Verrecchia 1991, Alizadeh, Brandt, Diebold, 2002[17]); the GARCH model (Bollersev et al. 1992, Engle 1992); the model variance as unobserved stochastic process (Jacquier 1994, Harvey and Shepard 1993, Harvey et al. 1994); the implicit forecast of volatility derived from option markets to forecast subsequent volatility in the spot market (Harvey and Whaley 1992, Canina and Figlewski 1993, Jorion 1994); the equity prices and the spread between the bid and ask quotes. Other interesting ways of study are, for example, the commonality in liquidity, the relation between volume imbalance and spread. The intriguing feature of such temporal intraday pattern is that it is not easy to explain it theoretically. My work tries to provide a new and significant contribution in this field of research.

Second, in the analysis of equity markets run by specialists. Here, much of the literature focuses on how market makers learn from trades, and how this in turn affects prices and quotes. The theoretical literature focuses on analysing the factors influencing a single market maker in his determination of the spread. Three main factors are identified: first, inventory carrying costs (Amihud and Mendelson 1980, Zabel 1981, Ho and Stoll 1983 and O'Hara and Oldfield 1986). Second, the existence of traders with private information (Kyle 1985, Glosten and Milgrom 1985, Easley and O'Hara 1987, 1992, Glosten 1989, Admati and Pfleiderer 1988, 1989) and finally, the other costs and the competitive conditions which help to determine the mark-up that the single market maker can charge. These conditions are frequently taken as being constant over the day, but in some models (Brock and Kleidon, 1992), they can be time varying.

Another issue of importance is whether high frequency data bases will reveal limitations to the efficiency of markets, thereby providing a way of making an excess return from trading.

Inter-market relationships form another main block of empirical research within the micro-market studies (Stephan and Wahley 1990, De Jong Nijman and Röell 1996, Ranaldo and Vukic 1999). The ability to access and analyse high frequency data bases provides enormous potential for advancing the understanding of financial markets.

[17] They explain the log range as a superior volatility proxy.

1.7. Conclusions

The positive changes in financial markets and the access to high frequency data permit researchers to deepen their understanding of the price formation process, where the bid-ask spread has always played an important role. It is widely recognized that there are three components constituting the bid-ask spread.

Apart from order processing costs, the market microstructure literature has focused on two additional costs of market making which are also reflected in the spread: the inventory and the adverse selection costs of trading. Demsetz (1968), Stoll (1978), Amihud and Mendelson (1980) and Ho and Stoll (1981, 1983) emphasize the inventory holding costs of market makers, whereas Copeland and Galai (1983), Kyle (1985), Glosten and Milgrom (1985), Easley and O'Hara (1987) concentrate on the adverse selection costs faced by liquidity suppliers when only some traders are informed. The detection and measurement of the components constituting the BAS has progressed since the seminal work of Demsetz (1968). Subsequent models have become more complete and complex. Several statistical models empirically measure the components of the BAS. In one class of models pioneered by Roll (1984), inferences about the BAS are made from the serial covariance properties of observed transaction prices. Following Roll (1984), other covariance spread models include Choi, Salandro and Shastri (1988), George, Kaul and Nimalendran (1991), who solve Roll's problem of time varying expectations of price return, and Stoll (1989) (order persistence). In another category of models, inferences about the spread are made on the basis of a trade indicator regression model. The latter is based solely on the direction of trade, whether incoming orders are purchases or sales. Also covariance models depend on the probabilities of changes in trade direction. Huang and Stoll (1997), who developed a general model for understanding all the relevant spread components, show that the existing trade indicator and covariance models fail to decompose the spread fully into all its components. Order processing and inventory costs are considered together even if these components are different. Glosten and Harris (1988) were the first to suggest such a decomposition model, but they did not have the quote data in order to assess the model directly. Lin, Sanger and Booth (1995) estimated the effect of trade size on the adverse information component of the spread, and Hasbrouck (1988, 1991) models the time series of quotes and trades for the NYSE in a vector autoregressive framework in order to make inferences about the sources of the spread. He concludes that there is evidence for inventory and information effects. Statistical models of spread components have been applied in a number of ways: for comparing dealer and auction markets (Affleck, Hedge and Miller 1994, Lin, Sanger and Booth 1995a, Porter and Weaver 1995), for analysing the source of short run return reversal (Jegadeesh and Titman 1995), for determining the sources of spread variation during the day (MRR 1997), for testing the importance of adverse selection of spreads of closed end funds (Neal and Wheatley 1998) and for assessing the effect of takeover announcements on the spread components (Jennings 1994).

CHAPTER 2

EMPIRICAL ANALYSIS OF THE FRENCH STOCK EXCHANGE TRADING STRUCTURE

2.1. Abstract

This chapter describes and analyses the trading structure at the Paris Bourse, before and after the merger with the Amsterdam and Brussels Stock Exchanges. In the empirical part, the stocks of the CAC 40 index over a one-year period are analysed. First, stylised facts based on intraday transactions and order book data are reported, focusing on the intraday behaviour of returns, volatility, trading activity and bid-ask spread. Second, the behaviour of the determinants of intraday market liquidity during the trading session is checked, and finally the relation between volume imbalance and spread is investigated.

My main empirical conclusions about intraday patterns are that:

(1) Volumes follow an J-shaped pattern, confirming in part the empirical regularities previously found on the US markets and in some European markets. (2) Volatility is highest at the beginning of the day, diminishes throughout the trading day, and rises again and at the end of the trading session. (3) Volume imbalance is strong during the first hours of trading. (4) This is true also for the different measures of the BAS, which follows a reverse J-shaped pattern.

The determinants of intraday market liquidity show that market depth, in terms of trading volume, follows a TARCH model, whereas market depth, estimated by order volume imbalance, and the tightness of intraday market liquidity follow a GARCH model. The time dimension and the intraday return volatility are also analysed, and both follow a GARCH model.

I also found a strong relationship between volume imbalance and spread, mainly during the period from December 1, 1999, to March, 31, 2000.

2.2. Introduction and literature review

Two aims for trades are widely recognized as important: liquidity and information (Admati and Pfleiderer 1988). In this chapter, my analysis focuses on the first objective. A fundamental quality sought by every investor is the liquidity of the financial market, which applies also to his choice and management of a portfolio. In the microstructure literature, many researchers (among others Kyle (1985), Admati and Pfleiderer (1988), Grossman and Miller (1988), Handa and Schwartz (1996) and Harris (1995)) show that the way the market is organized and works, the behaviour of market participants and the economic, technological and institutional environment can have an influence on market liquidity.

The purpose of this paper is fourfold. In order to assess more accurately the importance of different features of market design, I first describe and analyse the trading structure of the Paris Stock Exchange and of the Euronext. Second, I present some stylised facts, which allow us to check whether certain anomalies found in previous studies are also characteristic for the Paris Bourse. In this respect, I differentiate the intraday patterns of the stock market through the commonly used measures of stock liquidity: volume, return, volatility, waiting time between subsequent trades, liquidity ratio, flow ratio and bid-ask spread. For each liquidity proxy, I check if it provides the same degree of estimation of market liquidity and discuss also its patterns. Third, I investigate the determinants of intraday market liquidity and, finally, I deepen the analysis on the relationship between volume imbalance and spread.

In the literature, the liquidity is traditionally associated with the activity of market makers that provide the liquidity. The spread represents a measure of the value of the liquidity service provided by the dealer (Demsetz 1968). But the liquidity is a property that belongs to every market, even if no market makers are present. In fact, in an order-driven market, the liquidity is provided by the limit orders given by the agents. The latter, considered as liquidity demanders, bear the costs of the spread, i.e. the cost of immediacy[18].

As Handa and Schwartz (1996) put it, "investors want three things from markets: liquidity, liquidity and liquidity". But the liquidity concept of financial markets is ambiguous, and is used without a clear definition (Kyle 1985).

Some authors have tried to give a definition of market liquidity. Keynes (1930) says that "if an asset is more liquid than another, it is more certainly realizable at short notice without loss". This definition suggests that the degree of liquidity of an asset can be measured along two dimensions: the risk of its final value ("more certainly realizable") and the availability of a market which can readily absorb the sale without adverse price change ("realizable at short notice without loss").

The definition given by Biais, Focault, Hillion's (1997) includes also an adverse price variation argument. In addition, they suggest a rapidity concept, namely for an agent to find a counterpart.

[18] Hasbrouck and Schwartz (1988) assess liquidity provision in three market centers: the NYSE, the American Stock Exchange (agency/auction market) and the NASDAQ (dealer market).

Black (1971) gives another definition and says that four conditions must be fulfilled:

1. Spread (represents the implicit cost per unity of liquidity);
2. Depth (the market can absorb, immediately or over a long period of time, important volumes without weighting on actual prices);
3. Resiliency (the rapidity of the prices to return, after an increase or decrease, to the previous levels);
4. Immediacy (investors can buy or sell at every moment and immediately).

In other words, a liquid market is a continuous and efficient market, where any amount of stock (small or large) can be bought or sold immediately, or over a larger period, near the current market price (Black 1971).

Considering the definitions given above, liquidity seems to be determined by the behaviour of at least four market features: spread, volume, price movements and waiting time. The intraday and daily evolution of these liquidity proxies has been the subject of a number of studies[19], with controversial conclusions about causes and effects of these empirical regular patterns.

The measure of liquidity is an object of theoretical controversies, as the conditions that must be fulfilled are difficult to measure. The common denominators are the rapidity (Gouriéroux, Jasiak, Le Fol 1997) and the capacity of the market to absorb important transaction volumes (Poincelot, 1996).

Bernstein (1987) discusses the different measures of liquidity and presents a survey of the relevant literature. Many researchers (Harris (1995), Grossman and Miller (1988), Kyle (1985), Admati and Pfleiderer (1988)) show also that the market microstructure has an influence on its liquidity. In fact, the liquidity degree of a stock can be analysed as a result of the coexistence of agents with different motivations. The impatient investor who demands liquidity and places a market order, is a non-informed investor who wants to realize a transaction before a given deadline (Harris (1995)). On the other hand, if the deadline is sufficiently far and the spread large, the patient investor (informed investor, liquidity provider) will put a limit order (Handa and Schwartz 1996).

Theoretical models have been developed to explain these empirical regularities as the response of market participants to the nature of information flow, the trading hours of an exchange, and other properties of the trading environment. Admati and Pfleiderer (1988) and Foster and

[19] The market microstructure literature has demonstrated that there are intraday patterns in returns (Wood, McInish and Ord (1985)), in the variability of returns (Wood, McInish and Ord (1985), McInish and Wood (1990a)), in the volume of trading (Jain and Joh (1988), McInish and Wood (1990b)), in the number of trades and in the number of shares per trade (McInish and Wood (1991b)), and in the daily index autocorrelations (McInish and Wood 1991a). The volume of deals, the volatility of equity prices and the spread all broadly follow a U-shaped pattern in the NYSE (Foster and Viswanathan 1989, Lockwood and Linn, 1990, McInish and Wood 1990a, 1991, 1992, Stoll and Whaley 1990, Lee et al. 1993, Sheikh and Ronn 1994, Easley et al. 1993). Explications of these patterns can be found in Kyle (1985), Glosten and Milgrom (1985) and Admati and Pfleiderer (1988, 1989).

Viswanathan (1989, 1990) developed models in which the interaction between various traders (strategic behaviour of liquidity traders and informed traders) leads to certain patterns in trading volume, BAS, variability and returns. Admati and Pfleiderer (1988) show that the interaction between potentially informed investors (whose private information is short-lived), discretionary liquidity traders and market makers leads to specific patterns in price changes. These patterns occur due to the fact that buying and selling volume are greater in distinct periods. Osborne (1962) also provides a pattern of the activities of market participants. He noted that since individual investors have more time to devote to financial decisions during the weekend, they are relatively more active in the market on Monday, which tends to be a day of strategic planning.

Higher volumes may also occur during the first hour, because investors transact on information gathered during the night and in the morning before the market opens. And volume increases before the end of the day may reflect investors who close or hedge open positions which they cannot monitor or change overnight.

Brock and Kleidon (1992) focus on modelling a larger BAS and greater price variability during the first and last hours of trading, when the volume is heaviest. Gerety and Mulherin (1992) extended the work of Brock and Kleidon (1992) and found that trading volume at the end of one day and the opening of the following day is related to expected overnight return volatility. They also found that the volume at the opening is related to the unexpected return volatility from the previous night.

Atkins and Basu (1995) attribute, instead, the U-shaped pattern of volume to public announcements for two reasons. First, the large traded volume at the beginning of the day could be the result of the aggregate amount of new information that becomes known between the end of one day and the opening of the following day. Second, the traded volume at the end of the day is much more difficult to explain. The authors suppose that if an announcement made after closing was known before the market closes then an increase in volume may be observed at the end of the day (any foreknowledge of a public announcement constitutes private information).

Intraday patterns in BAS were examined by McInish and Wood (1992), who found over the all day a reverse J-shape (a large spread in the first minutes of trading, declining over about 15 minutes to a level which lasts until the last few minutes of the day). While there are also differences in spreads across days of the week, these differences are much less pronounced than those during a single day. Furthermore, there is evidence that the pattern of differences across days of the week is not stable over a longer period of time.

Niemeyer and Sandås (1995) analyse the intraday behaviour of returns, trading activity, order placement and BAS. Their results show that: (1) Intraday U-shape in trading activity found in earlier US studies can also be observed on the Stockholm Stock Exchange, (2) Limit order placement follows an intraday U-shape too, (3) There is no distinct pattern in returns, and (4) The volatility and BAS seem to be higher at the beginning of the trading day.

Werner and Kleidon (1996) analyse intraday patterns for UK and US cross-listed stocks, in order to examine whether the fact that these stocks are traded in multiple markets significantly affects the information flow, trading pattern and dealer competition as captured by intraday patterns of volatility, volume and spreads respectively. British cross-listed stocks generate distinct and separate intraday patterns for volatility (which increases significantly when NY starts trading the ADR), volume (which increases during the overlap period), and spreads for each trading venue. These patterns resemble the U-shaped patterns found in previous work, with the important exception that spreads for cross-listed stocks decline throughout the trading day in each market.

Ranaldo (1999) examined the commonly used liquidity proxies (trading volume, returns, spreads, waiting time between subsequent trades). Some proxies had already been used previously as an interday liquidity measure (liquidity ratio and variance ratio), but in addition he provided some new indicators (order ratio and flow ratio). He applied these proxies to the 15 most liquid equities traded on the Swiss Stock Exchange, and found the outline of the peculiar intraday liquidity pattern. All his liquidity proxies indicated that the Swiss intraday liquidity patterns do not precisely follow a U or M-shape.

Intraday patterns can also be explained by inventory-based models (Amihud and Mendelson 1982). They claim that specialists widen their spreads in response to inventory imbalances. If imbalances accumulate during the course of trading, spreads will be larger at the close of the trade. On the other hand, information-based models argue that informed traders have their greatest advantage when the market first opens since price is an important source of information for uninformed liquidity traders (Foster and Viswanathan 1990, Brock and Kleidon 1992). Therefore, adverse selection costs should be greatest at the beginning of the day. Empirical evidence of these information effect is provided by Wei (1992), Hasbrouck (1991), Foster and Viswanathan (1993) and Lin, Sanger and Booth (1995). Furthermore, Lin et al. (1995) find that adverse selection costs decrease throughout the day for all trade sizes. Their research also suggests that the order flow is most informative in the morning, or, more generally, immediately after non-trading periods.

Bessembinder (1994), Lyons (1995) and Huang and Masulis (1999), however, found an increasingly strong and large inventory cost component of FX spreads as the trading day is coming to its close. In short, the intraday patterns of order flow and transaction costs indicate that information is revealed through trades, resulting in progressively smaller adverse selection costs as the day evolves. The increase in the spread during the last half-hour most likely reflects an increase in the cost (risk) of holding inventory over the upcoming non-trading period.

Based on the results of all the above mentioned studies, in my paper, I shall try to answer to the following questions, taking the Paris Bourse as an example: (1) does an intraday pattern of market concentration exist, (2) how do different liquidity proxies interact and (3) do they come to the same conclusion about the liquidity of a stock and, finally, (4) how does the literature explain the intraday seasonalities. I shall make new contributions to this subject, in particular concerning the volatility and the relation between volume imbalance and spread. In contrast to previous investigations, my paper shall consider several liquidity proxies together.

In section 2.3 the trading system of the Paris Stock Exchange will be illustrated and analysed. Section 2.4 presents the data and the methodology used. Section 2.5 contains empirical results of intraday behaviour of volume, spread, waiting time, return and volatility. Section 2.6 describes the dimension of intraday market liquidity and finally, section 2.7 the relationship between volume imbalance and spread is established. Section 2.8 gives my conclusions, while the figures, the tables and the Appendix are shown in Sections 2.9, 2.10 and 2.11.

2.3. The structure of the Paris Bourse

From 1986 to 1990, the Paris Bourse gradually shifted from a daily call auction to a computerized limit order market, in which trading occurs continuously. The opening price is determined by a call auction, which is preceded by a sequence of tentative call auctions before the opening, in order to facilitate the price discovery process. The Paris Bourse is a centralized order-driven market, animated by trading members who take positions for their own account or for their customer. The trading mechanism of the Paris Bourse is based on three computer systems: RONA (computerized routing of orders), CAC (Cotation Assistée en Continu, computer-assisted quotation system), and information release. The automation of the exchange began on June 23, 1986, when the CATS (Computer Assisted Trading System) system of the Toronto Stock Exchange was installed. From June 1986 to December 1987, the most traded stocks were admitted to the CAC system. While at the end of 1986, only six stocks were traded on the CAC system, by 1991, all stocks were managed by it. The investors place their orders through brokers. The main characteristics of the Paris Bourse will be considered in the following section, where a detailed description of the Euronext (the result of the merger between Paris, Brussels and Amsterdam) is given.

A. Euronext Paris

On September 22, 2000, the Exchanges of Amsterdam, Brussels and Paris merged under the holding company Euronext NV to form the first pan-European exchange. 2002 saw the Portuguese Stock Exchange, Bolsa de Valores de Lisboa e Porto (BVLP) merging with Euronext, and the international derivatives exchange, LIFFE, joining the Euronext group. All Euronext products are now grouped under the Euronext liffe umbrella. The process of the acquisition of the LIFFE shares was completed on February 25, 2002. Also in February 2002, the merger of BVLP, the Portuguese cash and derivative market, with Euronext was completed (Euronext, 2000a, b, d, 2002).

This research includes both the period when the Paris Bourse was independent and the period when it had merged with the Amsterdam and Brussels Stock Exchanges, thus becoming the first integrated and transnational capital market using the Euro. In the meantime it has developed and became the leading market in Europe for stocks recorded on the central order book and for equity options.

It was the first time in the world that three Bourses of three different countries merged in order to create only one single company. The board of directors of the three Stock Exchanges had launched the project in answer to the growing trend towards consolidation of the European markets and the desire of investors (market operators) to have more liquidity and lower transaction costs. Euronext's objective is to offer market participants, issuers, investors and financial intermediaries a single trading platform for cash and derivatives, a single clearing house and a unified system for settlement and delivery (Euronext, 2000a, b, d).

For issuers, intermediaries and investors, Euronext created three points of access (via Amsterdam, Brussels and Paris) to its single market. By December 31, 2000, i.e. the end of the period under study, 1653 companies representing a market capitalization of 2.41 trillion Euro were listed on Euronext NV, making it the second biggest stock exchange after the London Stock Exchange (LSE). In terms of trading volume, however, Euronext has by far overtaken its European counterparts. In 2000, its central order book recorded 1.712 billion Euro for cash trading, compared to 969 billion Euro for the Deutsche Börse AG (DBAG), 963 billion Euro in Milan and 878 billion Euro for the LSE. The new pan-European exchange also outdid its main European competitors in equity options, with 140.4 million contracts exchanged in 2000, compared to 88.9 million for the DBAG, 33.7 million in Stockholm, 5.9 million in Milan and 5.5 million on the London International Financial Future Exchange (LIFFE)[20].

At the end of the year 2001, Euronext adopted a single trading platform, linking all the members of the three former markets and placing them under the unified regulations of the Euronext market model. A single central order book for each financial instrument increases the transparency of the market and the liquidity of the stocks listed.

B. The Euronext market model

The aim of the Euronext market model (hereafter EMM) is to provide a harmonized trading system with a central electronic order book and a single set of trading rules. The new market model was introduced on April 23, 2001 in Paris, on May 21, 2001 in Brussels and on October 29, 2001 in Amsterdam and was completed at the end of 2001. Euronext Lisbon, which joined the Euronext group in February 2002, will introduce the EMM and the Euronext NSC trading platform on its market in 2003. The trading system is order-driven, based on price / time priority. For companies with a good liquidity profile, trading will be continuous with an opening and closing auction at the start and at the end of each session. Other securities may also be traded, provided that there is a liquidity provider willing to fulfil certain obligations. For less liquid securities, trading will be non-continuous and based on intraday auctions, with or without a liquidity provider (Euronext, 2001b).

[20] One year later, at the end of December 2001, Euronext had 1,539 companies listed on its regulated and unregulated markets, representing a market capitalization of Euro 2,070 billion. Euronext is the largest exchange in Europe in terms of trading volume on the central order book, and the second largest in terms of capitalization. In 2001, Euronext's central order book recorded Euro 1.668 billion for equities compared to Euro 1.047 billion for the London Stock Exchange, Euro 952 billion for Deutsche Börse AG and Euro 658 billion for Milan.

C. Trading phases

Before the opening auction, there is a pre-opening period during which orders can be entered, modified or deleted. A theoretical opening price is calculated and disseminated by the trading system in real time. At the opening, the order book is frozen momentarily, while the matching algorithm is running.

Once the price determination process for each security is complete, continuous trading begins and orders can be entered, maintained and deleted. All unexecuted orders from the opening auction are forwarded to continuous trading, unless otherwise restricted by the market participant. Each new order triggers one or more transaction(s), if a matching order or orders exists on the central order book; the execution price is the price limit of the matching order on the book. If there is no matching order, then the incoming order is ranked on the book according to its own limit and time entry. The order book is open and anonymous for both pre- and post-trading.

The closing auction starts with an initial pre-closing phase of five minutes, only, since all orders entered during the trading day, orders from continuous trading and orders restricted to auction or closing auction only, by that time are already in the system. The processes in this closing auction are the same as during the opening auction. During the trading at the last price phase, orders can be entered and matched at the last price only. For continuously traded securities, this facility is extended to ten minutes (Euronext, 2000a, b, d).

TABLE 2.3.1: Trading cycles at the Paris Bourse

1. Trading phases for continuously traded securities

7:00 - 9:00	pre-opening phase	Order entry and calculation of theoretical opening price
9:00		Opening auction
9:00 - 17:25		Continuous trading
17:25 - 17:30		End of compensation trading pre-closing phase, indicative price, no execution
17:30		Closing auction
17:30 - 17:40		Trading at the last price phase
17:40		End of trading

2. Trading phases for non-continuously traded securities

7:00 -10:30	pre-opening phase	Order entry and calculation of theoretical price
10:30		First auction
10:30 - 11:00		Trading at auction price
11:00 - 16:00	pre-closing phase	Order entry and calculation of theoretical price
16:00		Second auction
16:00 - 16:30		Trading at auction price

Source: Euronext Paris (2000a, b, d)

On September 20,1999, the Paris Bourse SBF SA took an initial step towards a longer business day, moving the beginning of trading up from 10:00 a.m. to 9:00 a.m. This implemented the agreement reached by eight European exchanges in September to harmonize trading hours from 9:00 a.m. to 5:30 p.m. Since April 3, 2000 all continuously traded stocks on the Premier Marché, Second Marché and Nouveau Marché are traded from 9:00 a.m. to 5:30 p.m., followed by a closing call auction at 5.35 p.m. Times for call auctions on Le Nouveau Marché have also changed. The first is now held at 9:30 a.m. instead of 10:30 a.m., and the second at 5:00 p.m. instead of 4:30 p.m. As a result, since April 3, 2000, dissemination of closing prices for all Paris Bourse SBF SA indices begins at 5:35 p.m. (Euronext, 2001a).

D. Trading reservations and circuit breakers

The Euronext market model contains circuit breakers with a set of trading halt thresholds: the trading of a security is halted, if the entry of an order would produce a fluctuation of more than 10% from the reference price. At the opening of the session, the reference price is the previous closing price, whilst during the session, it is the opening price. In addition to these static thresholds, dynamic thresholds are fixed for continuously traded securities: no price can differ by more than 2% from the previous one without a trading halt of five minutes: one minute freeze and four minutes reservation. These dynamic thresholds enable Euronext to reduce intraday volatility (Euronext, 2000a, b, d).

E. Order types

The Euronext market model recognizes the following different order types (Euronext, 2000c):

1. Limit orders (pre-opening phase, continuous phase and trading at last price) are bid/ask orders that must be executed at their specified limit or better.
2. Market orders (pre-opening phase and continuous phase) are unlimited bid/ask orders, to be executed at the next prices determined by the system. As much of the order as possible is executed immediately, and any remainder is ranked on the order book as a market order. If a market order cannot be matched, it remains in the book until executed or deleted, either by the market participants, or on reaching the specified expiry.
3. Must be filled orders (pre-opening phase and continuous phase) are unlimited bid/ask orders, to be fully executed immediately. This type of order cannot be partially executed. If the order cannot be immediately executed in full, the system places a freeze on the instrument. If the order that caused the freeze is confirmed, Euronext market surveillance initiates a reservation on this instrument.
4. Market to limit orders (auction phase and continuous phase) are orders which have to be executed immediately at the best price level on the opposite side of the book. The unexecuted amount, instead of being matched to the next price level, is automatically

transformed by the system into a limit order at the last executed price. In the pre-opening phase, a market to limit order is a market on opening order.

5. Stop orders: These orders are designed to allow investors to protect their positions against trend inversion. Stop orders are available during the pre-opening and the continuous phase. Two stop order types can be used in order to support trading strategies. They are available for execution after reaching a price limit (stop limit).
   a. Stop loss order: when a stop limit is reached (exceeded or fallen below), a market order or a must be filled order is automatically generated and sent to the order book.
   b. Stop limit order: when the stop limit (trigger price) is reached (exceeded or fallen below), a limit order is automatically generated and sent to the order book.
   c. Both types of stop orders can be executed during an auction.

F. Tick size

One important feature of the trading structure is the minimum price difference allowed between limit orders, normally referred to as the tick size. Harris (1991, 1992, and 1994) finds that the tick used at the NYSE and the AMEX has an economically significant impact on market liquidity. The tick sizes expressed in Euro for the Paris Bourse, valid from January 1999, are: 0.01 up to 50 EUR, 0.05 from 50 EUR to 100 EUR, 0.10 from 100 EUR up to 500 EUR, and 0.50 above 500 EUR.

2.4. Dataset and methodology

The dataset contains the tick-by-tick history of trades and orders of 43 stocks which belong, or have belonged, to the CAC40 index, over 256 trading days between 01.12.1999 and 30.11.2000. The data used in this study comes from one source: the Société Bourse Française, which has provided the transaction and order book data. The transaction data file (named Bdm1d2) includes the second by second transaction prices, their applications[21], as well as the volume data. The total number of transactions is 23'525'550. For each order, in the Bdm2d2 file, the dataset reports the execution time (precise to the second), the best bid and offer prices and the number of shares demanded and offered at each of the bid and ask quotes. In my dataset I do not consider order placements or cancellations outside of the best buying or selling limit orders, nor the hidden orders. In order to rebuild the order book, I match the transaction and order files. In order to determine the trade direction, I adopt the Lee and Ready (1991) procedure. The quote midpoint, MID_t, is calculated from the bid-ask quotes that prevail just before a transaction. The price transaction at time t is denoted as P_t. I also defined D_t as the buy-sell trade indicator variable for the transaction price, P_t. D_t equals, +1 if the transaction is buyer-initiated and occurs above the midpoint; it equals -1 if the transaction is seller-initiated and occurs below the midpoint, and 0, if the transaction occurs at the midpoint. The ability to classify accurately buyer- or seller-initiated trades enhances the reliability of my dataset.

All the information in my dataset is available to market participants in real time through computerized information dissemination systems. All brokers are directly connected to the CAC system. Most banks and fund managers dealing in French stocks, in Paris as well in London or New York, obtain the information in real time through information vendors such as Reuters, Telekurs and Bloomberg, or from a subsidiary of the Bourse. My dataset does not include the identities of the bidding brokers. However, this type of information is available to brokers electronically, and the brokers can forward this information to their customers.

Before starting my analysis, I eliminated those data which I considered as not pertinent: applications recorded by the electronic system, and fixing transactions. I dropped application trades for two reasons: first, applications do not represent any liquidity, nor any possible trade for the other investors, since an application is a sell/buy agreement, i.e. the investor arrives at the market with his/her counterpart. The second reason is the recorded time of trade, since it is not always the time at which the trade occurred, but rather the time at which the trade is introduced into electronic system. Over the considered period, 125'976 applications were dropped. As in other studies (Gouriéroux, Jasiak, LeFol 1997), I retained in my dataset only the trades recorded

[21] Essentially all trades are executed at the quotes outstanding in the book. The exception are pre-matched block trades, which can take two forms. First, prearranged trades can be executed between or at the current best bid and ask price. When they are executed at the quotes, they bypass the time priority of the limit orders previously posted at that price. There is no size priority in the Bourse. These are called applications. Second, a block can also be traded outside the current spread, but then the priority of previously posted limit orders is respected. For example, if the block price exceeds the best ask, then the limit orders between the best ask and the block price are purchased by the block buyer at the block price.

after the opening, because the opening procedure is the result of a call auction, whereas right after the opening, the market switches to a continuous matching procedure.

The analysed one-year period is divided into two distinct sub-periods, one before and one after the introduction of the longer time of trading. In fact, since the April 3, 2000 trading is possible until 17.30 CET. In order to avoid problems due to this new trading rule, my first sub-period lasts from December 1, 1999 until March 31, 2000, and the second period from April 3, 2000 until November 30, 2000. Intraday patterns will be documented for the trading activity at the CAC 40 index, which includes the most heavily traded stocks.

Essentially, four big categories will be considered and presented: volume, spread, waiting time between subsequent trades and returns. I calculated every proxy continuously within each successive 5 minutes period[22] throughout the day for each stock and then assembled the index containing all 43 stocks. All the mathematical expressions of each liquidity proxy are presented in Appendix 2.11.2. Tables 2.10.2 to 2.10.7 list also the successive t- values for each liquidity proxy, whereby two adjacent means are compared.

A. Measures of intraday market liquidity

As the liquidity is a complex and multidimensional concept, the utilization of a unique indicator can be misleading (Amihud and Mendelson 1986, Grossman and Miller 1988 and Kugler and Stephan 1997). My objective is to characterize the intraday market liquidity pattern through the common measures of market liquidity. The next section provides a survey of the indicators used in this research: spread, weighted average spread (hereafter WAS), volume, volume imbalance, return, volatility, waiting time between subsequent trades, liquidity ratio and flow ratio. For each liquidity proxy, I discuss the resulting shapes, which are plotted at the end of this chapter (Figures 2.9.1 to 2.9.16)[23], as well as the t-values, whereby two adjacent means are compared (Tables 2.10.2 to 2.10.7). In each figure, the 44 graphs represent the 43 single stocks contained in the CAC40 index, and the standardized, equally weighted, stocks forming the index (named TOT_AVERAGE). There are two graphs for the quoted half spread (Figure 2.9.1.A and 2.9.1.B), corresponding respectively to the first (December – March) and second period (April – November[24]). The figures are then reported for the first period only, as there are no major changes in the second period with respect to the first.

B. Spread

Much of the empirical work to date has focused on the spread as a proxy for market liquidity. Different measures of spread were used in the literature. My objective is to calculate, within an interval of 5 minutes, the mean of every of these liquidity proxies, and then to plot and explain

[22] This short time interval has also been considered by Andersen and Bollersev (1996).
[23] Each liquidity proxy has been standardized following the procedure explained in Appendix 2.11.2.
[24] For the second period the t- table is not included.

them. These indicators, which are explained in detail in Appendix 2.11.2 are: first, the midquote (MID), which is the average between ask price and bid price, but cannot be considered as a real spread measure. The MID, however, represents the correct price considering the bid-ask bounce problem. It is calculated as follows:

$$MID_{i,j} = \frac{1}{n}\sum_{t=1}^{n}\left(Ask_{i,j,t} + Bid_{i,j,t}\right) / 2$$

Second, the effective half spread (labeled EHS), which represents the reduction in trading costs attributable to trades executed within the quotes (percentage execution cost actually paid by a trader and percentage of gross revenue to the supplier of immediacy). It is calculated as follows:

$$EHS_{i,j} = \frac{1}{n}\sum_{t=1}^{n} 100\, D_{i,j,t}\left(p_{i,j,t} - MID_{i,j,t}\right) / \left(MID_{i,j,t}\right)$$

Third, the quoted half spread (QHS), i.e. the difference between the two best order limits of the limit order book on each side, divided by the MID, is represented by the following formula:

$$QHS_{i,j} = \frac{1}{n}\sum_{t=1}^{n} 100\left(Ask_{i,j,t} - Bid_{i,j,t}\right) / \left(2 * MID_{i,j,t}\right)$$

And, last the average difference spread (DSPR), within a 5 minutes interval, which is calculated as the difference between ask price and bid price:

$$DSPR_{i,j} = \frac{1}{n}\sum_{t=1}^{n}\left(Ask_{i,j,t} - Bid_{i,j,t}\right)$$

<u>*C. Weighted average spread*</u>

The Paris Bourse gives the possibility to access, in its database, the Bdfmd2 file[25], containing the weighted average spread (hereafter WAS). The WAS represents the price for blocks exceeding normal market size. It is calculated for a given quantity of shares in real time by taking the average bid and ask prices for all orders placed on the central SUPERCAC system, weighted by the number of shares displayed at successive bids and asks (but, does not take into account hidden quantities). The price is comparable to that which would result if the block were traded on the central market. Following the same procedures as before, I calculated the spread measures,

[25] The file contains one record for the WAS at the buy side (bid) and at the sell side (ask). If the SUPERCAC order book (either at the buy-side or at the sell-side) does not have the required minimum quantity to compute WAS, there will be a zero (the WAS, either at the buy side or at the sell side, will be equal to zero).

QHS_WAS and DSPR_WAS[26], for a 5 minutes period. The MID_WAS and the EHS_WAS were not calculated. In particular, the EHS_WAS was not calculated, because that file is not matched against the transaction file, and it is therefore impossible to classify the trade direction. The following formula, which is explained in detail in Appendix 2.11.2, is the calculation of the QHS_WAS which is identical to the QHS, from the order data, but in this case the weighted average spread file is taken into account:

$$\mathrm{QHS\_WAS}_{i,j} = \frac{1}{n}\sum_{t=1}^{n} 100\left(\mathrm{Ask}_{i,j,t} - \mathrm{Bid}_{i,j,t}\right) / \left(2 * \mathrm{MID}_{i,j,t}\right)$$

D. Volume

In this section, intraday patterns in trading activity at the Paris Bourse will be documented. A significant intraday pattern in trading activity could imply that the information content in prices differs in various periods of the trading day. Since information is incorporated into prices at least partly through trading, a period of high trading activity would produce more informative prices than a period of low trading activity.

Volume has been considered as a standard measure of market liquidity, but this has been criticized, because it treats smalls and a big traded quantities in the same way. Within an interval of 5 minutes period, I look at the following several measures related to volume, that are presented below, such as (1) cumulated traded volume (labelled SUMVOL), (2) number of trades (NBTR), (3) volume imbalance (VIMB) and (4) sum of volume imbalance in absolute terms (SABSVIMB). For the explication of each proxy see Appendix 2.11.2.

$$\mathrm{SUMVOL}_{i,j} = \sum_{t=1}^{n} \frac{q_{i,j,t}}{\text{NB OF SHARES OUTSTANDING}}$$

$$\mathrm{NBTR}_{i,j} = \sum_{t=1}^{n} \mathrm{obs}_{i,j,t}$$

$$\mathrm{VIMB}_{i,j} = \sum_{t=1}^{n}\left(\mathrm{VBuy}_{i,j,t} - \mathrm{VSell}_{i,j,t}\right)$$

$$\mathrm{SABSVIMB}_{i,j} = \sum_{t=1}^{n}\left|\mathrm{VBuy}_{i,j,t} - \mathrm{VSell}_{i,j,t}\right|$$

In order to test whether the resulting shape are significant, the observations must be statistically independent. For this reason, I adjusted my series in order to eliminate trends. For the cumulated traded volume of each stock, I took the quantity traded within a five minutes period on different days, divided by the number of outstanding shares.

[26] The DSPR_WAS graph is not shown. Its and the formula is identical to the DSPR calculated from the order data, and for this reason it is not presented.

E. Return and volatility

The economic significance of an intraday pattern in returns is obvious. Patterns in returns and/or volatilities would indicate profit opportunities, at least for traders with small transaction costs. Furthermore, intraday patterns in volatilities would have obvious consequences for option pricing, and could also affect the profitability of submitting limit orders (a short-term volatility could imply a certain compensation for submitting limit orders). I calculated the average compound rate of return (RET) within a 5 minutes period, taking into account also the return in absolute terms (ABSRET), as follows:

$$\mathrm{RET}_{i,j} = \frac{1}{n}\sum_{t=1}^{n}\left(\ln\left(p_{i,j,t}\right) - \ln\left(p_{i,j,t-1}\right)\right)$$

$$\mathrm{ABSRET}_{i,j} = \left|\mathrm{RET}_{i,j}\right|$$

For the volatility, two approaches were used. First, the classical method applied in the majority of studies: variance of returns (VARRET).

$$\mathrm{VARRET}_{i,j} = \left[\frac{\sum_{i=1}^{n}\left(\ln\left(\frac{p_{i,j,t}}{p_{i,j,t-1}}\right) - \frac{1}{n}\sum_{i=1}^{n}\ln\left(\frac{p_{i,j,t}}{p_{i,j,t-1}}\right)\right)^{2}}{n-1}\right]$$

Second, the log range volatility (VOLA), which was explained by Alizadeh, Brandt and Diebold (2002).

$$\mathrm{VOLA}_{i,j} = \ln\left(\sup_{i,j} - \inf_{i,j}\right)$$

The latter is superior as a volatility proxy for two reasons. First, it is more efficient, because the intraday sample path information contained in the range causes fewer errors in the measurement of variance than the daily log absolute or squared returns. Second, the log range is very well approximated as Gaussian. The log range is also an attractive volatility proxy for Gaussian quasi-maximum likelihood estimation of stochastic volatility models (Alizadeh, Brandt and Diebold, 2002). The liquidity proxies presented in this section are explained in detail in Appendix 2.11.2.

F. Waiting time

The waiting time (WT), i.e. the definition of liquidity as the time until an asset is exchanged for money (Lipman and McCall 1996), is a measure for the first time theoretically explained and empirically used by Gouriéroux, Jasiak and LeFol (1997). The average waiting time between subsequent trades, explained in detail in Appendix 2.11.2, is calculated as follows within a five minutes period:

$$WT_{i,j} = \frac{1}{n}\sum_{t=1}^{n}\left(time_{i,j,t} - time_{i,j,t-1}\right)$$

G. Liquidity ratio and flow ratio

I also introduce, always on a 5 minutes basis, two other measures: liquidity ratio (LR) and flow ratio (FR), which are represented by the following formulas respectively:

$$LR_{i,j} = \frac{\sum_{t=1}^{n}\left(q_{i,j,t} \cdot p_{i,j,t}\right)}{\left|\left[\frac{p_{i,j,n} - p_{i,j,1}}{p_{i,j,1}}\right] . 100\right|}$$

$$FR_{i,j} = \frac{\frac{1}{n}\sum_{t=1}^{n}\left(q_{i,j,t} \cdot p_{i,j,t}\right)}{\frac{1}{n}\sum_{t=1}^{n}\left(time_{i,j,t} - time_{i,j,t-1}\right)}$$

As noted by Cooper, Groth and Avera (1985) and Kluger and Stephan (1997), liquidity ratio is a measure based on the relationship between the number or value of shares traded during a certain time period and the absolute value of the percentage price change over the same time period. According to the definition of the liquidity, the market ought to be able to absorb an important trading volume without weight on actual prices. A high liquidity ratio represents high market liquidity. This measure considers the depth of the market, but not the time dimension. There are other problems associated with the use of this proxy, as mentioned by Ranaldo (2000). Concerning my database, the most important one is caused by the use of a particularly short time period (5 minutes), which reduces the probability of a price change.

Flow ratio, on the other hand, is a measure representing the short-term average number of shares traded in Euro, i.e. value, divided by the average waiting time between subsequent trades.

2.5. Empirical results

In this section, some general descriptive statistics from my sample will be reported, over the one-year period. Table 2.10.1.A provides some key features: market capitalization, number of trades, average number of trades, number of applications and business sector. The sample is extremely heterogeneous, as shown by the activity of the companies. In Table 2.10.1.A of the descriptive statistics, a division into two categories is made: one without major changes, and one with stocks that proceeded to a split or a merger. There are 30 companies in the first category (PANEL A) and 13 in the second (PANEL B). Table 2.10.1.B and 2.10.1.C, however, show the average value of each of the sixteen liquidity indicators, always during a five minutes period, for all the months under study.

The figures concerning the intraday liquidity patterns are presented in Section 2.9 (Figures 2.9.1 to 2.9.16). For every liquidity proxy, in Section 2.10, I also list the t-values, whereby two adjacent means are compared (Tables 2.10.2 to 2.10.7).

A. Spread

Three of the four spread measures show an inverse J-shaped pattern (EHS (Figure 2.9.1.A and 2.9.1.B), QHS (Figure 2.9.2) and DSPR (Figure 2.9.3)). In particular, these patterns are characterized by a wide spread at the beginning of the day, which decreases constantly during the first hour. The afternoon shows 3 peaks (see also Tables 2.10.2.A, 2.10.2.B and 2.10.2.C): the first one around 14:30 (significant increase of the spread); the second one around 15:30 (a slowdown followed by an immediate resumption 10 minutes later even if not significant); and around the closing time (significant increase of the spread). The MID (Figure 2.9.4), instead, is clearly U-shaped, showing a fall of the average spread during the lunch break[27].

My results are similar to those of Lee, Mucklow and Ready (1993) who also found a lower liquidity at the beginning and at the end of the trading sessions. However, they contend that it is impossible to make inferences about overall liquidity on the basis of quoted spreads or quoted depths alone. They show for a sample of NYSE firms that the combination of wider (narrower) spreads and lower (higher) depths is sufficient to infer a decrease (increase) in quoted liquidity. Using this criterion, they show that quoted liquidity decreases both after periods of high trading volume and immediately before the release of earnings news. In particular, Lee, Mucklow and Ready (1993) report a U-shaped pattern in quoted spreads and trading volume, thus confirming previous studies (McInish and Wood 1992), plus two new findings: effective spreads follow a similar J-shape pattern, and quoted depths follow a reverse U-pattern. The patterns indicate that market liquidity is indeed lower both at the beginning and the end of the day. Brockman and Chung (1999), studying the Hong Kong Stock Exchange, also found a low depth at the opening of trading and a fall at the closing, but they report an inverted U-shaped spread pattern. They give three theories to explain these intraday patterns: (1) existence of adverse selection, (2)

[27] There is only one significant change at 12:40 p.m. as shown in Table 2.10.2.D.

differential liquidity demand elasticities (liquidity demand is more inelastic at the open and close of the market and (3) inventory management is responsible for some of the empirical regularities.

Porter (1988) and Jaffe and Patel (undated) also found that spreads are widest in the morning, narrow around midday, and then rise sharply in the last few minutes before the close.

Admati and Pfleiderer (1988) predict narrow spreads when the volume is high and prices are more volatile, while Foster and Viswanathan (1990) predict narrow spreads when the volume is high and prices are less volatile. In a model of strategic trading between two asymmetrically informed traders, however, Foster and Viswanathan (1993) predict a high volume, a high variance and wide spreads near the open.

Chan, Chung and Johnson (1995) confirm previous findings that stocks in the NYSE have a U-shaped spread pattern, while options (CBOE market) display a very different intraday pattern: it declines sharply after the open, and then levels off. This is similar to the findings of Chan, Christie and Schultz (1995) for NASDAQ stocks, and of Kleidon and Werner (1993) for cross-listed London stocks. Chan, Chung and Johnson (1995) explain the NYSE BAS pattern with the specialist market power model of Brock and Kleidon (1992) or the inventory model of Ho and Stoll (1983), and the CBOE spread with the model of Madhavan (1992), where information asymmetry is partially resolved as investors become informed by observing trade price, leading to a decline in the BAS during the day. They argue that CBOE spreads behave differently from NYSE spreads because of the difference in the market making structure[28]. They suggest that the degree of competition in market making and the extent of informed trading are important for understanding the intraday behaviour of spreads.

Chung, Van Ness and Van Ness (1999) propose an alternative explanation for the intraday pattern of spread. They checked, for the NYSE market, whether a quote comes from the specialist, the LOB or both. Then they examined intraday variation in spreads which originates from specialists as well as those which originate from the LOB, and found that competition among limit order traders is lower during the early and late hours of trading than around midday. Based on these findings, the authors conclude that the U-shaped intraday pattern of NYSE spreads is largely determined by limit orders placed by outsiders rather than by specialists' quotes. Since the spreads set by specialists do not tend to increase near the close of trading, their results do not support the inventory-based explanations for the U-shaped pattern. However, their conclusions concern the spread pattern is not applicable to the French Stock Exchange, as the two trading structures are different and there are no specialist present on the Paris Bourse.

Chung and Zhao (2002) show that intraday variations in spreads for NASDAQ listed stocks have converged to intraday variations in spreads for NYSE listed stocks after the implementation of the new order handling rules. They attribute this convergence to the Limit Order Display Rule, which requires that limit orders be displayed in the NASDAQ best bid and offer (BBO) when they are better than quotes posted by market makers. Their findings suggest that the different patterns of intraday spreads between NYSE and NASDAQ stocks reported in prior studies can largely be attributed to the different treatment of limit orders between the NYSE and NASDAQ

[28] For example, NYSE opens with a call, whereas the CBOE opens with continuous trading.

before the market reform. Differently from my conclusion are the results found by Chan, Christie and Schultz (1995) about the intraday behaviour of the spread before the end of the trading day. According to them, the NASDAQ spread remains relatively wide after the open, narrows gradually during the day, and then declines sharply during the last 30 minutes of trading.

B. Weighted average spread

Figure 2.9.5 shows the intraday evolution of the quoted half spread obtained from the weighted average spread file (WAS). In particular, TOT_AVERAGE exhibits an inverse J-shaped pattern. Significant changes, as demonstrated in the Table 2.10.3, occur in the early morning, around 14:30 (when the majority of US macroeconomic news are released) and before the market closes (when maybe the uncertainty is higher). These results confirm previous results concerning specific points in time when changes occur in the European markets (Ranaldo 2000). The increase in the last few minutes of the trading session is not as evident as in the spread measures obtained from the order data. To my knowledge, this is the first time that the intraday evolution of the quoted spread is shown from the WAS file too. This measure seems to be a good illiquidity indicator, as will be demonstrated in Section 2.7.

C. Volume

The intraday cumulated volume (Figure 2.9.6) exhibits a somewhat J-shaped pattern instead of the classical U-shape pattern reported in earlier studies. Maybe this is due to the small interval chosen for the analysis. Jones, Kaul and Lipson (1994) emphasize, however, that the number of transactions, instead of the size traded, is a better proxy of market liquidity. The pattern in the number of transactions, NBTR (Figure 2.9.7), is clearly U-shaped. Looking at Figures 2.9.6 and 2.9.7, we can say that the morning trade is characterized by many small quantity trades, the afternoon shows many high quantity trades.

In general, the cumulated traded volume (Figure 2.9.6) follows a J-shaped pattern, with the biggest volume at the end of the trading session with respect to the morning[29], when the volume is almost constant. The lunch break lasts for 2 hours and 20 minutes (12:00 p.m. – 14:20 p.m.), as demonstrated by the low volume registered during this period. Three peaks (see also Tables 2.10.4.A and 2.10.4.B), in the Figure 2.9.6 (SUMVOL) and in the Figure 2.9.10 (NBTR), are found, which had also been considered in previous studies: the first one at the end of the lunch break at 14:30 (significant increase), during the release of the majority of US macroeconomic news and the consistent adjustment of investors' portfolios. The second one at 15:30 (significant increase), the time when the US market opens. Third, a strong increase at the end of the trading day (significant changes are observed from 16:35), which is due to investors' attitude. One explanation for the latter has been given by Brock and Kleidon (1992), namely that the investors' optimal overnight portfolios change simply because continuous trading is not possible, so that the distribution of returns during the closed period is different from the one during continuous

[29] The number of trades is, however, at a similar level in the morning and in the late afternoon.

trading[30]. Miller (1989) claims, instead, that short sellers wish to close their positions, trying to achieve a net zero overnight situations in order to avoid settlement. Another reason for strong trading demand at certain times of the day, apart from general portfolio considerations, is that brokers want to execute orders at their discretion over the trading day. As close approaches, the need to execute any remaining orders clearly increases.

The relatively high volume at the beginning of the day is caused by the periodic inability to trade, so that a trader who wishes to be at the same position at the open of trade the next day as he would have been if the market had been open overnight, must execute his net overnight trades at the first trade the next day. This provides a natural explanation for the high opening volume (Brock and Kleidon, 1992). Periodic closure implies that demand to trade will in general be stronger and relatively inelastic at open and close, because overnight price changes imply changes in the number of shares held in order to maintain the optimal portfolio weights. The price at the close will typically differ from the price at the following open, implying a change in the number of shares required for maintaining the optimal proportions.

One of the most used explications for these intraday regularities is the one given by Admati and Pfleiderer (1988). In their paper, high volume at a specific point in time is due to the attitude assumed by informed traders, discretionary liquidity traders (they can time their trades strategically) and nondiscretionary liquidity traders (must trade a particular number of shares at a particular time). Their model shows, that in equilibrium, discretionary liquidity trading is typically concentrated, and that informed traders trade more actively in such periods when liquidity trading is concentrated. Their hypothesis is that the trading volume might be concentrated at the open and close because before and after this period it is impossible to trade. This lead to an increase in especially in nondiscretionary liquidity trading at the open and close. As a result, discretionary liquidity trading, as well as informed trading, will also be concentrated in these periods. The authors underline that the concentration of trading at the end of the trading day may also be due to settlement rules.

Atkins and Basu (1995) consider, on the other hand, the fact that announcements of new information can affect the U-shaped pattern of trading volume of common stocks. They document that a large percentage of all announcements occur after the stock market closes, and suggest the U-shaped volume pattern may be the result of public announcements made when the market is closed. Their conclusion is in contrast to the theoretical models developed to explain this U-shaped pattern, which is also often attributed to the private information effect (Admati and Pfleiderer 1988 and Neal 1987.

Liquidity proxies associated with volume imbalance do not follow a clear shape, but in some cases they seem to follow a U-shape (VIMB, Figure 2.9.8) or an inverse J-shape pattern (SABSVIMB, Figure 2.9.9). As demonstrated in Table 2.10.4.D, SABSVIMB shows significant changes around 14:30 (significant increase), 15:30 (significant increase) and last before the closing (significant increase).

[30] French and Roll (1986) show that the variance rate during the night differs significantly from that during the day.

D. Return and volatility

The average return (RET) within a 5 minutes period, as shown in Figure 2.9.10, is based on transaction prices. In contrast to the results of the American studies, there is no clear pattern, but three points must be discussed. First, there is a high average return at the beginning which then falls after 5 minutes (significant change). Second, two significant changes (see Table 2.10.5.A) happen around 14:30, namely a significant increase, and around 15:30, when a significant fall is observed for 10-30 minutes after the US market opens. Return in absolute terms (Figure 2.9.11), similar to an inverse J-shape pattern, shows a decrease for the first hour and then levels off. A significant increase is evident in the last five minutes (Table 2.10.5.B).

The classical volatility measure shows that the variance of return follows a L-shape (Figure 2.9.12). Volatility is high at the beginning of the day and then falls, remaining practically constant till the end.

In contrast, volatility (Figure 2.9.13), measured by the log range methodology, clearly follows a U-shaped pattern with 3 peaks during the afternoon. Besides the great volatility at the beginning of the day, I observed, in fact, a significant increase around 14:30, a significant increase around 15:30 as well as twenty minutes before the market closes (see Table 2.10.5.D).

In previous price analyses it was found that transitory price volatility is greater at the open of trading than at the close. There are two possible explanations for the greater transitory volatility at the open: 1. Trading mechanisms such as the use of call auctions (Amihud and Mendelson 1987) and the participation of specialists (Stoll and Whaley 1990) at the open are one source of the noisier opening price. 2. Price formation models such as Dow and Gorton (1993), Grundy and McNichols (1989), Leach and Madhavan (1993), Romer (1993) link the noisier opening prices with the fact that the overnight interruption of trading clouds the process of price formation provided by trading itself.

The intraday U-shaped pattern in variance is similar to the pattern in volume found in the stock and option markets (Stephan and Whaley (1990), Lockwood and Linn (1990) and Foster and Viswanathan (1993)). The larger variances are consistent with the predictions of the models of Admati and Pfleiderer (1988) and Foster and Viswanathan (1990), in which discretionary liquidity traders pool their trades at times when trading costs are lowest. Since periods of concentrated trading and low trading costs are also times when informed traders choose to trade, prices are most informative and variable in such periods.

Harris (1986), using transaction data, found that on Monday mornings during the first 45 minutes after the market opens, prices drop, while on the other weekday mornings they rise. Otherwise, the pattern of intraday returns is similar on all weekdays (very large at the beginning and the end of the trading day). Systematic return patterns, especially with Monday negative returns, have been identified among others by Cross (1973), French (1980), Gibbons and Hess (1981), Lakonishok and Levi (1982), Harris (1986) and Rogalski (1984). However, all these studies were unable to explain their cause fully.

Dickinson and Peterson (1989) indicate the presence of seasonality in call returns, with returns significantly higher in early January and significantly lower on Mondays. For the put options, there are no statistically significant differences in returns[31]. A pattern has also been noted by Keim (1986) and others in the sense that the higher stock returns in January differ significantly from the returns earned during the other months of the year. French (1980) detects a day of the week effect, whereby stock returns on Mondays tend to be lower than those on other days. Other authors examine patterns in the derivative market. Among them are Cornell (1985) and Dyl and Maberly (1985, 1986) who conducted a study for the S&P 500 Stock Index Futures market. Cornell (1985) does not detect any difference in mean futures returns across days for a close-to-open period, whereas Dyl and Maberly (1985, 1986) document a significant close-to-open weekend effect which is similar to that observed in the stock market. Smirlock and Starks (1986) also found intraday patterns of returns, but based on hourly returns. Monday returns in the first hour of trading are positive, while returns accruing later in the day are negative. This pattern is then reversed during his period of study (see also Harris 1984).

Sheikh and Ronn (1994) identify daily and intraday systematic patterns in the means and variances of returns on options; they decompose the option returns into patterns which are related to the means and variances of the underlying stocks, and, by inference, those which are independent of patterns in the means and variances of the underlying assets. They shed light on the possibility that informed and liquidity traders may simultaneously trade in both markets, thus inducing independent yet similar patterns in option returns. However, there are patterns in option returns which are not replicated in the underlying stocks. These differences may be due to structural differences between the stock and options markets.

Hsieh and Kleidon (1996) document that return volatility and BAS follow the usual U-shaped patterns (Lockwood and Linn (1990) and Andersen and Bollersev (1998)) which have been explained by the clustering of informed trading (Admati and Pfleiderer 1988). The U-shape do not reflect particularly informative trading during the opening or closing hours, but may, instead, constitute a rational response to the abrupt changes in dealer exposure which occurs when dealers periodically withdraw from the market place (Brock and Kleidon (1992), Hong and Wang (1995)).

E. Waiting time

Concerning the waiting time between subsequent trades (Figure 2.9.14), my findings show an inverse U-shaped pattern, with a short waiting time during the first 30 minutes and a strong increase during the lunch break, reaching a peak around 13:20. Then it decreases continuously until the end of the trading session. The main significant changes (see Table 2.10.6) occur around 14:30 (significant decrease) and 15:30 (significant decrease), and just before the market closes (significant decrease).

There are not very many studies on the waiting time between subsequent trades. Besides Gouriéroux, Jasiak and LeFol (1997) who examined the intraday waiting time on the Paris Bourse and found a M-shape pattern, Ranaldo (2000) applied the waiting time proxy, on a tick-by-tick

[31] Lower January returns are found for in and out of the money options.

basis, for the Swiss market, finding a reverse U-shaped pattern. The major criticism of this type of measurement concerns the multidimensional concept of liquidity. It can be seen as an intensity proxy of market activity, but its information content changes according to the market situation.

Furthermore, even if the immediacy of exchanges is a major determinant of market liquidity, the proxy of waiting time fails to recognize aspects such as breadth, depth and resiliency, because it informs us only on the frequency of transactions.

F. Liquidity ratio and flow ratio

In contrast to Ranaldo (2000), the liquidity ratio, named LR, (Figure 2.9.15) observed by me does not follow any clear pattern. It shows a constant increase during the whole day and only one decrease just toward the end of the lunch break (see also Table 2.10.7.A). This shape may indicate that the market is able to absorb high volumes without weighting excessively on actual prices. Higher value indicate higher liquidity.

Concerning the flow ratio, named FR, (Figure 2.9.16), Ranaldo (2000) found in his study on the Swiss Stock Exchange a U-shaped pattern. Rather than a U-shape, I saw something like a J-shape pattern, where 3 peaks are evident (see also Table 2.10.7.B). The first one at 14:30, the second at 15:30 and the last at the end of the trading session. The decrease in waiting time between subsequent trades leads to an increase in the flow ratio.

G. Conclusive remarks

In my investigation, if considers trading activity as the cumulated traded volume within consecutive 5 minutes periods, the intraday liquidity proxy shows, in agreement with McInish and Wood (1992), a negative relation between quoted spread[32], from the WAS file, and cumulated traded volume. However, I found the relation between the cumulated traded volume and EHS, QHS, DSPR and MID to be slightly positive in the first period (the correlation is bigger if I take NBTR), which confirms the relation previously seen by Brock and Kleidon (1992). On the whole, if I measure the general market activity by the sum of volume, the sum of volume imbalance and the number of trades, I get a positive correlation of these indicators with the spread (see Table 2.10.8.A and 2.10.8.B). This fact is also evident from the graphs, where the increase in volume (Figure 2.9.6) and in volume imbalance in absolute term (Figure 2.9.9) may be caused by the uncertainty due to wider spread (see for example Figure 2.9.3), which in turn may be caused by uncertainty due to the high volume (Demos and Goodhart 1996). This result is in contrast with the observations made by Lee, Mucklow and Ready (1993), who claim a negative relation between spread and volume imbalance. In their view the average volume imbalance in absolute terms is negatively correlated with the spread. Wide spreads are accompanied by low depth and spreads widen and depths fall in response to higher volume.

[32] Differently from McInish and Wood (1992) the relation is negative with the quoted spread calculated from the WAS file, and not with the quoted spread from the order data.

The three peaks found in most of the liquidity proxies is also characteristic for the Swiss Stock Exchange, as was confirmed by Ranaldo (2000), and for the German market (Röder 1996, Röder and Bamberg 1996, Kirchner and Schlag 1998). This behaviour has been explained by the adjustment of French and International traders' positions following the release of most of the macroeconomic news (Becker, Finnerty and Friedman 1995). Other interpretation consider the end of the lunch break, the linkage between European markets and the behaviour of informed and liquidity traders.

The liquidity ratio and flow ratio can also serve as a liquidity proxy, as was demonstrated by their high correlation with some other intraday liquidity measures (Table 2.10.8.A and Table 2.10.8.B).

Again consistent with Ranaldo's (2000) findings, my research reveals that the liquidity status of a stock can vary according to the liquidity proxy used. Thus, even if in some cases the liquidity proxies are highly correlated (cf. for example Table 2.10.8.A and 2.10.8.B), the status of a single share may be completely different. This is the case, for example, for France Telecom when the volatility of return and volatility as log range are considered. In general the most appropriate measures of intraday market liquidity seem to be the following: EHS, QHS, DSPR, QHS_WAS, SUMVOL, NBTR, VARRET, VOLA, WT, LR and FR. On the other hand, it is difficult to judge if a stock is more liquid than another when, for example the MID measure is considered. The latter represent the correct price when the bid-ask bounce problem is taken into account. The measures of volume imbalance, i.e. VIMB and SABSVIMB, can be good liquidity indicators, if the imbalance is effectively transformed into trading volume. This positive relation seems to occur, as documented by the analysis made in Section 2.6. RET and ABSRET alone are difficult to interpret and it is better to associate these measures with another proxy. Liquidity ratio, for example, can be a solution. In fact the latter is a measure based on the relationship between the number or value of shares traded during a time period and the absolute value of the percentage price change over the same time period. In general, from Table 2.10.9.A and 2.10.9.B it is difficult to draw any conclusion about which is the most liquid asset, but Alcatel, France Telecom and Vivendi seem well positioned in all the months under study for most of the liquidity indicators.

2.6. Determinants of intraday market liquidity

In view of the presence of such intraday patterns, a deeper investigation of market liquidity seems to be indicated. In this section, my objective is to shed new light on the determinants of market liquidity. In order to achieve this, it was necessary first to eliminate the seasonal components found in the high frequency data, which might lead to serious bias in the model (Andersen and Bollersev 1997). In order to adjust the data for intraday seasonality, different filtering procedures have been used in the literature. Bollersev and Ghysel (1996) proposed a method that captures the repetitive seasonal variations in volatility changes by allowing periodically varying coefficients in the conditional variance equation. Taylor and Xu (1995) model intraday seasonality by a set of multiplicative deflators. They estimate the seasonal multipliers after having averaged the sums of squared returns across similar time periods. A deseasonalized return series is then calculated by dividing each return by its seasonal multiplier. Instead, I apply a method similar to Ranaldo's (2000), which consists in not using the current level market liquidity, but rather the logarithmic ratio between the current level and its normal value at the current moment. More detailed explanations and the mathematical expression of this intraday adjustment are provided in Appendix 2.11.2. In Appendix 2.11.3 I also show the regression procedure and the tests used in the regression analysis in order to validate my results. Five analyses are performed: depth in terms of trading volume; depth estimated by order volume imbalances; the time dimension of intraday market liquidity; the tightness of intraday market liquidity; and last the intraday return volatility.

The majority of the models that try to explain these empirical regularities hypothesize that the behaviour of informed and non-informed traders play a dominant role. There are periods when the information asymmetry between traders is more likely: when informed traders are present, or when the liquidity traders are dominant. The levels of volume size and return volatility allow a better assessment of different intraday market situations (Glosten 1994). The results of the following regressions are presented in Tables 2.10.10 to 2.10.14, but only significant coefficients are shown.

A. Depth in terms of trading volume

My first analysis concerns the market depth. In this section, I use the cumulated traded volume as a depth proxy, and in the next section the order volume imbalance. The first regression analysis considers an ARMA model that may include lagged variables. The following general equation, labelled Equation (1), is used for both periods under study.

$$RSUMVOL_i = C + \sum_{v=1}^{p}\gamma_v RSUMVOL_{i-v} + \sum_{w=0}^{q}\beta_w RSABSVIMB_{i-w} + \sum_{k=0}^{r}\delta_k RVARRET_{i-k} + \sum_{l=0}^{s}\phi_l RWT_{i-l} + \sum_{m=0}^{z}\theta_m \varepsilon_{i-m}$$

Table 2.10.10 presents the results of the regression and shows that the ratio of waiting time between subsequent trades and RVARRET are lagged in the second period. Clear evidence of this result, i.e. lagged waiting time between subsequent trades, has been reported by Dufour and

Engle (2000). However, I established that the value of q, r and s must not be higher than 12 (one hour lag) in the sensitivity analysis of the lagged dependent variables. This value has been considered after studying the correlogram. After running the ARMA models, several tests are available in order to find the best fit. The common empirical approach implies the use of information criteria, such as the Akaike Information Criterion (AIC), the Schwarz Information Criterion (SIC) and the procedure developed by Ng and Perron (1995). Finally, as recommended by Mills (1990), the Schwartz information criterion was used as a model selection criterion as it helps in the choice of the magnitudes of p and z. I found that ARMA (2,1)[33] in the first period, and ARMA (2,3)[34] in the second period have the biggest explanatory power. Nevertheless, the White Heteroskedasticity test still indicates the presence of heteroskedasticity and the ARCH LM test clearly indicates that for several variables the hypothesis stating that all coefficients of the lagged squared residuals are zero should not be accepted. When necessary, I tried out all plausible ARCH models. The likelihood ratio test was finally singled out in order to find the most adequate solution. Other tests and conditional variance equations are presented in detail in Appendix 2.11.1. Depth in terms of trading volume shows a TARCH (1,2) model in the first period and a GARCH (1,1) model in the second period. The regression result shows that the ratio of cumulated trading volume is negatively related (in the first period) and positively (in the second period) to the ratio of waiting time between subsequent trades, and is positively related to the ratio of the volume imbalance, suggesting that volume imbalance tends to be transformed into trading volume. This confirm that both indicators, namely RSUMVOL and RSABSVIMB inform on market depth. The results of the regression can also be interpreted as follows: the positive relation to the volume imbalance may be due to a price revision following the release of public information or a wider diffusion of private information, as suggested by Ranaldo (2000). The ratio of cumulated traded volume is negatively related to the ratio of volatility of return. This result is different from the one found by Ranaldo (2000), Admati and Pfleiderer (1988) and Kyle (1985) who found that high volume is accompanied by high volatility. In contrast, my result is consistent with Foster and Viswanathan (1990) who predicted a negative relation between volume and volatility. Also the Foucault (1999) model explains that during a period of high uncertainty (high volatility) the trading volume may be reduced by the limit order traders' attitude. The positive relation between trade frequency and market depth is similar to the results found previously by Ranaldo (2000)[35] on the Swiss market, who hypothesized, in this case, that discretionary liquidity traders are more likely to be present. Madhavan and Sofianos (1998), with respect to specialist control, hypothesize, in cases when the volume is constituted many small trades rather than infrequent large sized trades that the negative relation between RWT and RSUMVOL is caused by divergence and asymmetry information. It can also be explained by the protective behaviour assumed by the discretionary liquidity traders, who reduce trade frequency. On the other hand the informed traders use waiting time to act strategically. Similar to Ranaldo's

[33] The p parameter assume value 2 and z value 1.

[34] The p parameter assume value 2 and z value 3.

(2000) study is the TARCH model (Zakoian (1990) and Glosten, Jaganathan, and Runkle (1993), in the first period, which is explained in Appendix 2.11.1, and which concerns the conditional variance of residuals of the cumulated trading volume. The leverage effect term is significant, and it appears to be an asymmetric one. The literature interprets this result by the fact that good news brings increased trading volumes, whereas bad news slows market activity and reduces intraday market depth. For this reason, the market reaction is asymmetrical, i.e. intraday market liquidity react differently according to good or bad news. I have used a quasi-likelihood standard error, since the residuals are highly leptokurtic.

B. *Depth estimated by order volume imbalance*

In this section, an analysis is made of volume imbalance, used as proxy of market depth, in relation to two independent variables: RQHS and RWT. The utilization of volume imbalance as a proxy of market liquidity has been criticized, but the results, similar to Engle and Lange (1997) and Lee, Mucklow and Ready (1993) are encouraging. The following general ARMA regression model, labelled Equation 2, was analysed:

$$RSABSVIMB_i = C + \sum_{v=1}^{p}\gamma_v RSABSVIMB_{i-v} + \sum_{w=0}^{q}\beta_w RQHS_{i-w} + \sum_{k=0}^{r}\delta_k RWT_{i-k} + \sum_{m=0}^{z}\theta_m \varepsilon_{i-m}$$

The procedure used in order to find out the most powerful model is the same as the one explained for equation 1. In agreement with Engle and Lange (1997), Lee, Mucklow and Ready (1993) and Ranaldo (2000), I found a negative relation between the ratio of volume imbalance and the ratio of spread and the ratio of waiting time (Table 2.10.11). The most significant result is obtained when the lagged spread is considered as an independent variable. In this case, it seems that the spread has a leading explanatory power on the volume imbalances in both periods under study. The negative relation during, for example price revision time, may support the idea of a wider spread during periods of high uncertainty when demand and supply are more rigid. Uncertainty may induce discretionary liquidity traders to put off trades, thus reducing depth. This interpretation may also be related to the behaviour of limit order and market order traders, who observe the order book. The latter traders might be motivated by private information or liquidity reasons. Consistent with Lee, Mucklow and Ready (1993) and Kavajecz (1999), there may be a deterministic moment of adverse selection (information disclosure) where limit order traders tend to widen the spread reducing and thus the market depth. This idea supports my result that the spread tends to lead the volume imbalance. I also found that the ratio of waiting time between subsequent trades increases when the ratio of volume imbalance decreases.

The conditional variance of residuals derived from the regressions represents a GARCH process. In this case, the autocorrelated stochastic process does not have an asymmetric component.

[35] He uses an intraday interval of 30 minutes. My model may be more sensitive to changes of independent variables.

C. Time dimension of intraday market liquidity

The time between subsequent trades is regressed on the ratio of volume imbalance, ratio of volatility and ratio of cumulated traded volume in order to establish the time dimension of intraday market liquidity. The general ARMA regression model, labelled Equation 3, is the following one:

$$RWT_i = C + \sum_{v=1}^{p} \gamma_v RWT_{i-v} + \sum_{w=0}^{q} \beta_w RSUMVOL_{i-w} + \sum_{k=0}^{r} \delta_k RSABSVIMB_{i-k} + \sum_{l=0}^{s} \phi_l RVARRET_{i-l} + \sum_{m=0}^{z} \theta_m \varepsilon_{i-m}$$

The same procedure already used in previous equations, for finding the best model, also applies for Equation 3. The results of this regression (Table 2.10.12) do not differ substantially between period 1 and period 2, but in period 2 the high autocorrelation of the residuals and of the squared residuals does not allow to draw any significant conclusion. However, I found in period 1 that the ratio of waiting time is negatively related to ratio of trading volume, like in the Ranaldo's (2000) paper, and positively related to ratio of volume imbalance and ratio of volatility.

Another result is that the RWT follows an ARMA (2,1) model in the first period and an ARMA (3,1) in the second period. In this case the conditional variance of the residuals follows a GARCH (1,1) model for both periods.

D. Tightness of intraday market liquidity

The tightness of intraday market liquidity is also investigated in section 2.7 where, instead of the spread of the Bm2d2 file, I used the weighted average spread (WAS). The following ARMA regression, labelled Equation 4, was carried out in order to deepen the analysis of the relationship between spread and trading volume:

$$RQHS_i = C + \sum_{v=1}^{p} \gamma_v RQHS_{i-v} + \sum_{w=0}^{q} \beta_w RWT_{i-w} + \sum_{k=0}^{r} \delta_k RSABSVIMB_{i-k} + \sum_{l=0}^{s} \phi_l RVARRET_{i-l} + \sum_{m=0}^{z} \theta_m \varepsilon_{i-m}$$

My empirical findings (Table 2.10.13) help to understand the behaviour of the BAS. In period 1 there is a positive relation between the ratio of quoted spread and ratio of volume imbalance, i.e. a wide spread corresponds to an increase in volume imbalance. In the second period, this contemporaneous relation is not present and the RSABSVIMB variable is not statistically different from zero. A more powerful model, as shown in Table 2.10.13.B, considers a lagged volume imbalance variable which has a negative relation to the QHS, as reported by Ranaldo (2000) and Lee, Mucklow and Ready (1993). In this case, as noted by Ranaldo (2000), the trading activity may be dominated by the liquidity traders and also by informed traders. In fact, informed traders tend to trade during period when also liquidity traders are present. Lee, Mucklow and Ready (1993) sustain that spread widens and depth fall in response to higher trading volume.

McInish and Wood (1992) show that the spread is positively related to the risk level and to the amount of information, but negatively related to the trading activity and to the level of competition. In section 2.7 I give an interpretation which takes into account the behaviour of the more patient traders, who supply the liquidity through limit order trading, and of the eager traders who submit market orders motivated by private information or liquidity reasons. The results presented in section 2.7 are stronger in respect of equation (4). Finally, the ratio of quoted spread follows an ARMA (2,2)-GARCH (1,1) model.

E. Intraday volatility of returns

In this last regression, labelled Equation 5, I tried to analyse the volatility of return through the following ARMA model:

$$RVARRET_i = C + \sum_{v=1}^{p}\gamma_v RVARRET_{i-v} + \sum_{w=0}^{q}\beta_w RQHS_{i-w} + \sum_{k=0}^{r}\delta_k RSABSVIMB_{i-k} + \sum_{l=0}^{s}\phi_l RWT_{i-l} + \sum_{m=0}^{z}\theta_m \varepsilon_{i-m}$$

The results of this regression (Table 2.10.14) show a positive relation between the ratio of quoted spread and ratio of volatility and a negative one with ratio of volume imbalance in the first period. All coefficients are significantly different from zero, thus enhancing the results found. One explication of the positive relation between RVARRET and RQHS is the fact that either may increase or decrease in times when there is more asymmetric information and more uncertainty. The negative relation between ratio of volume imbalance and ratio of volatility may be interpreted as a price revision, so that the divergence between buyer and seller is higher. If I consider volume imbalance as a depth proxy, I ought to find, in contrast, a positive relation between RVARRET and RMABSVIMB (informed and liquidity traders may be active). Return volatility is also considered as an indicator of the intensity of the market activity. The relation between RAVARRET and RWT may be interpreted as follows: a decrease in waiting time may correspond to an increase in return volatility, so that an increase in market activity can be caused by the higher activity of the informed traders. But the informed traders try to hide their orders when the activity of the discretionary liquidity traders is more evident. If it is more likely that suppliers of liquidity trades are present, a rise in return volatility may correspond to a wider uncertainty, thus inducing a lower market activity (positive RWT).

The literature gives another interpretation for the positive relation between volatility and spread. In particular, Foucault (1999) considers that if the volatility increases, the bid-ask spread widens. In fact, consistent with the winner's curse problem, the risk for a limit order trader to be picked off is higher, and thus limit order buyers (sellers) request a higher (lower) reservation price, thus widening their reservation spread. Therefore, when volatility increases, limit order traders require a larger compensation. At the same time market order trading becomes more costly and, on the whole, the higher proportion of limit orders instead of market orders reduces the execution probability of limit order trading.

Furthermore, my results show that the return volatility follows an ARMA (1,2)-GARCH (1,1) model in the first period and an ARMA (2,2)-GARCH (1,1) model in the second one.

Some criticism about the regression used in this study and the choice of the best model has been reported at the end of Chapter 4.

2.7. The relation between spread and volume imbalance

A large body of the literature has studied the link between trading activity, usually represented by trading volume, and stock market returns (Benston and Hagerman 1974, Gallant, Rossi and Tauchen 1992, Hiemstra and Jones 1994, Lo and Wang 2000 and Karpoff 1987). Imbalance can provide additional power beyond volume in explaining stock returns. Intuition suggests that prices and liquidity should be more strongly affected by more extreme order imbalances, regardless of volume, for two reasons: first, order imbalances sometimes signal private information, which should reduce liquidity at least temporarily and could also affect the market price permanently, as was also suggested by Kyle's (1985) theory of price formation. Second, even a random large order imbalance exacerbates the inventory problem faced by the market maker, who can be expected to respond by changing BAS and revising price quotations. Hence, order imbalances should be important influences on stock returns and liquidity (spread), and are conceivably more important than volume (Chordia, Roll and Subrahmanyam 2001).

Most existing studies analyse order imbalance around specific events or over short periods of time. Sias (1997) looks at order imbalances in the context of institutional buying and selling of closed end funds; Lauterbach and Ben-Zion (1993) and Blume, MacKinlay and Terker (1989) analyze order imbalance around the October 1987 crash; and Lee et al. (1993) does the same around earnings announcements. Chan and Fong (2000) investigate how order imbalance changes the contemporaneous relation between stock volatility and volume, using data of a six months period. Hasbrouck and Seppi (2001) and Brown, Walsh and Yuan (1997) study order imbalances for thirty stocks (over one year) and twenty stocks (over two years) respectively. They focus on: characterizing properties and determinants of market-wide daily order imbalance; studying the relation between order imbalance and aggregate measure of liquidity; and investigating the extent to which daily stock market returns are related to order imbalances, after having checked the effects of market liquidity. They saw a strong contemporaneous link between stock returns and order imbalance. In their view market prices tend to reverse after declines, and then follow previous up-moves. These results are consistent with the inventory paradigm, which suggests that imbalances cause price pressure.

Hopman (2002) shows that stock returns are in large part due to supply and demand imbalances, rather than information. He suggests that mechanical price pressure through supply and demand imbalances provides a better explanation of price changes than information.

Chordia and Subrahmanyam (2002) shed new light on the inventory effect, underlying the relation between order imbalance and daily returns of individual stocks. They found empirical evidence that market makers dynamically accommodate autocorrelated imbalances, which causes a positive relation between lagged imbalances and returns[36]. Chordia, Roll and Subrahmanyam (2001) raise the inventory problem faced by the market maker following an increase in volume imbalance, but what happens in an order-driven market ? I shall try to give an answer to this question by establishing a relation between spread and volume imbalance.

Four regressions are performed between spread measures (RQHS_WAS and RDSPR_WAS) of the WAS file and volume imbalance (MABSVIMB and SABSVIMB). Such a relation can be interpreted as a market tightness proxy and it is different from the one presented in section 2.6. In fact, the spreads are obtained by considering the ask and bid prices as prices for blocks. In the regression I also look at the volatility and waiting time, as suggested by Easley and O'Hara (1987) and Chang and Fong (2000). All the time series are seasonally adjusted.

A. Quoted half spread and volume imbalance

The following ARMA regression model, labelled Equation 6, was carried out and presented in Table 2.10.15:

$$RQHS\_WAS_i = C + \sum_{v=1}^{p} \gamma_v \, RQHS\_WAS_{i-v} + \sum_{w=0}^{q} \beta_w RSABSVIMB_{i-w} + \sum_{k=0}^{r} \delta_k RVARRET_{i-k} + \sum_{l=0}^{s} \phi_l RWT_{i-l} + \sum_{m=0}^{z} \theta_m \varepsilon_{i-m}$$

My empirical findings, presented in Table 2.10.15.A (first period) and in Table 2.10.15.B (second period), help to understand the behaviour of the bid-ask spread. The final result, in Table 2.10.15, shows that normalized RQHS_WAS follows, in the first period (December – March) an ARMA (2,1), while the conditional variance follows a GARCH (1,1). The results of the second period (April – November) seem less strong than for the first period. Furthermore for the conditional variance, I found an asymmetric component (TARCH (1,1)). The model indicates, in the second period, a negative relation between the ratio of spread (dependent variable) and the independent variables (waiting time, imbalance and volatility), but a positive relation between ratio of volatility, ratio of waiting time and spreads during the first period. Easley and O'Hara (1987) have already noted the dependency of the spread on the time between trades, with the spread decreasing when this time increases. The negative relation between imbalance and spread, as Ranaldo (2000) says, can be explained by thinking of volume imbalance as a market depth proxy. Another interpretation can be attributed to the activity of liquidity traders. High volatility can be associated to a period of uncertainty that induces a higher spread. Ranaldo (2000) uses also unexpected trading volume as a proxy of market uncertainty, finding a positive relation between unexpected volume and spread on the SWX.

The result of the regression is different from Equation (4)[37] where I found a positive relation between spread and volume imbalance (see Table 2.10.13.A), but the former result seems to be more logical if the results are interpreted as the ability of investors to observe the state of the order book. The trading strategies of sellers and buyers may be different, if the composition of the sell and buy side is structurally different. Volume imbalance means that one side of the book is thicker. For example, from a buyer's point of view, the thicker the book is on the buy side, the

[36] Relation inverse sign after checking for current imbalance.

[37] The positive relation was only found in the first period (December 1999 – March 2000).

greater the willingness will be to submit a market order (aggressive trader). Consistent with Ranaldo (2001), the use of market orders is more frequent when the volume available on the same side as that of the incoming trader exceeds the quoted volume on the opposite side (Ahn, Bae and Chan, 2000, Chung, Van Ness and Van Ness, 1999, Griffiths, Smith, Turnbull and White, 2000). On the other side of the book, the seller will continue to provide liquidity through limit orders as long as he sees, through the limit order book, that there is an imbalance on the buy side. The aggressive market order will match the limit order. Considering that an aggressive trader may want his order to be passed first, he has to trade within the spread, reducing *de facto* the spread and causing this negative relation.

My regression analysis shows that the volatility is positively related to the spread. Also in this case, the behaviour of traders can be considered as the dominant factor. An increase of volatility can reduce aggressiveness and encourage limit order trading. This supports the model of Foucault (1999), in which an increase in volatility leads a larger reservation spread by limit order traders, a decrease of their execution probability and a decrease of the market imbalance. The reduced aggressiveness of traders can be explained by the information asymmetry and the higher profitability due to liquidity events. Traders widen the reservation spread because of the risk of being picked off by informed traders (Foucault, 1999). Also Lee, Mucklow and Ready (1993) had noted that the liquidity providers are sensitive to changes in information asymmetry, and this leads them to widen their spread due to higher adverse selection risk. The limit order strategy, when the spread is larger, is also evident in Griffiths et al. (2000) and in Biais, Hillion and Spatt (1995).

Comparing the result of the regression (6) with the results obtained in Equation (4), it seems that the weighted average spread is a better indicator of market illiquidity than the spread measures derived from the order book.

B. Average spread and volume imbalance

Also in this section, an ARMA regression model, labelled Equation 7, is made by changing the measure of the spread. RDSPR_WAS is used, i.e. the difference between the two best order limits of the order book.

$$RDSPR\_WAS_i = C + \sum_{v=1}^{p}\gamma_v\, RDSPR\_WAS_{i-v} + \sum_{w=0}^{q}\beta_w RSABSVIMB_{i-w} + \sum_{k=0}^{r}\delta_k RVARRET_{i-k} + \sum_{l=0}^{s}\phi_l RWT_{i-l} + \sum_{m=0}^{z}\theta_m \varepsilon_{i-m}$$

The results of Equation (7) does not significantly differ from Equation (6) and for this reason is not presented. The relation between spreads and other liquidity proxies are maintained, and so is the asymmetric component of the residual variance for the period April – November 2000. The high relation between RDSPR_WAS and volume imbalance is maintained also during the second period, where the decrease is lower than the decrease registered for the relation between RQHS_WAS and RSABSVIMB.

2.8. Conclusions

In chapter 2 I analytically described the market trading structure of the Paris Bourse before and after the merger with the Amsterdam and Brussels Stock Exchanges, which has led the three Bourses to become the first integrated and transnational capital market using the Euro.

In the empirical part, the intraday evolution of the commonly used liquidity proxies was analysed over a one year period, such as spread, return, volatility and volume of the 43 stocks belonging to the CAC40 index. Spread measures were divided into effective half spread (EHS), which represents the reduction in trading costs attributable to trades executed within the quotes; midquote (MID), which is the average between ask price and bid price; quoted half spread (QHS), that is the difference between the two best limits of the LOB on each side of the book divided by the midquote; and last the difference spread (DSPR), which represents the difference between ask and bid price. Spread had always been considered as a proxy of market liquidity. EHS, QHS and DSPR patterns show that the spread is wide during the first hours of trading, diminishes throughout the trading, and then rises again in the last hour before the market closes, but not to the same level as in the morning. In addition, this reverse J-shaped pattern shows two other peaks, which were reported also in previous studies: one around 14:30 (time when the majority of US macroeconomic news is released), and the second one around 15:30, even if not significant. The latter corresponds to the opening of the US markets when we see a decrease of the spread followed by resumption 10 minutes later. The midquote, instead, even if cannot be considered as a spread measure, clearly shows a U-shaped pattern. The same procedure has been used for the weighted average spread, which represents the price for a block trade. However, in this case, I retained only QHS and DSPR, finding a reverse J-shaped pattern too. The volume, in contrast to the majority of the empirical findings in the US market, follows a J-shape pattern, with the cumulated traded volume very light in the early morning and then constantly increasing after the lunch break. As suggested by Jones, Kaul and Lipson (1994), I also used also the average number of trades as a liquidity proxy. The resulting U-shape indicates a high number of trades, but no higher quantities, in the morning, whereas the afternoon characterized by high trades and quantities.

The average return does not follow any clear pattern, in contrast to American studies but in agreement with Niemeyer and Sandås (1995). Volatility measured as variance of return and as log range, shows a reverse J-shaped pattern and a U-shaped pattern respectively, thus confirming previous studies on the subject.

The waiting time follows an inverse U-shaped pattern. I also introduced two other liquidity proxies: liquidity ratio and flow ratio. The former, which was previously considered as an interday proxy does not correspond to the findings of Ranaldo (2000), who had used it on an intraday basis. I didn't found any precise shape, but a constant increase which is logically related to the volume and return shapes. The flow ratio follows a reverse J-shaped pattern too. None of liquidity proxies allows to draw a conclusion about which stock is more liquid.

The definition of liquidity calls for a deeper investigation of intraday market liquidity with respect to several dimensions: time, depth, breadth and resiliency. I analysed the intraday market liquidity determinants in relation to each other. In particular, the depth dimension in terms of trading volume shows a negative relation between trading volume and waiting time between trades, and a positive relation between cumulated traded volume and volume imbalance, suggesting that volume imbalance tends to be transformed into trading volume. A negative relation is found between volume and volatility. Market depth, estimated by the cumulated traded volume follows an ARMA (2,1) – TARCH (1,2) in the first period and an ARMA (2,3) – GARCH (1,1) in the second period. The depth of the market was also measured by the volume imbalance indicator, and shows a negative relation with spread and waiting time.

The time dimension of intraday market liquidity gives weak results, in particular concerning the behaviour of the residuals and squared residuals. It seems, however, that the waiting time is negatively related to the trading volume, and positively to volume imbalance and volatility.

Furthermore, the tightness of the market was estimated through the quoted bid-ask spread. I found a positive relation between spread and volume imbalance only in the first period, and a negative one in the second period and in Equations (6) and (7). The regression analysis seems to support the idea of certain strategies employed by the supplier and demander of liquidity (their patience or their aggressiveness). The weighted average spread, calculated in relation to volume imbalance in Equations (6) and (7), has a bigger explanatory power and seems to be a good illiquidity proxy. The volatility of returns, which was also estimated, presents a positive relation to the spread and a negative one with the volume imbalance.

The results of the regressions suggest, with respect to market depth, that an asymmetric effect exists. The TARCH models support the idea that negative and positive shocks have different effects on the conditional variance, inducing a different impact of bad and good news on the market liquidity.

The behaviour of informed and discretionary liquidity traders has not been tested to the same extent as in other investigations, but my general approach seems to sustain the previously found hypothesis, namely that the positive relation between spread and volume may be due to the presence of liquidity traders, whereas the opposite occurs when informed traders are operating.

FIGURES

FIGURE 2.9.1.A: Intraday patterns of the effective half spread from December 1, 1999 to March 31, 2000 for the 43 stocks and the index. This figure shows the intraday evolution of the effective half spread (EHS) within successive intraday periods of 5 minutes for each stock belonging to the CAC 40 index. TOT_AVERAGE represents the average evolution for all the 43 stocks. The liquidity indicator has been calculated following the procedure described in Appendix 2.11.2 and it has been standardized by subtracting by its mean and then divided by its standard deviation. Hence the vertical axis presents the standardized extent of market liquidity. The horizontal axis corresponds to the time axis based on 96 periods of 5 minutes.

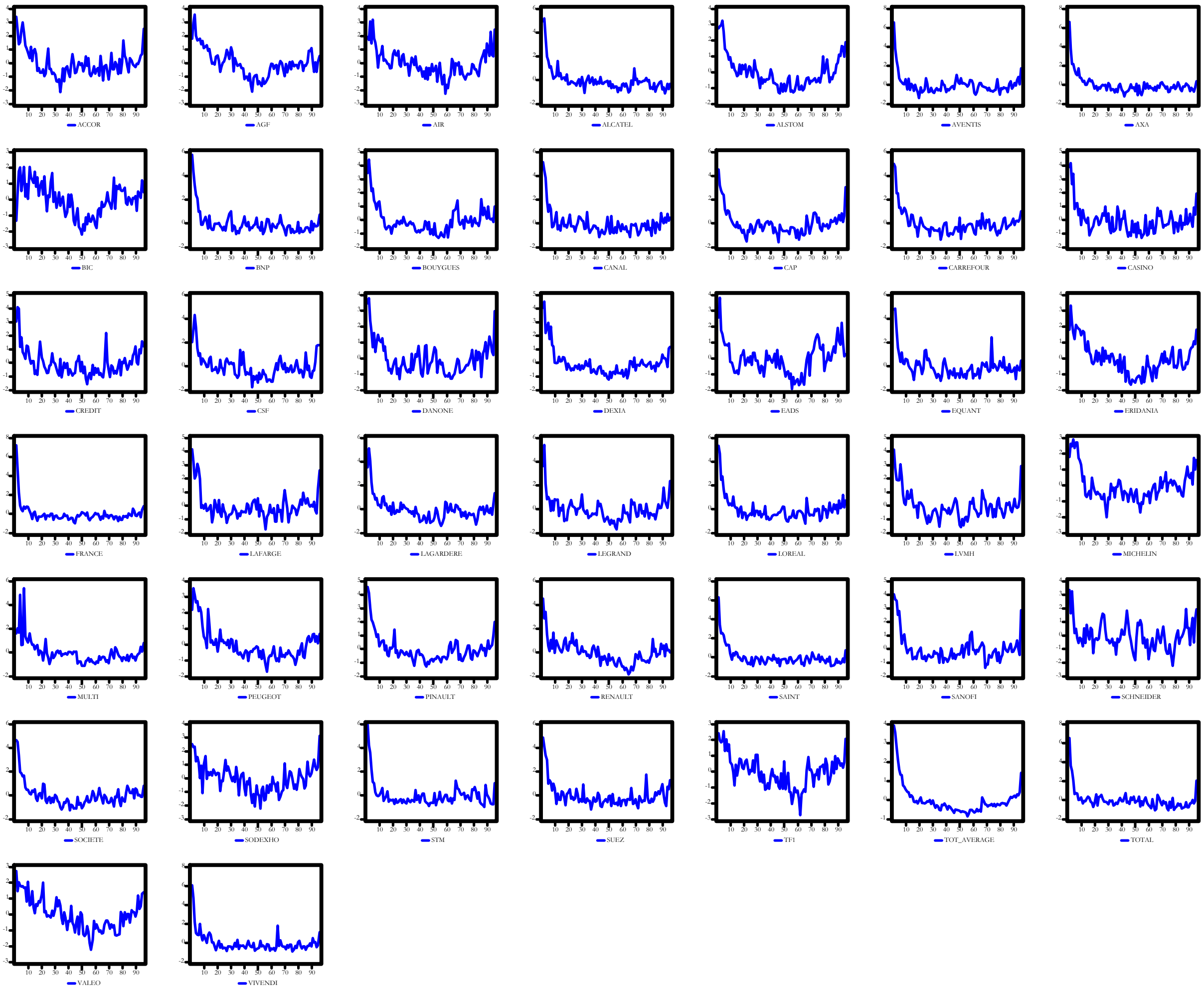


FIGURE 2.9.1.B: Intraday patterns of the effective half spread from April 1, 2000 to November 30, 2000 for the 43 stocks and the index. This figure shows the intraday evolution of the effective half spread (EHS) within successive intraday periods of 5 minutes for each stock belonging to the CAC 40 index. TOT_AVERAGE represents the average evolution for all the 43 stocks. The liquidity indicator has been calculated following the procedure described in Appendix 2.11.2 and it has been standardized by subtracting by its mean and then divided by its standard deviation. Hence the vertical axis presents the standardized extent of market liquidity. The horizontal axis corresponds to the time axis based on 102 periods of 5 minutes.

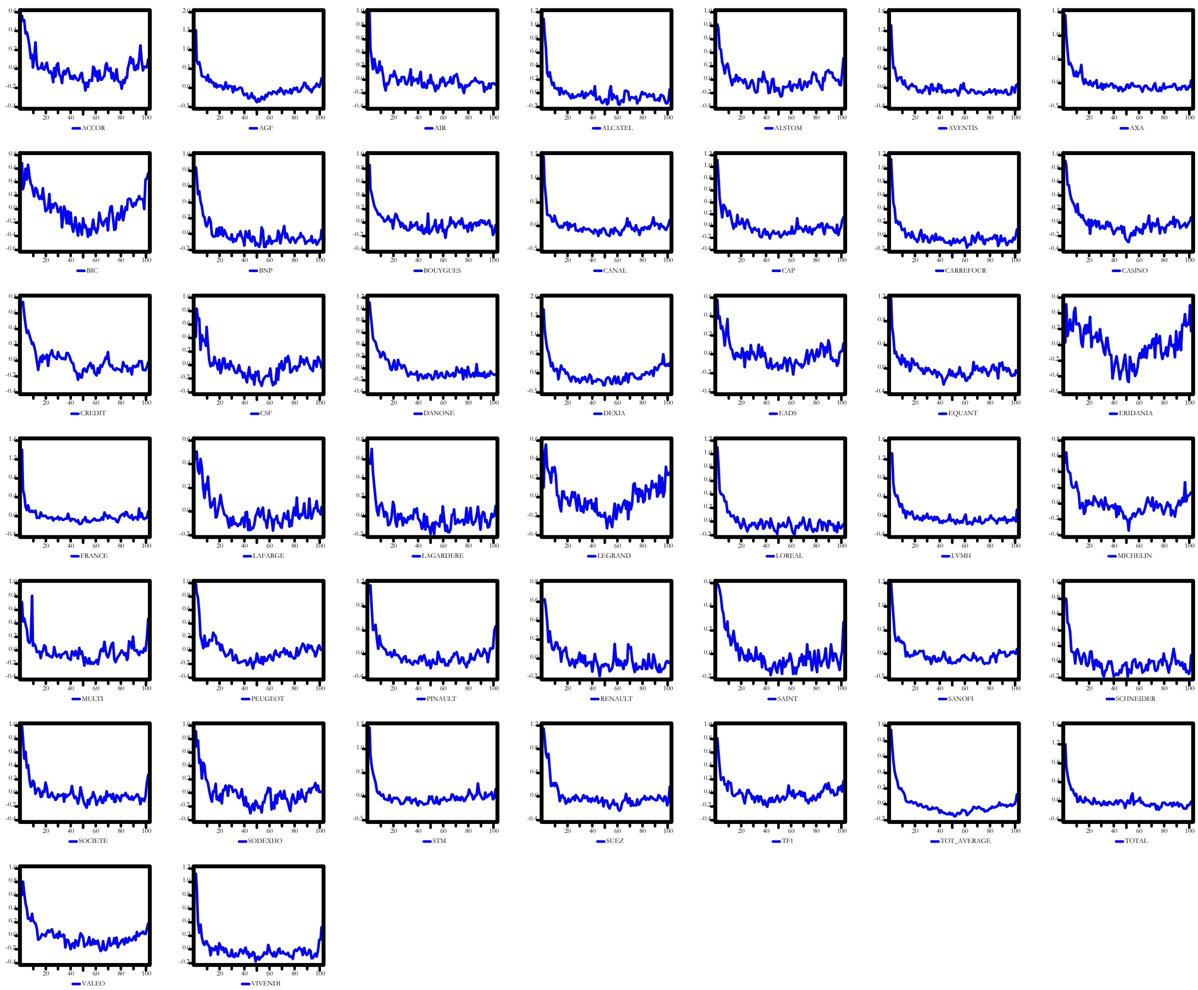


FIGURE 2.9.2: Intraday patterns of the quoted half spread from December 1, 1999 to March 31, 2000 for the 43 stocks and the index. This figure shows the intraday evolution of the quoted half spread (QHS) within successive intraday periods of 5 minutes for each stock belonging to the CAC 40 index. TOT_AVERAGE represents the average evolution for all the 43 stocks. The liquidity indicator has been calculated following the procedure described in Appendix 2.11.2 and it has been standardized by subtracting by its mean and then divided by its standard deviation. Hence the vertical axis presents the standardized extent of market liquidity. The horizontal axis corresponds to the time axis based on 96 periods of 5 minutes.

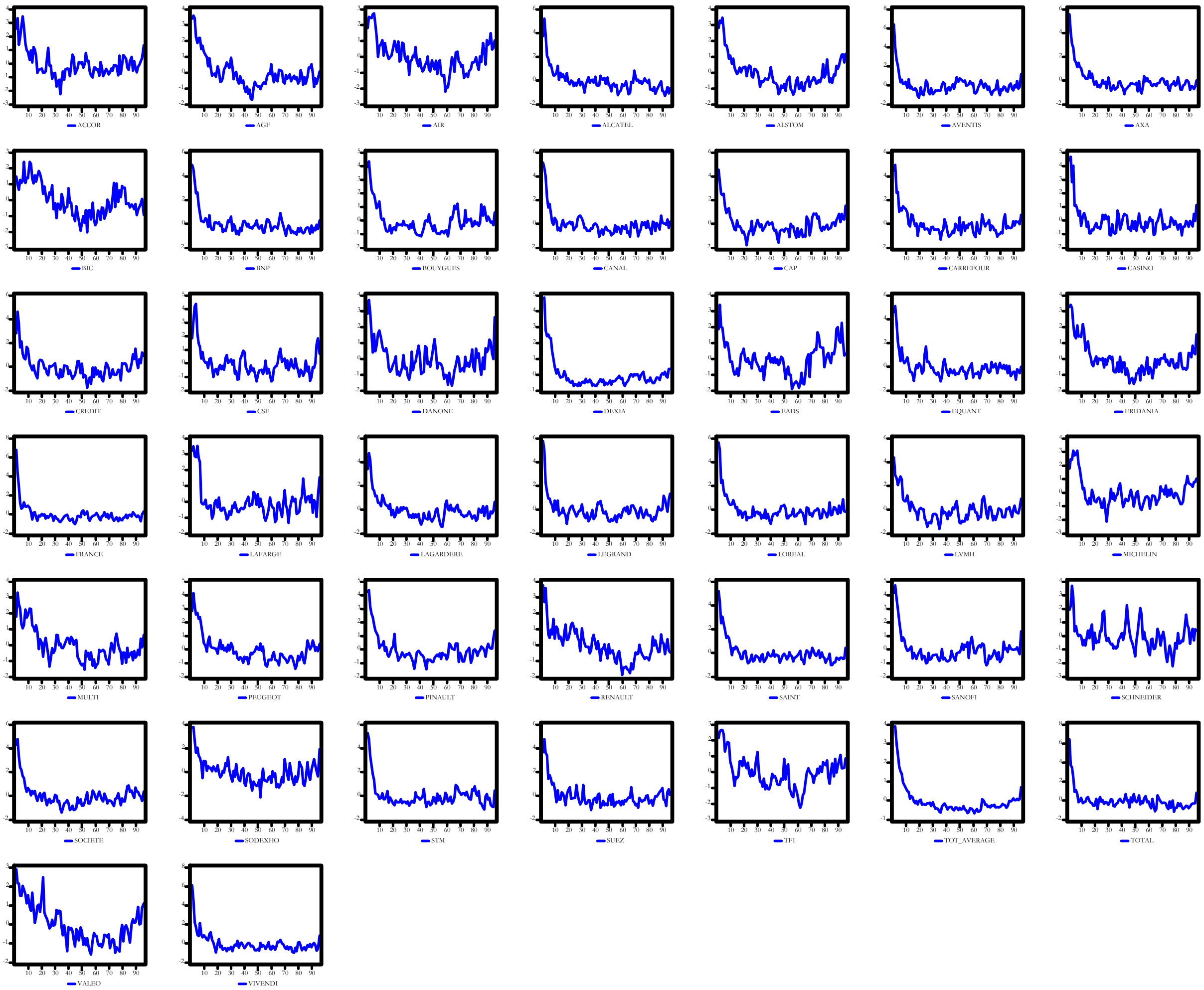


FIGURE 2.9.3: Intraday patterns of the difference spread from December 1, 1999 to March 31, 2000 for the 43 stocks and the index. This figure shows the intraday evolution of the difference spread (DSPR) within successive intraday periods of 5 minutes for each stock belonging to the CAC 40 index. TOT_AVERAGE represents the average evolution for all the 43 stocks. The liquidity indicator has been calculated following the procedure described in Appendix 2.11.2 and it has been standardized by subtracting by its mean and then divided by its standard deviation. Hence the vertical axis presents the standardized extent of market liquidity. The horizontal axis corresponds to the time axis based on 96 periods of 5 minutes.

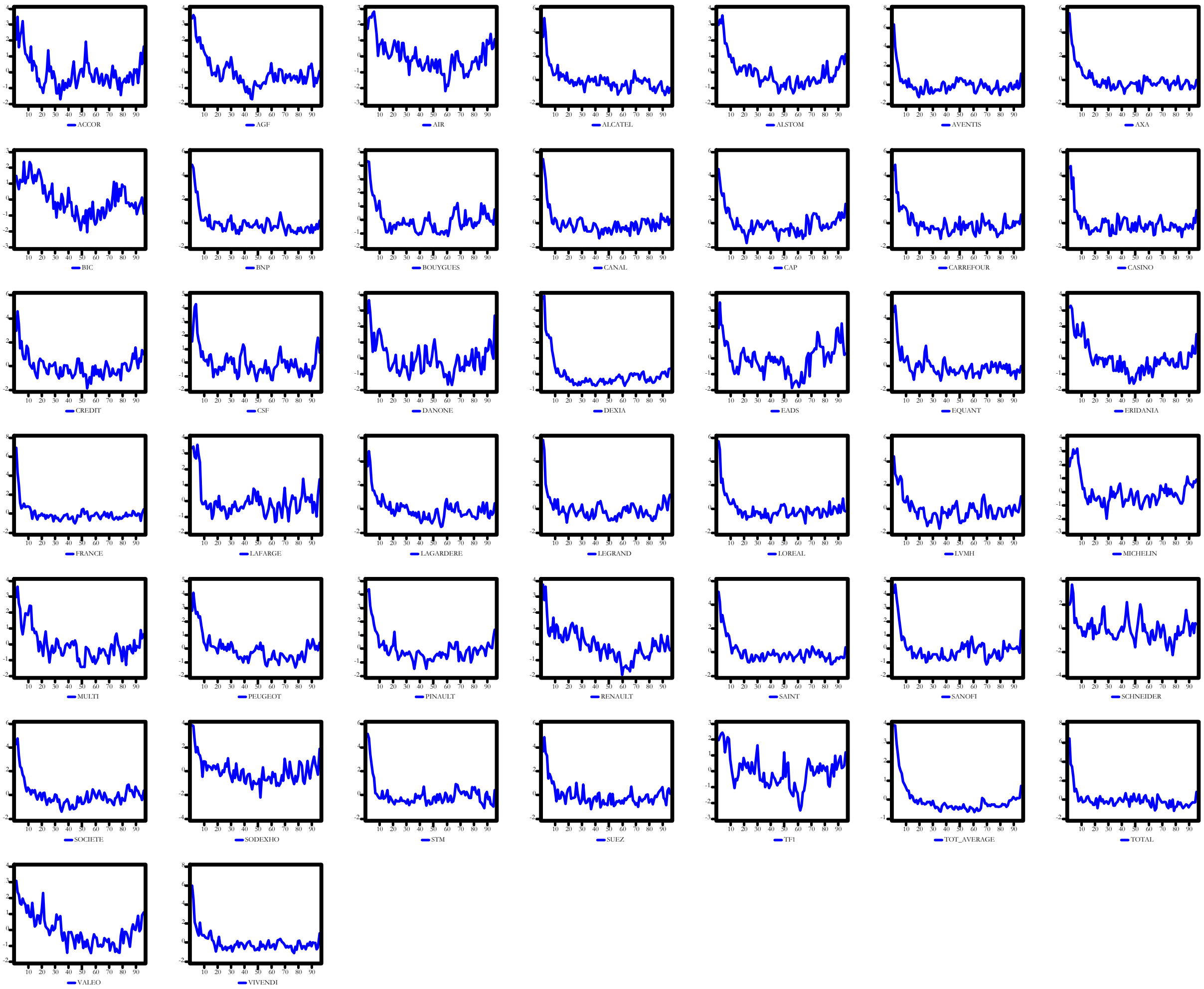


FIGURE 2.9.4: Intraday patterns of the midquote from December 1, 1999 to March 31, 2000 for the 43 stocks and the index. This figure shows the intraday evolution of the midquote (MID) within successive intraday periods of 5 minutes for each stock belonging to the CAC 40 index. TOT_AVERAGE represents the average evolution for all the 43 stocks. The liquidity indicator has been calculated following the procedure described in Appendix 2.11.2 and it has been standardized by subtracting by its mean and then divided by its standard deviation. Hence the vertical axis presents the standardized extent of market liquidity. The horizontal axis corresponds to the time axis based on 96 periods of 5 minutes.

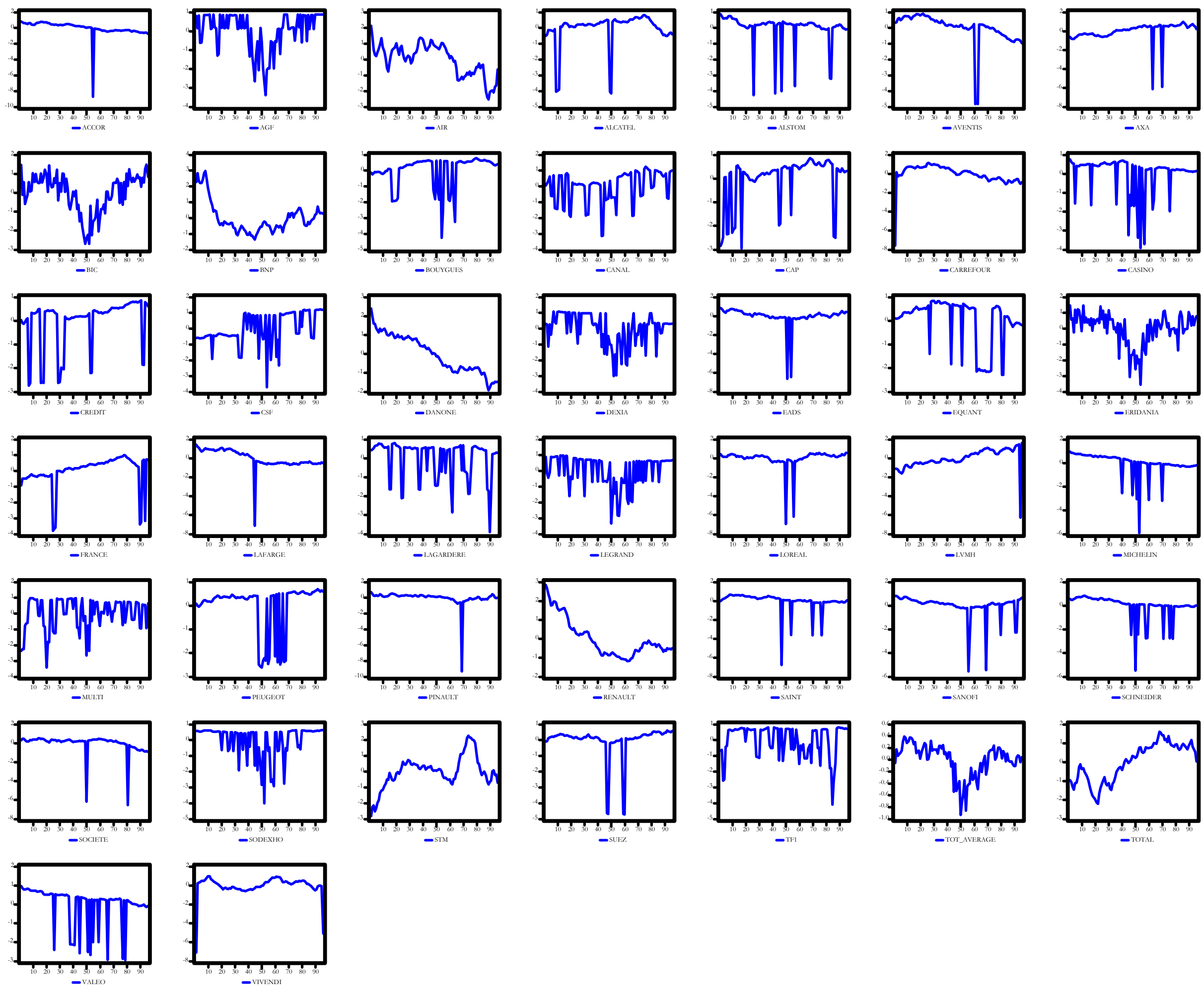


FIGURE 2.9.5: Intraday patterns of the QHS_WAS from December 1, 1999 to March 31, 2000 for the 43 stocks and the index. This figure shows the intraday evolution of the quoted spread from the WAS file (QHS_WAS) within successive intraday periods of 5 minutes for each stock belonging to the CAC 40 index. TOT_AVERAGE represents the average evolution for all the 43 stocks. The liquidity indicator has been calculated following the procedure described in Appendix 2.11.2 and it has been standardized by subtracting by its mean and then divided by its standard deviation. Hence the vertical axis presents the standardized extent of market liquidity. The horizontal axis corresponds to the time axis based on 96 periods of 5 minutes.

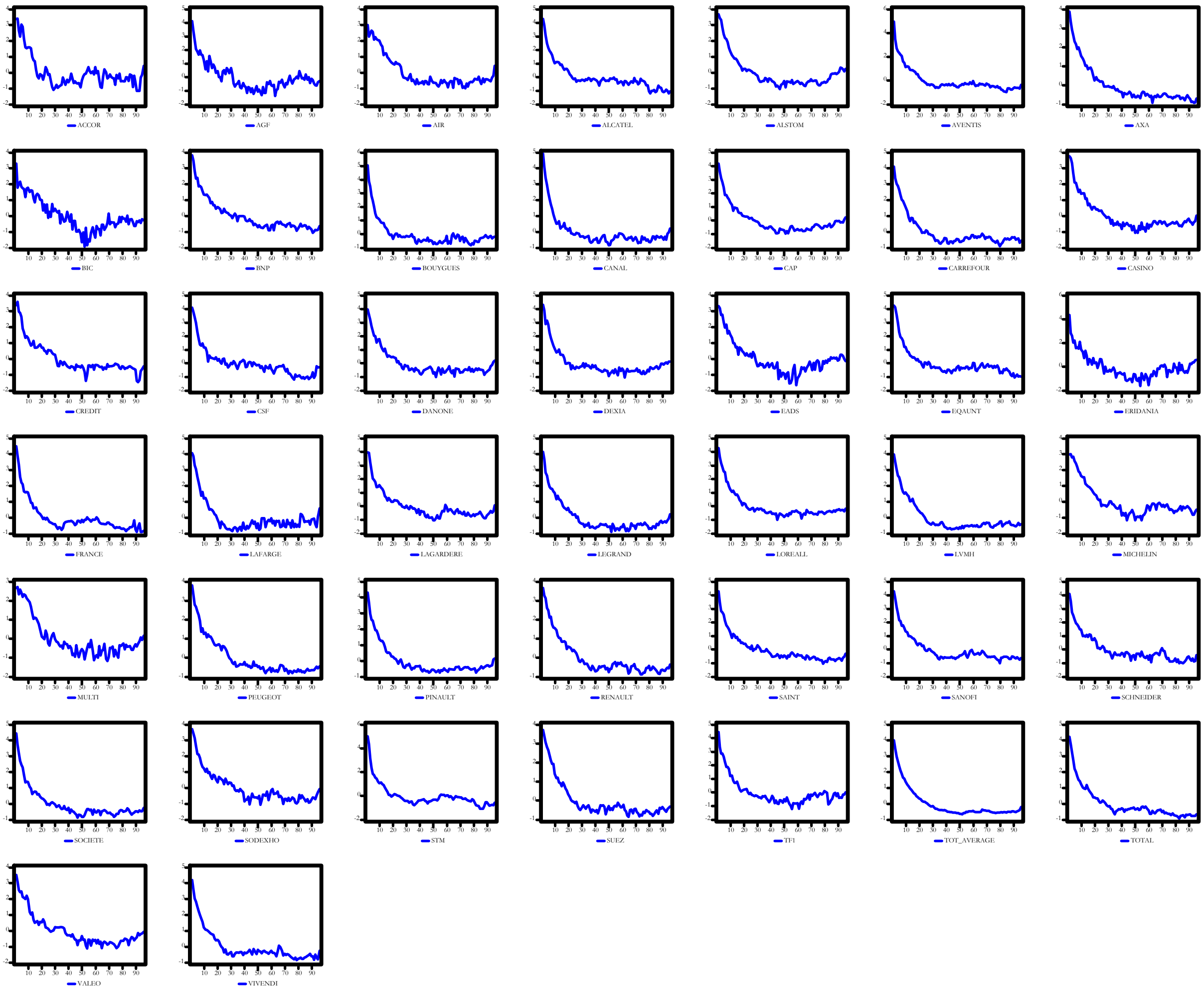


FIGURE 2.9.6: Intraday patterns of the cumulated traded volume from December 1, 1999 to March 31, 2000 for the 43 stocks and the index. This figure shows the intraday evolution of the cumulated traded volume (SUMVOL) within successive intraday periods of 5 minutes for each stock belonging to the CAC 40 index. TOT_AVERAGE represents the average evolution for all the 43 stocks. The liquidity indicator has been calculated following the procedure described in Appendix 2.11.2 and it has been standardized by subtracting by its mean and then divided by its standard deviation. Hence the vertical axis presents the standardized extent of market liquidity. The horizontal axis corresponds to the time axis based on 96 periods of 5 minutes.

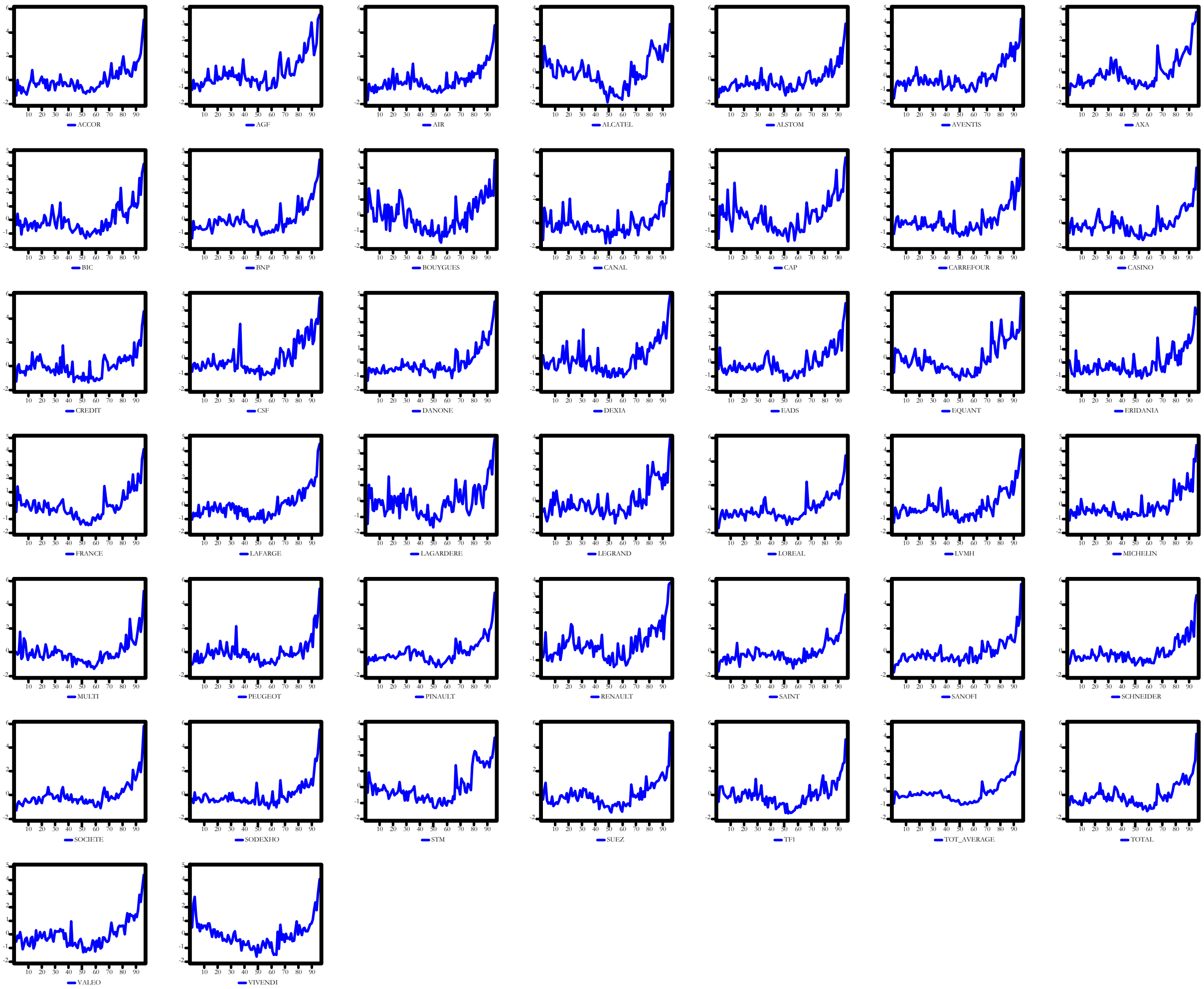


FIGURE 2.9.7: Intraday patterns of the number of trades from December 1, 1999 to March 31, 2000 for the 43 stocks and the index. This figure shows the intraday evolution of the number of trades (NBTR) within successive intraday periods of 5 minutes for each stock belonging to the CAC 40 index. TOT_AVERAGE represents the average evolution for all the 43 stocks. The liquidity indicator has been calculated following the procedure described in Appendix 2.11.2 and it has been standardized by subtracting by its mean and then divided by its standard deviation. Hence the vertical axis presents the standardized extent of market liquidity. The horizontal axis corresponds to the time axis based on 96 periods of 5 minutes.

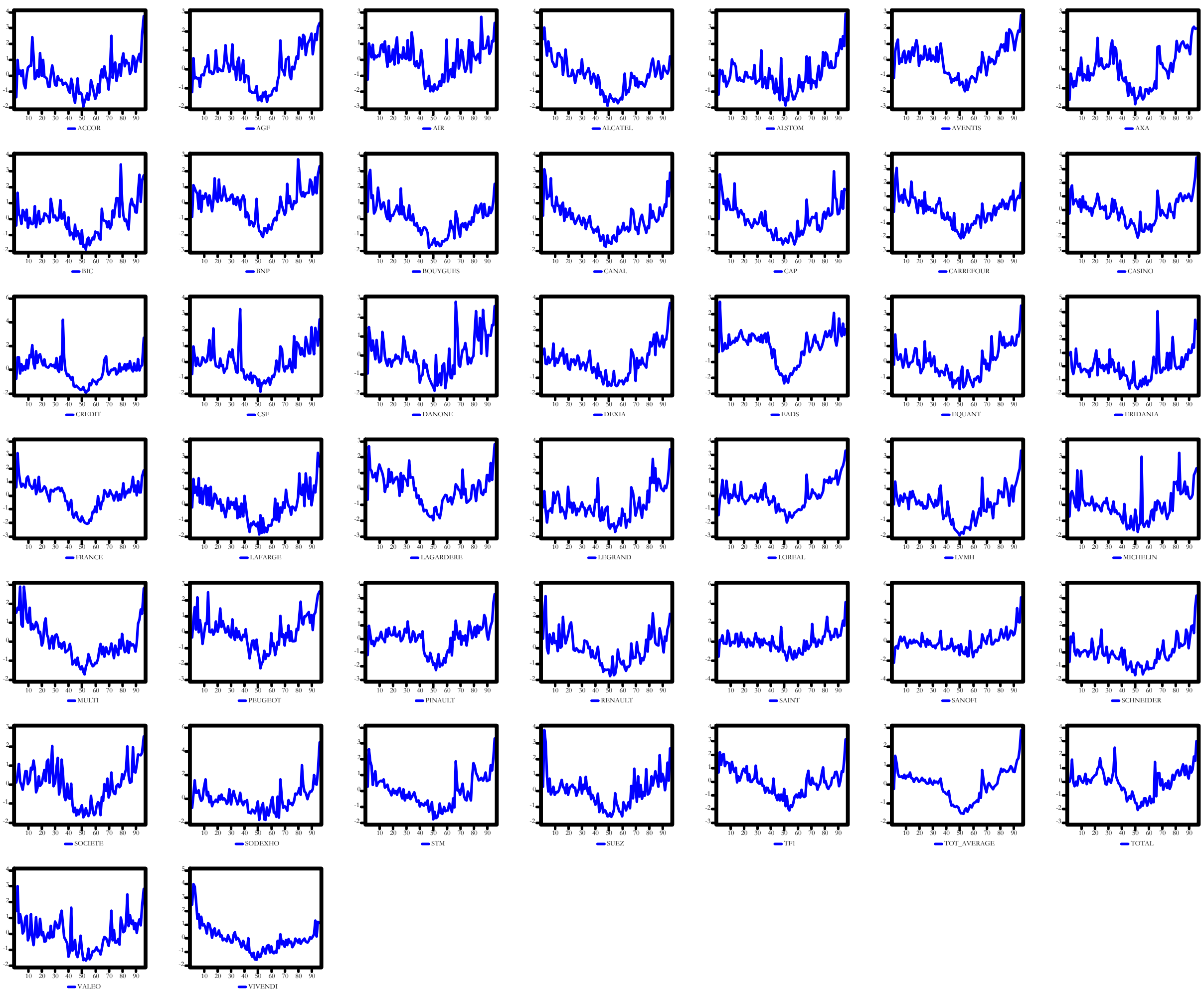


FIGURE 2.9.8: Intraday patterns of the cumulated volume imbalance from December 1, 1999 to March 31, 2000 for the 43 stocks and the index. This figure shows the intraday evolution of the cumulated volume imbalance (VIMB) within successive intraday periods of 5 minutes for each stock belonging to the CAC 40 index. TOT_AVERAGE represents the average evolution for all the 43 stocks. The liquidity indicator has been calculated following the procedure described in Appendix 2.11.2 and it has been standardized by subtracting by its mean and then divided by its standard deviation. Hence the vertical axis presents the standardized extent of market liquidity. The horizontal axis corresponds to the time axis based on 96 periods of 5 minutes.

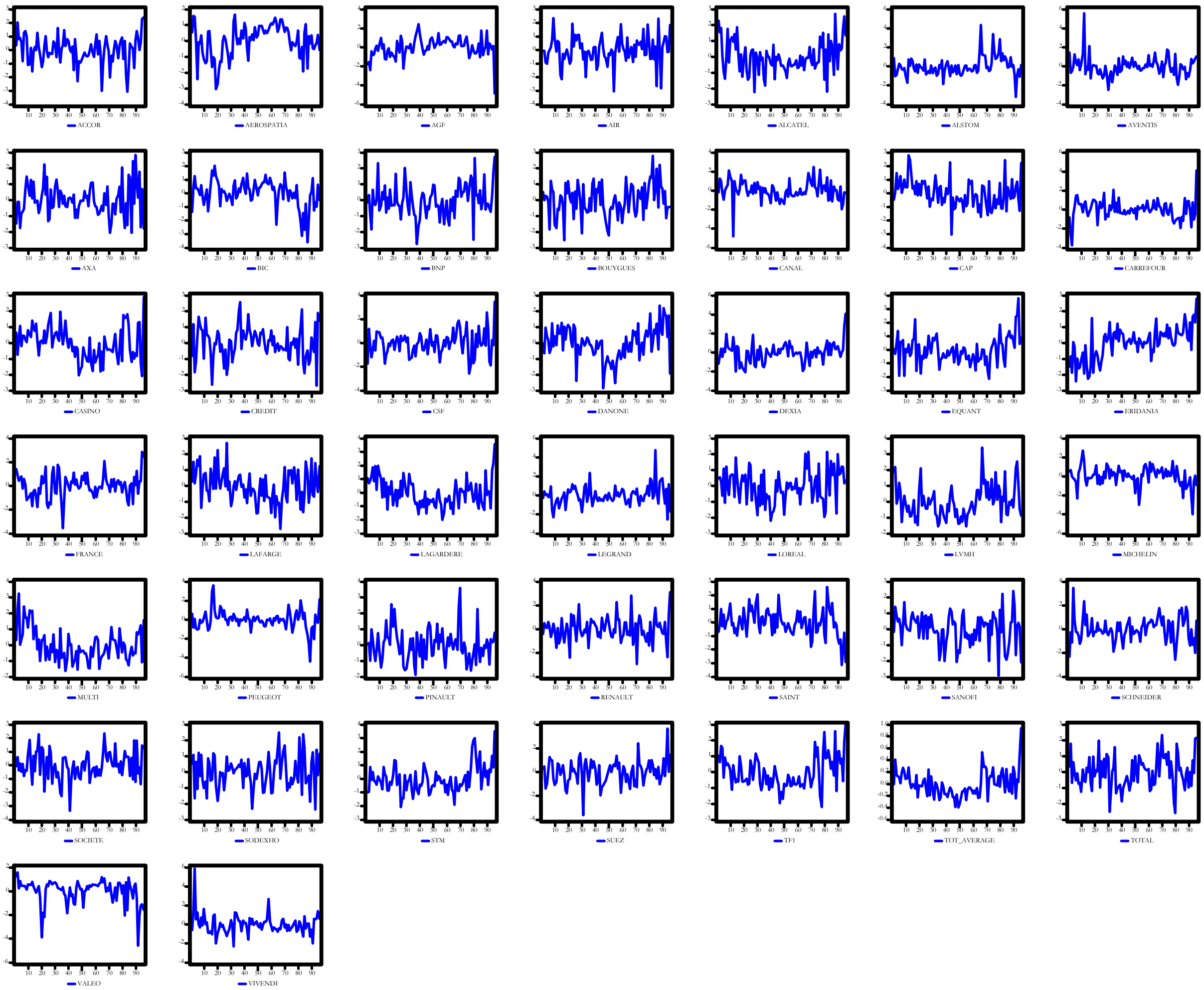


FIGURE 2.9.9: Intraday patterns of the SABSVIMB from December 1, 1999 to March 31, 2000 for the 43 stocks and the index. This figure shows the intraday evolution of the cumulated volume imbalance in absolute terms (SABSVIMB) within successive intraday periods of 5 minutes for each stock belonging to the CAC 40 index. TOT_AVERAGE represents the average evolution for all the 43 stocks. The liquidity indicator has been calculated following the procedure described in Appendix 2.11.2 and it has been standardized by subtracting by its mean and then divided by its standard deviation. Hence the vertical axis presents the standardized extent of market liquidity. The horizontal axis corresponds to the time axis based on 96 periods of 5 minutes.

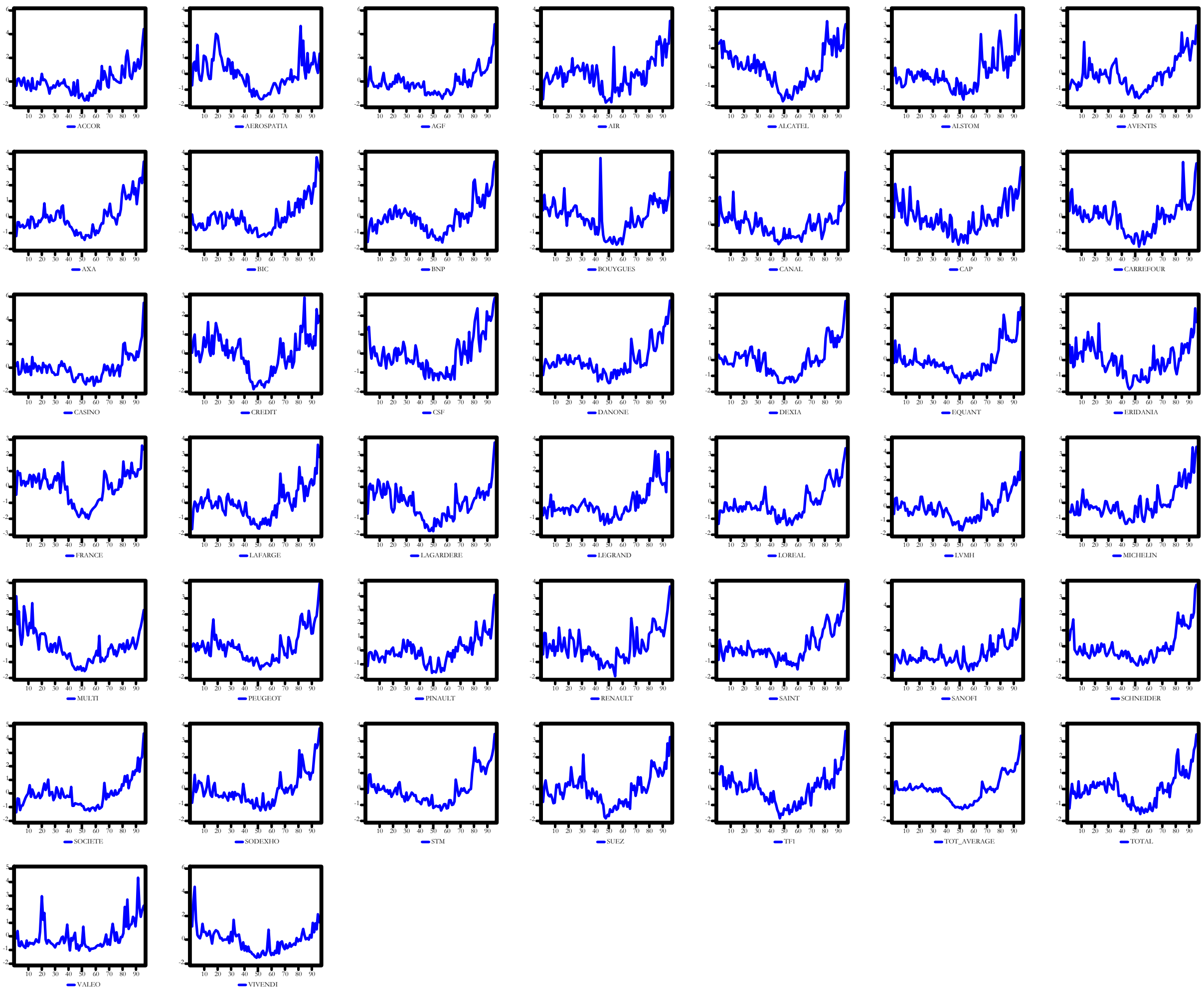


FIGURE 2.9.10: Intraday patterns of the average return from December 1, 1999 to March 31, 2000 for the 43 stocks and the index. This figure shows the intraday evolution of the average return (RET) within successive intraday periods of 5 minutes for each stock belonging to the CAC 40 index. TOT_AVERAGE represents the average evolution for all the 43 stocks. The liquidity indicator has been calculated following the procedure described in Appendix 2.11.2 and it has been standardized by subtracting by its mean and then divided by its standard deviation. Hence the vertical axis presents the standardized extent of market liquidity. The horizontal axis corresponds to the time axis based on 96 periods of 5 minutes.

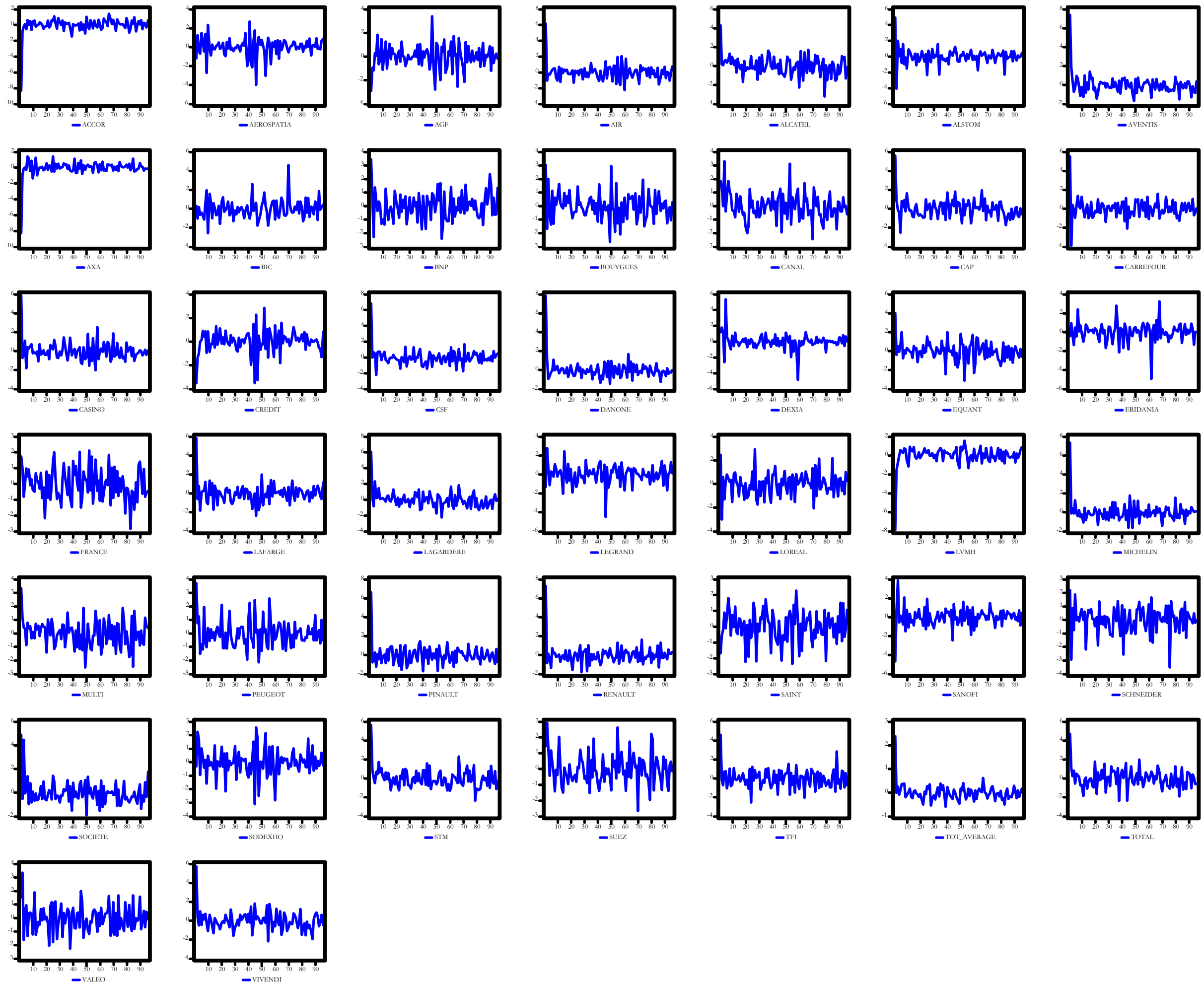


FIGURE 2.9.11: Intraday patterns of the return in absolute terms from December 1, 1999 to March 31, 2000 for the 43 stocks and the index. This figure shows the intraday evolution of the return in absolute terms (ABSRET) within successive intraday periods of 5 minutes for each stock belonging to the CAC 40 index. TOT_AVERAGE represents the average evolution for all the 43 stocks. The liquidity indicator has been calculated following the procedure described in Appendix 2.11.2 and it has been standardized by subtracting by its mean and then divided by its standard deviation. Hence the vertical axis presents the standardized extent of market liquidity. The horizontal axis corresponds to the time axis based on 96 periods of 5 minutes.

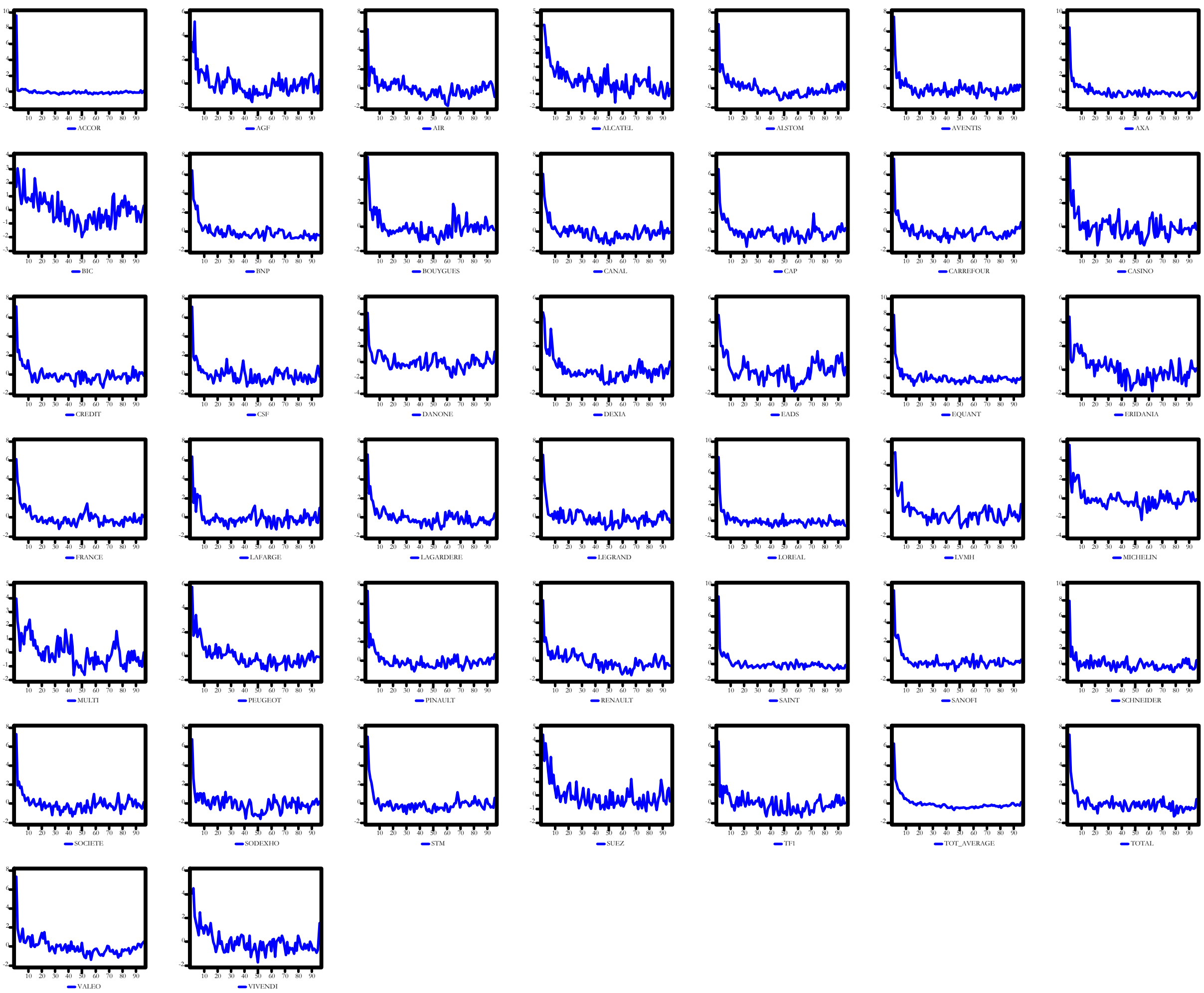


FIGURE 2.9.12: Intraday patterns of the volatility of returns from December 1, 1999 to March 31, 2000 for the 43 stocks and the index. This figure shows the intraday evolution of the volatility of returns (VARRET) within successive intraday periods of 5 minutes for each stock belonging to the CAC 40 index. TOT_AVERAGE represents the average evolution for all the 43 stocks. The liquidity indicator has been calculated following the procedure described in Appendix 2.11.2 and it has been standardized by subtracting by its mean and then divided by its standard deviation. Hence the vertical axis presents the standardized extent of market liquidity. The horizontal axis corresponds to the time axis based on 96 periods of 5 minutes.

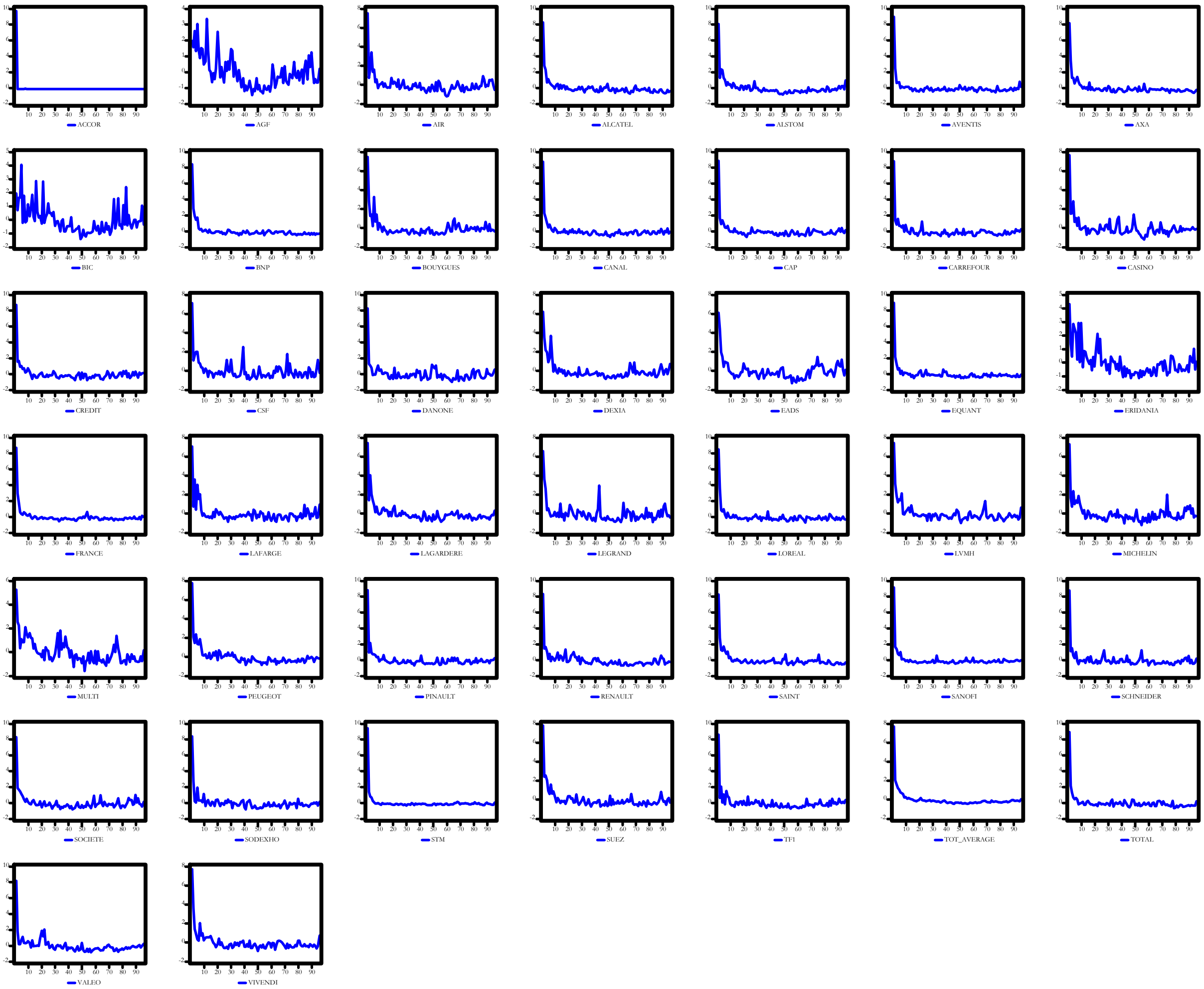


FIGURE 2.9.13: Intraday patterns of the volatility as log range from December 1, 1999 to March 31, 2000 for the 43 stocks and the index. This figure shows the intraday evolution of the volatility (VOLA) as log range within successive intraday periods of 5 minutes for each stock belonging to the CAC 40 index. TOT_AVERAGE represents the average evolution for all the 43 stocks. The liquidity indicator has been calculated following the procedure described in Appendix 2.11.2 and it has been standardized by subtracting by its mean and then divided by its standard deviation. Hence the vertical axis presents the standardized extent of market liquidity. The horizontal axis corresponds to the time axis based on 96 periods of 5 minutes.

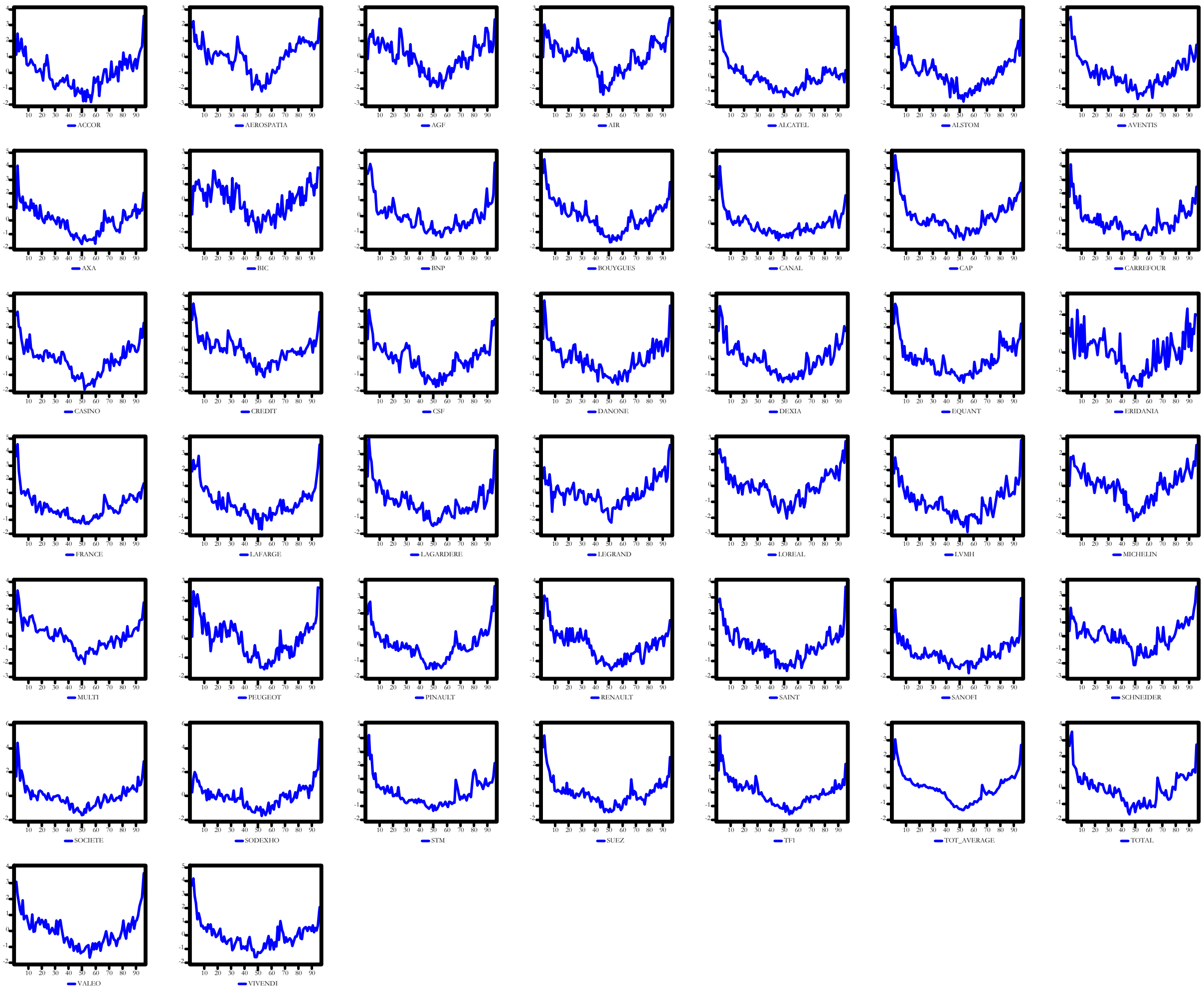


FIGURE 2.9.14: Intraday patterns of the waiting time from December 1, 1999 to March 31, 2000 for the 43 stocks and the index. This figure shows the intraday evolution of the waiting time between subsequent trades (WT) within successive intraday periods of 5 minutes for each stock belonging to the CAC 40 index. TOT_AVERAGE represents the average evolution for all the 43 stocks. The liquidity indicator has been calculated following the procedure described in Appendix 2.11.2 and it has been standardized by subtracting by its mean and then divided by its standard deviation. Hence the vertical axis presents the standardized extent of market liquidity. The horizontal axis corresponds to the time axis based on 96 periods of 5 minutes.

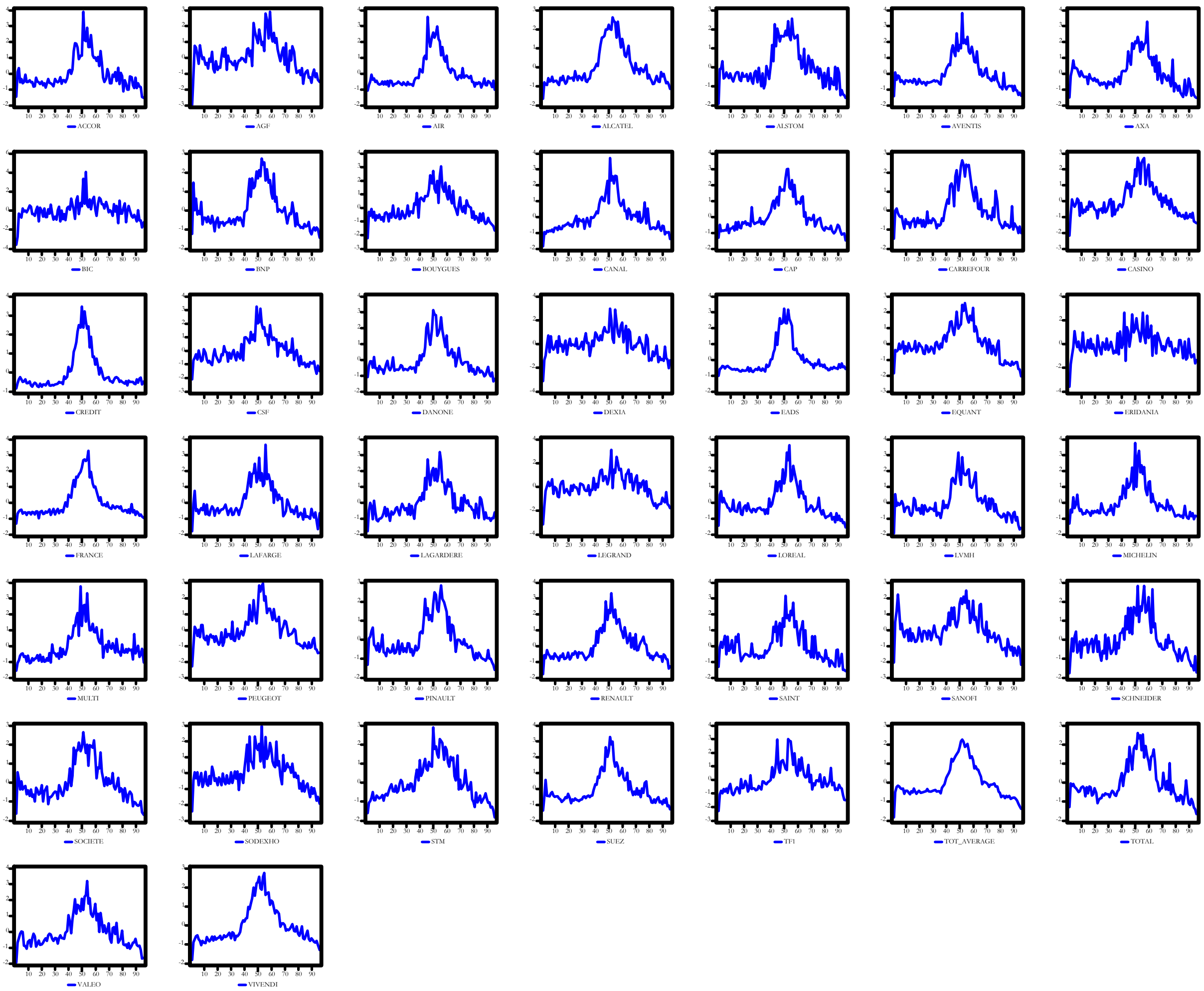


FIGURE 2.9.15: Intraday patterns of the liquidity ratio from December 1, 1999 to March 31, 2000 for the 43 stocks and the index. This figure shows the intraday evolution of the liquidity ratio (LR) within successive intraday periods of 5 minutes for each stock belonging to the CAC 40 index. TOT_AVERAGE represents the average evolution for all the 43 stocks. The liquidity indicator has been calculated following the procedure described in Appendix 2.11.2 and it has been standardized by subtracting by its mean and then divided by its standard deviation. Hence the vertical axis presents the standardized extent of market liquidity. The horizontal axis corresponds to the time axis based on 96 periods of 5 minutes.

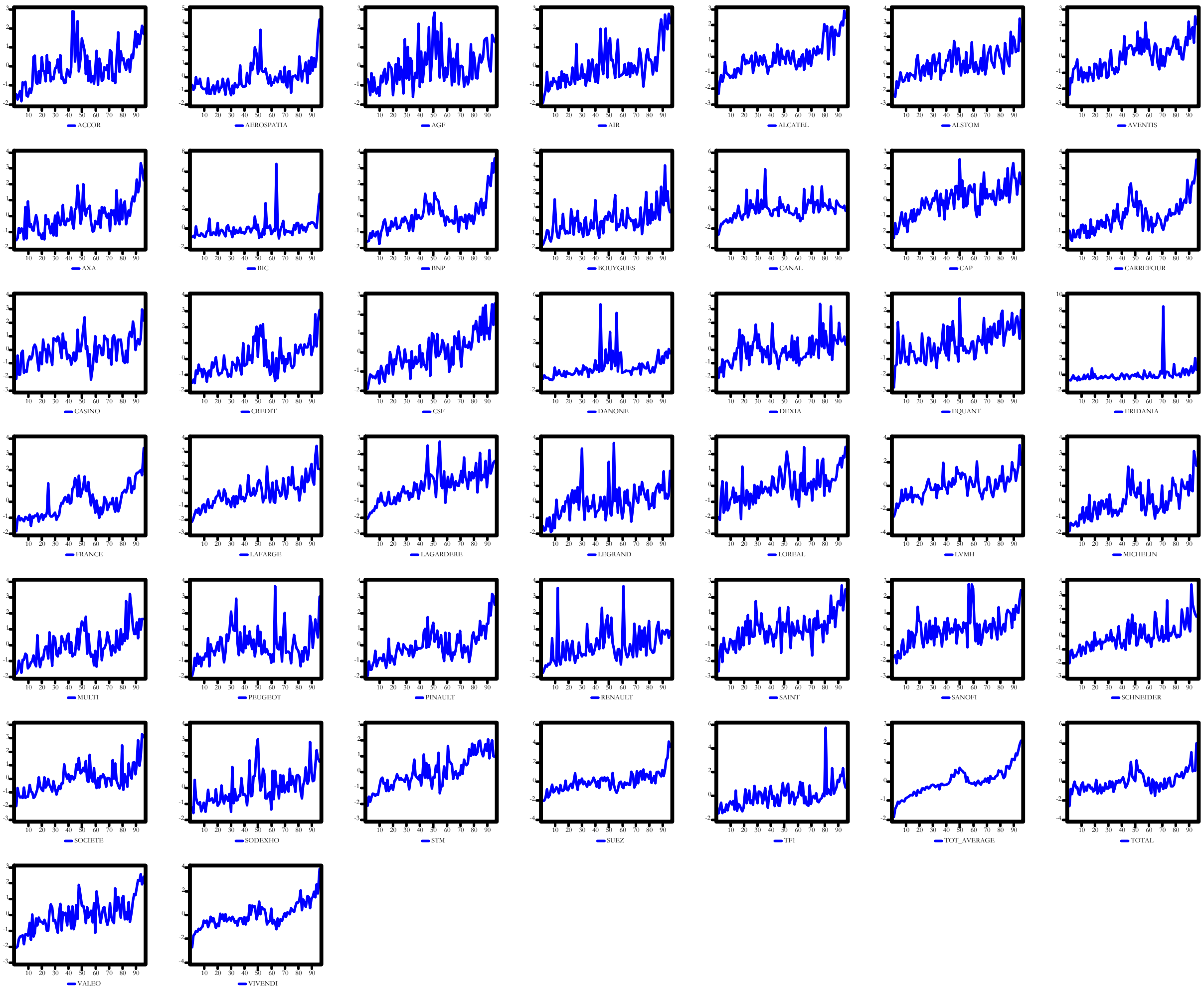
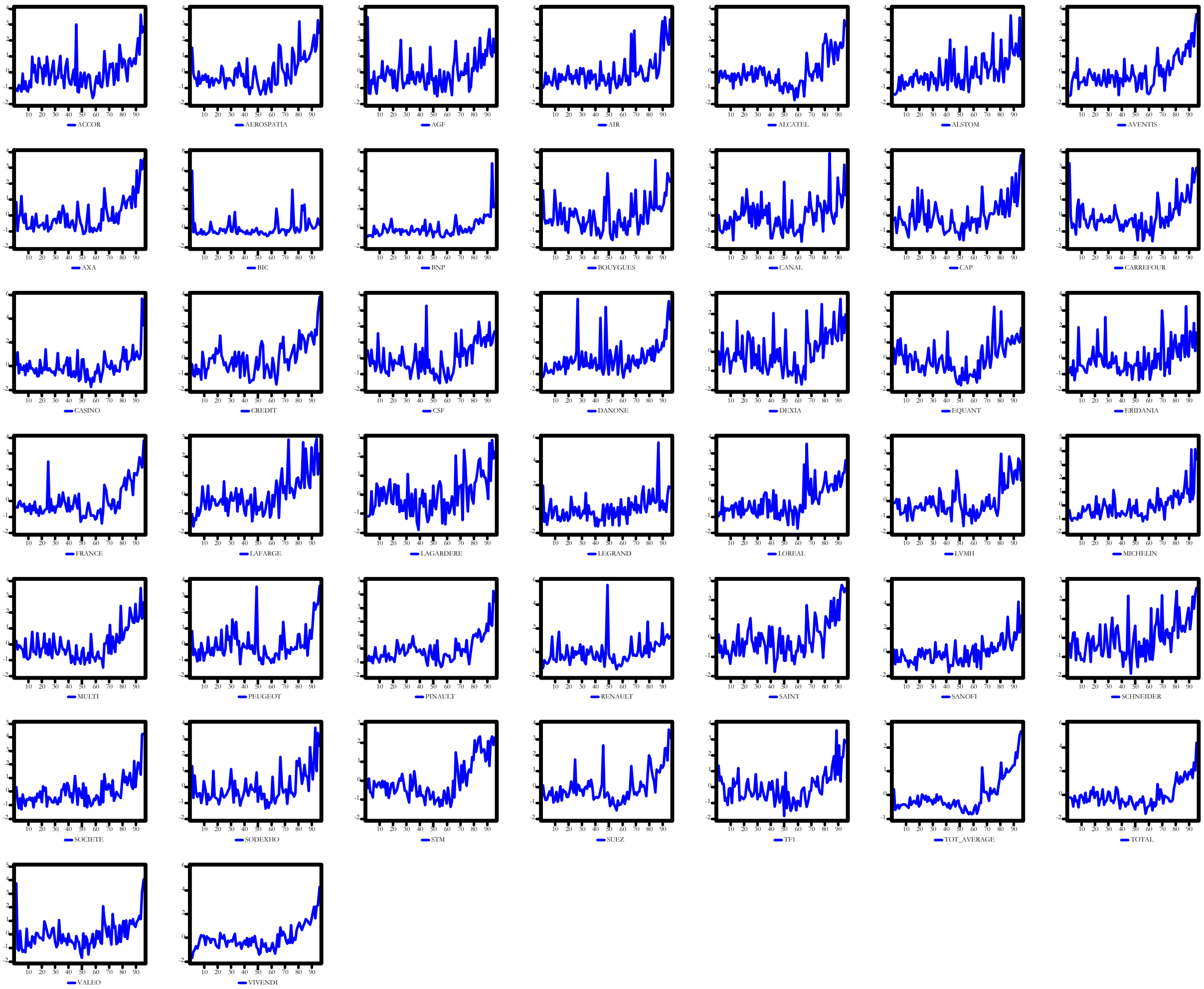


FIGURE 2.9.16: Intraday patterns of the flow ratio from December 1, 1999 to March 31, 2000 for the 43 stocks and the index. This figure shows the intraday evolution of the flow ratio (FR) within successive intraday periods of 5 minutes for each stock belonging to the CAC 40 index. TOT_AVERAGE represents the average evolution for all the 43 stocks. The liquidity indicator has been calculated following the procedure described in Appendix 2.11.2 and it has been standardized by subtracting by its mean and then divided by its standard deviation. Hence the vertical axis presents the standardized extent of market liquidity. The horizontal axis corresponds to the time axis based on 96 periods of 5 minutes.



TABLES

TABLE 2.10.1.A: Descriptive statistics. For each stock, the table shows company name, market capitalization, weight in the index, price change over the sample period from December 1, 1999 to November 30, 2000, overall number of trades, average number of shares traded every day, quantity traded, quantity traded per day, number of applications and the business sector of each company.

Company Name	MarketCap	Index Weight	Price Change 01.12.99	30.11.00	Var %	NbTrades	Average Trades p.d.	Volume	Volume p.d.	No. of application	Business Sector
					PANEL A						
Agf	9'881'148'945	0.84%	54.3	68.3	25.71%	148'960	581.88	67'398'866	263'276.82	945	Insurance
Air Liquide	12'617'100'753	1.08%	151.1	146.8	-2.84%	452'200	1'766.41	41'160'281	160'782.35	1918	Basic Materials
Alstom	5'940'658'878	0.51%	31.8	27.2	-14.53%	335'066	1'308.85	118'054'586	461'150.73	1399	Industrial
Axa	57'129'278'200	4.87%	140.0	162.0	15.67%	522'386	2'040.57	210'086'377	820'649.91	3868	Insurance
Bic	2'530'868'590	0.22%	42.8	41.0	-4.36%	71'520	279.38	16'520'139	64'531.79	757	Consumer goods
Bnp	41'542'116'914	3.54%	90.8	90.2	-0.65%	654'552	2'556.84	278'712'563	1'088'720.95	4534	Financial Institution
Canal Plus	26'151'009'863	2.23%	111.9	158.1	41.32%	728'102	2'844.15	111'179'973	434'296.77	2981	Television
Cap Gemini	22'738'312'534	1.94%	213.8	167.0	-21.86%	901'530	3'521.60	112'957'633	441'240.75	3234	Computer Services
Casino Guichard	8'263'886'113	0.70%	115.9	107.5	-7.30%	206'861	808.05	36'822'821	143'839.14	1366	Food Retail
Credit Lyonnais	13'664'533'413	1.16%	33.1	39.0	17.98%	529'793	2'069.50	128'053'242	500'207.98	1826	Financial Institution
Dexia Sico	13'666'469'381	1.16%	157.0	181.9	15.83%	142'855	558.03	26'850'367	104'884.25	570	Financial Institution
Equant	15'431'623'594	1.32%	98.9	36.0	-63.57%	812'594	3'174.20	295'370'027	1'153'789.17	5782	Telecom Services
Eridania Beghin	2'530'062'421	0.22%	105.6	105.3	-0.23%	76'939	300.54	6'890'039	26'914.21	855	Food and Beverage
France Telecom	145'948'601'889	12.44%	113.9	100.2	-11.98%	1'863'965	7'281.11	524'546'895	2'049'011.31	8141	Telecom Services
Lafarge	9'208'521'841	0.78%	100.1	85.4	-14.73%	443'585	1'732.75	95'322'709	372'354.33	2309	Construction
Lagardere	9'577'283'774	0.82%	49.5	60.3	21.87%	514'608	2'010.19	128'227'857	500'890.07	2718	Multimedia
Legrand	4'510'453'696	0.38%	221.5	193.9	-12.46%	139'220	543.83	11'379'639	44'451.71	862	Electric Products
Michelin	4'767'243'799	0.41%	39.4	33.6	-14.83%	294'391	1'149.96	89'238'922	348'589.54	1677	Rubber-tires
Peugeot	9'978'589'909	0.85%	203.2	227.3	11.84%	228'903	894.15	30'236'967	118'113.15	1292	Auto-Cars/Light Trucks
Pinault	25'167'440'985	2.14%	229.3	205.5	-10.40%	362'844	1'417.36	49'521'039	193'441.56	1910	Retailers
Renault	11'490'044'369	0.98%	45.8	55.6	21.41%	472'853	1'847.08	136'389'052	532'769.73	1802	Auto-Cars/Light Trucks
Saint Gobain	12'563'648'185	1.07%	169.1	154.7	-8.49%	378'292	1'477.70	60'347'382	235'731.96	1999	Building and
Sanofi	35'199'269'636	3.00%	40.2	67.1	66.75%	362'301	1'415.24	246'565'083	963'144.86	2371	Medical-Drugs
Schneider	11'426'911'501	0.97%	71.1	71.7	0.80%	294'784	1'151.50	89'792'900	350'753.52	1642	Machinery-Electrical
Sodexho	5'632'088'753	0.48%	184.3	195.5	6.04%	172'092	672.23	14'969'659	58'475.23	871	Food-Catering
Suez Lyonnaise des Eaux	34'409'032'814	2.93%	156.8	190.5	21.47%	615'739	2'405.23	126'860'383	495'548.37	3569	Water
Thomson-csf	7'098'289'225	0.60%	30.0	52.4	74.79%	213'433	833.72	53'534'424	209'118.84	854	Aerospace/Defense
Total Fina	112'487'946'368	9.59%	131.7	168.5	27.95%	771'538	3'013.82	333'413'802	1'302'397.66	6835	Oil Comp-Integrated
Valeo	4'666'916'391	0.40%	73.2	54.4	-25.68%	340'155	1'328.73	71'088'801	277'690.63	1934	Auto/Trk Prts&Equip-Orig
Vivendi	60'685'848'634	5.17%	88.1	75.2	-14.70%	1'558'531	6'088.01	661'049'177	2'582'223.35	9971	Multimedia
					PANEL B						
Accor	8'504'448'767	0.72%	227	43.03	-5.22%	473'725	1'850.49	130'298'631	508'979.03	1982	Hotels&Motels
Aerospatia Matra	17'074'565'199	1.46%	21.29	24.01	12.78%	560'690	2'190.20	167'750'177	655'274.13	1263	Aerospace/Defense-Equip
Alcatel	74'545'766'570	6.35%	189	57.25	51.46%	1'986'674	7'760.45	846'679'362	3'307'341.26	9283	Telecommunication
Aventis	46'431'642'472	3.96%	61.75	90.4	46.40%	613'072	2'394.81	425'086'754	1'660'495.13	5210	Medical-Drugs
Bouygues	20'965'460'705	1.79%	456	50	9.65%	403'548	1'576.36	86'704'849	338'690.82	2262	Building&Construct-
Carrefour	52'632'599'567	4.49%	175	69.5	-20.57%	1'002'378	3'915.54	251'756'085	983'422.21	5841	Food-Retail
Danone	18'810'626'067	1.60%	232.5	151.7	30.49%	508'459	1'986.17	84'880'028	331'562.61	3111	Food-Misc/Diversified
L'Oreal	51'449'339'578	4.38%	657.5	91.5	39.16%	428'682	1'674.54	94'656'899	369'753.51	2406	Cosmetics&Toiletries
LVMH	41'713'036'882	3.55%	323	75.5	16.87%	416'816	1'628.19	91'879'355	358'903.73	2100	Diversified Operations
Société Générale	24'676'041'281	2.10%	213.9	61.2	14.45%	463'654	1'811.15	144'237'431	563'427.46	2325	Money Center Banks
Stmicroelectronics	52'922'065'071	4.51%	125.2	48.41	16.00%	1'023'209	3'996.91	602'450'693	2'353'323.02	5506	Electronic Compo-Semicon
TF1	14'069'644'537	1.20%	358	50	39.66%	437'622	1'709.46	66'297'862	258'976.02	2307	Television
Thomson-Multimedia	12'727'033'582	1.08%	43.5	44	102.30%	596'429	2'329.80	89'664'743	350'252.90	1588	Audio/Video Products
Total	1'173'427'471'64					23'525'550	91'897	7'254'884'47	28'339'392	125'976	
Mean	27'289'010'968					547'106	2'137	168'718'244	659'056	2'930	
Median	14'069'644'537					452'200	1'766	95'322'709	372'354	2'100	
StDev	29'474'668'772					419'381	1'638	186'389'188	728'083	2'297	

TABLE 2.10.1.B: Descriptive statistics of the sixteen liquidity indicators during the first period. For each stock, the table shows the average value, for a 5 minutes period, of the sixteen liquidity indicators considered in this study, namely: effective half spread (EHS), quoted half spread (QHS), difference spread (DSPR), midquote (MID), quoted half spread from the WAS file (QHS_WAS), cumulated traded volume (SUMVOL), number of transactions (NBTR), volume imbalance (VIMB), volume imbalance in absolute terms (SABSVIMB), return (RET), return in absolute terms (ABSRET), volatility of return (VARRET), volatility as log range (VOLA), waiting time between subsequent trades (WT), liquidity ratio (LR) and flow ratio (FR). The calculation of each proxy is explained in detail in Appendix 2.11.2.

Company	EHS	QHS	DSPR	MID	QHS_WAS	SUMVOL	NBTR	VIMB	SABSVIMB	RET	ABSRET	VARRET	VOLA	WT	LR	FR
Accor	0.078	0.073	0.125	58.287	0.220	0.002183	1267.71	166752.54	873699.91	-0.000573%	0.052%	0.006323%	0.385%	0.000187	0.000848	0.981
Agf	0.074	0.081	0.085	31.924	0.339	0.000699	301.41	-34320.91	485560.71	-0.000283%	0.056%	0.000194%	0.192%	0.000672	0.000476	0.692
Air	0.083	0.077	0.230	95.153	0.512	0.001193	1198.83	67638.30	482191.81	0.000031%	0.058%	0.000210%	0.407%	0.000175	0.000716	1.382
Alcatel	0.054	0.048	0.211	140.098	0.471	0.003065	3462.69	848889.76	2613311.96	0.000042%	0.034%	0.000071%	0.415%	0.000062	0.001371	3.034
Alstom	0.113	0.107	0.061	18.201	0.793	0.001351	926.33	125748.19	834811.00	0.000113%	0.076%	0.000434%	0.453%	0.000285	0.000293	0.332
Aventis	0.062	0.058	0.065	36.053	0.486	0.001975	1516.33	213306.94	3516667.43	0.000160%	0.043%	0.000116%	0.370%	0.000119	0.000231	0.678
Axa	0.062	0.059	0.157	83.753	0.477	0.001086	1117.97	55381.49	1298940.23	-0.000226%	0.046%	0.000124%	0.334%	0.000162	0.000619	1.348
Bic	0.145	0.171	0.152	24.795	1.007	0.000853	203.16	-11928.55	78202.13	0.001551%	0.099%	0.000633%	0.190%	0.000958	0.000927	0.755
Bnp	0.049	0.046	0.079	54.194	0.392	0.001424	1653.54	193465.67	2272239.21	-0.000045%	0.033%	0.000074%	0.301%	0.000111	0.000403	0.866
Bouygues	0.095	0.094	1.272	434.087	0.520	0.001734	701.09	44976.07	165061.99	0.000595%	0.067%	0.000293%	0.383%	0.000369	0.008612	13.666
Canal	0.104	0.092	0.339	121.737	0.540	0.002411	2123.63	145365.03	892162.52	-0.000006%	0.063%	0.000257%	0.641%	0.000112	0.001523	2.986
Cap	0.088	0.082	0.407	156.669	1.014	0.002913	1531.93	81886.49	623710.68	0.000114%	0.059%	0.000234%	0.497%	0.000163	0.003243	4.871
Carrefour	0.060	0.054	0.175	102.280	0.482	0.001069	2116.04	324444.53	1268149.00	-0.000043%	0.037%	0.000094%	0.425%	0.000095	0.000386	1.086
Casino	0.099	0.099	0.208	66.066	0.553	0.001185	534.85	46272.81	286277.14	0.000060%	0.072%	0.000299%	0.350%	0.000426	0.000955	1.553
Credit	0.086	0.080	0.064	24.782	1.770	0.001119	1773.27	-108732.31	1593188.89	-0.000143%	0.053%	0.000228%	0.383%	0.000122	0.000206	0.277
Csf	0.111	0.111	0.087	23.749	0.439	0.001097	692.45	51088.85	521570.90	0.000491%	0.079%	0.000458%	0.405%	0.000422	0.000456	0.436
Danone	0.062	0.057	0.249	137.974	0.384	0.001751	1379.73	104347.51	474914.89	0.000162%	0.040%	0.000113%	0.311%	0.000150	0.002218	3.029
Dexia	0.068	0.079	0.230	89.033	0.677	0.000869	281.73	-15659.00	200739.92	-0.000575%	0.053%	0.000156%	0.162%	0.000737	0.001809	2.177
EADS	0.098	0.094	0.038	13.042	0.755	0.000371	1085.89	-43591.10	991266.70	-0.000479%	0.065%	0.000330%	0.436%	0.000188	0.000037	0.067
Equant	0.087	0.080	0.175	68.536	0.715	0.002374	1233.59	261703.07	1236724.25	0.000010%	0.055%	0.000192%	0.492%	0.000192	0.000727	1.914
Eridania	0.134	0.148	0.295	57.499	0.549	0.000679	226.67	-6591.73	51943.75	-0.002282%	0.102%	0.000602%	0.227%	0.000930	0.001149	1.077
France	0.060	0.054	0.153	90.655	0.659	0.000929	3775.81	424611.03	5164786.09	0.000090%	0.037%	0.000084%	0.497%	0.000052	0.000198	0.619
Lafarge	0.091	0.083	0.156	58.687	0.425	0.002334	1267.46	162291.35	687662.76	0.000034%	0.055%	0.000210%	0.407%	0.000204	0.000725	1.534
Lagardere	0.097	0.090	0.136	47.629	0.643	0.002647	1276.88	272396.07	1012775.46	0.000227%	0.063%	0.000275%	0.517%	0.000216	0.000745	1.669
Legrand	0.107	0.114	0.479	131.453	0.596	0.001574	383.00	13203.41	106086.67	-0.000264%	0.079%	0.000398%	0.284%	0.000591	0.004671	4.617
L'Oreal	0.075	0.074	1.015	434.284	0.454	0.000676	835.85	5557.45	166589.07	-0.000001%	0.055%	0.000175%	0.369%	0.000252	0.002545	4.653
Lvmh	0.067	0.066	0.527	249.657	0.537	0.000977	938.08	2005.80	311168.59	-0.000262%	0.049%	0.000155%	0.335%	0.000237	0.004314	3.736
MEAN	0.067	0.066	0.140	102.456	0.466	0.002126	2127.26	126498.50	2501763.86	0.000017%	0.047%	0.000245%	0.381%	0.000280	0.001418	2.147
Michelin	0.079	0.076	0.055	23.056	0.410	0.001779	823.01	27028.92	781060.79	-0.000054%	0.055%	0.000215%	0.306%	0.000284	0.000680	0.591
Multi	0.156	0.142	0.216	51.382	2.307	0.001062	1200.27	174148.40	501160.05	0.000147%	0.107%	0.000774%	0.667%	0.000250	0.000266	0.788
Peugeot	0.089	0.089	0.391	137.740	0.527	0.001973	583.54	41275.74	254179.58	0.000533%	0.066%	0.000275%	0.301%	0.000388	0.002630	4.970
Pinault	0.072	0.069	0.304	138.948	0.400	0.001160	1042.71	103554.79	446089.08	0.000123%	0.050%	0.000168%	0.345%	0.000217	0.001530	2.084
Renault	0.080	0.073	0.068	29.276	0.623	0.001505	1305.64	150742.20	1088005.52	0.000257%	0.052%	0.000198%	0.385%	0.000172	0.000458	0.555
Saint	0.083	0.080	0.251	98.433	0.530	0.001811	993.95	40774.07	497752.07	-0.000140%	0.059%	0.000223%	0.384%	0.000239	0.001384	2.302
Sanofi	0.093	0.091	0.072	24.815	0.711	0.000762	881.71	80387.98	1246928.67	0.000102%	0.062%	0.000318%	0.376%	0.000265	0.000321	0.275
Schneider	0.101	0.096	0.134	44.387	0.655	0.001575	806.98	11295.06	651503.65	-0.000116%	0.069%	0.000304%	0.383%	0.000313	0.000529	0.964
Société	0.068	0.065	0.278	134.295	0.736	0.001398	998.56	87285.64	460605.78	0.000095%	0.048%	0.000155%	0.315%	0.000206	0.002065	2.606
Sodexho	0.096	0.100	0.318	99.786	0.495	0.001212	470.98	11522.17	134117.92	0.000531%	0.071%	0.000309%	0.271%	0.000543	0.001732	2.236
Stm	0.063	0.057	0.194	108.328	0.655	0.001664	1799.08	406730.43	1544217.57	0.000196%	0.040%	0.000107%	0.442%	0.000109	0.000883	1.898
Suez	0.052	0.047	0.153	102.722	0.277	0.001968	2110.21	109750.31	1621523.72	-0.000030%	0.033%	0.000068%	0.310%	0.000103	0.000855	1.840
Tf1	0.136	0.132	1.533	370.126	0.537	0.001485	710.02	40323.22	98581.84	0.000789%	0.090%	0.000553%	0.485%	0.000361	0.006090	8.229
Total	0.057	0.053	0.143	84.998	0.597	0.000949	1780.33	676840.31	2310165.10	0.000074%	0.039%	0.000088%	0.376%	0.000101	0.000353	0.918
Valeo	0.086	0.080	0.102	40.924	0.431	0.002104	1026.25	-221188.13	552116.01	-0.000259%	0.054%	0.000216%	0.377%	0.000267	0.000521	1.007
Vivendi	0.057	0.049	0.104	66.109	0.476	0.002551	4303.77	308455.52	6836088.07	-0.000004%	0.037%	0.000076%	0.480%	0.000048	0.000292	1.030

TABLE 2.10.1.C: Descriptive statistics of the sixteen liquidity indicators during the second period. For each stock, the table shows the average value, for a 5 minutes period, of the sixteen liquidity indicators considered in this study, namely: effective half spread (EHS), quoted half spread (QHS), difference spread (DSPR), midquote (MID), quoted half spread from the WAS file (QHS_WAS), cumulated traded volume (SUMVOL), number of transactions (NBTR), volume imbalance (VIMB), volume imbalance in absolute terms (SABSVIMB), return (RET), return in absolute terms (ABSRET), volatility of return (VARRET), volatility as log range (VOLA), waiting time between subsequent trades (WT), liquidity ratio (LR) and flow ratio (FR). The calculation of each proxy is explained in detail in Appendix 2.11.2.

Company	EHS	QHS	DSPR	MID	QHS_WAS	SUMVOL	NBTR	VIMB	SABSVIMB	RET	ABSRET	VARRET	VOLA	WT	LR	FR
Accor	0.085	0.083	0.073	28.245	0.497	0.002369	1644.63	171766.67	1354414.56	-0.000033%	0.060%	0.000236%	0.342%	0.000280	0.011699	0.462
Agf	0.078	0.092	0.108	36.138	0.594	0.001465	662.56	66781.92	955230.83	-0.000132%	0.064%	0.000245%	0.230%	0.000680	0.000405	0.718
Air	0.075	0.072	0.202	89.222	0.492	0.001675	1571.82	23856.91	683203.15	0.000054%	0.057%	0.000190%	0.334%	0.000281	0.000693	1.250
Alcatel	0.052	0.044	0.093	65.763	0.516	0.005039	8741.36	3432789.58	17943109.83	0.000050%	0.031%	0.000061%	0.487%	0.000045	0.000413	1.003
Alstom	0.093	0.093	0.052	17.402	0.689	0.002095	1241.09	46975.72	1244340.46	-0.000005%	0.068%	0.000305%	0.323%	0.000403	0.000315	0.316
Aventis	0.054	0.052	0.078	48.122	0.811	0.002057	2389.73	618079.20	4820995.62	0.000049%	0.038%	0.000097%	0.315%	0.000156	0.000338	0.675
Axa	0.052	0.051	0.163	100.446	0.515	0.002479	2185.86	1007269.89	2934707.88	0.000068%	0.038%	0.000096%	0.295%	0.000169	0.000898	1.702
Bic	0.096	0.128	0.121	24.632	0.743	0.001312	286.37	-24452.94	140208.18	-0.001259%	0.070%	0.000302%	0.124%	0.001104	0.000935	0.686
Bnp	0.052	0.050	0.098	61.983	0.584	0.002560	2536.88	387486.29	4252791.12	0.000061%	0.036%	0.000080%	0.286%	0.000146	0.000475	0.972
Bouygues	0.086	0.084	0.519	177.651	0.799	0.002645	1868.24	148221.09	1204906.74	-0.000362%	0.062%	0.006282%	0.403%	0.000261	0.001894	3.753
Canal	0.066	0.064	0.239	116.206	0.717	0.003257	2597.10	-22883.48	1372679.30	-0.000105%	0.045%	0.000128%	0.384%	0.000232	0.001518	2.609
Cap	0.069	0.061	0.252	128.984	0.705	0.004680	4301.90	276637.65	1790105.64	0.000009%	0.043%	0.000122%	0.415%	0.000110	0.001339	2.429
Carrefour	0.057	0.052	0.082	49.834	0.568	0.002371	4178.67	667770.65	4389133.63	0.000054%	0.037%	0.000093%	0.369%	0.000098	0.000214	0.531
Casino	0.084	0.091	0.188	63.745	0.573	0.001940	814.83	18899.03	508178.01	-0.000048%	0.064%	0.000235%	0.238%	0.000565	0.000923	1.513
Credit	0.091	0.090	0.079	27.806	1.170	0.001435	1790.19	-118529.06	1709018.36	-0.000102%	0.061%	0.000274%	0.381%	0.000248	0.000356	0.331
Csf	0.112	0.130	0.116	28.162	0.685	0.000989	698.68	54010.09	546958.12	-0.000069%	0.085%	0.000468%	0.283%	0.000643	0.000552	0.402
Danone	0.071	0.070	0.253	114.564	0.573	0.003069	1842.96	86689.52	1104722.00	-0.000608%	0.050%	0.000409%	0.319%	0.000248	0.001630	2.413
Dexia	0.057	0.069	0.219	97.306	0.355	0.001175	579.43	27355.28	425869.90	0.000094%	0.046%	0.000117%	0.133%	0.000769	0.001657	2.272
EADS	0.088	0.085	0.035	12.933	0.627	0.001613	2547.24	14426.68	4441586.33	-0.000242%	0.052%	0.000228%	0.375%	0.000227	0.000068	0.120
Equant	0.077	0.068	0.071	31.620	0.627	0.007685	4034.66	513885.89	4702307.57	-0.000098%	0.049%	0.000161%	0.500%	0.000142	0.000687	0.963
Eridania	0.092	0.124	0.240	50.182	0.567	0.000957	255.98	-9420.45	95188.04	-0.001558%	0.072%	0.000296%	0.120%	0.001159	0.001215	1.298
France	0.052	0.045	0.125	87.165	0.718	0.002118	8137.16	9867518.53	19702205.86	-0.000008%	0.033%	0.000060%	0.457%	0.000049	0.000173	0.569
Lafarge	0.071	0.069	0.118	53.841	0.616	0.003144	1473.85	2958.96	1029560.58	0.000194%	0.051%	0.000162%	0.296%	0.000298	0.000899	1.259
Lagardere	0.085	0.079	0.113	45.233	0.760	0.003720	2066.78	317920.73	1565774.47	-0.000053%	0.058%	0.000220%	0.393%	0.000261	0.000548	1.040
Legrand	0.113	0.139	0.586	123.685	0.796	0.001730	480.20	5264.01	118907.80	0.000297%	0.082%	0.000414%	0.229%	0.000870	0.004063	3.678
L'Oreal	0.073	0.073	0.531	202.728	0.684	0.001137	1822.10	71334.52	1294505.20	0.000340%	0.054%	0.000182%	0.362%	0.000228	0.001114	1.990
Lvmh	0.071	0.072	0.303	134.249	0.816	0.001393	1689.46	184605.76	1288191.32	-0.000858%	0.055%	0.001816%	0.339%	0.000251	0.001969	1.654
MEAN	0.076	0.078	0.103	41.328	0.542	0.003770	4215.75	541018.07	7872009.09	-0.000114%	0.042%	0.000184%	0.326%	0.000204	0.001236	1.387
Michelin	0.087	0.089	0.062	21.915	0.598	0.002237	1011.89	57145.17	963921.47	-0.000277%	0.063%	0.000260%	0.279%	0.000451	0.000601	0.538
Multi	0.101	0.091	0.146	48.144	1.203	0.002762	2668.21	13954.87	1896436.62	0.000006%	0.067%	0.000307%	0.492%	0.000216	0.000287	0.657
Peugeot	0.074	0.080	0.353	139.036	0.546	0.002382	912.70	10961.78	364061.03	0.000635%	0.058%	0.000205%	0.240%	0.000511	0.003723	3.900
Pinault	0.068	0.069	0.290	133.166	0.498	0.001514	1316.46	23188.86	564904.57	0.000048%	0.052%	0.000167%	0.279%	0.000338	0.001566	1.822
Renault	0.085	0.082	0.082	31.353	0.801	0.001923	1691.09	128286.24	1360111.01	-0.000151%	0.060%	0.000239%	0.354%	0.000277	0.000408	0.518
Saint	0.074	0.073	0.201	88.130	0.626	0.002324	1338.26	180566.23	804105.07	0.000222%	0.055%	0.000200%	0.305%	0.000335	0.001174	1.674
Sanofi	0.080	0.083	0.086	33.426	0.861	0.001313	1421.87	188748.70	2352668.05	-0.000025%	0.056%	0.000216%	0.346%	0.000310	0.000283	0.421
Schneider	0.083	0.086	0.125	45.855	0.670	0.001943	1101.51	138753.80	938602.75	0.000062%	0.062%	0.000237%	0.302%	0.000429	0.000579	0.923
Société	0.074	0.072	0.135	58.264	0.529	0.002174	1990.02	373342.15	2304928.70	-0.000299%	0.053%	0.000181%	0.366%	0.000207	0.000639	0.976
Sodexho	0.090	0.109	0.388	110.266	0.610	0.001594	616.08	11403.60	216232.28	-0.000752%	0.066%	0.000265%	0.210%	0.000717	0.002232	2.638
STM	0.056	0.050	0.088	53.397	0.412	0.003827	4473.42	627774.09	9659826.88	0.000012%	0.035%	0.000083%	0.431%	0.000085	0.000345	0.873
Suez	0.055	0.053	0.189	113.277	0.422	0.002344	2055.16	582166.40	2190733.06	0.000030%	0.039%	0.000098%	0.267%	0.000200	0.001212	1.913
Tf1	0.094	0.088	0.560	178.725	0.871	0.003850	2172.04	128582.42	989140.26	-0.000098%	0.061%	0.000257%	0.426%	0.000246	0.001405	2.842
Total	0.046	0.044	0.147	105.011	0.518	0.001806	3056.47	255848.10	4254606.68	0.000011%	0.033%	0.000066%	0.302%	0.000109	0.000579	1.182
Valeo	0.090	0.090	0.100	35.007	0.710	0.003744	1258.25	124294.61	897469.30	-0.000061%	0.064%	0.000253%	0.320%	0.000388	0.000755	1.099
Vivendi	0.049	0.044	0.086	60.200	0.556	0.004081	5141.96	2581541.16	9490828.56	-0.000016%	0.033%	0.000064%	0.352%	0.000068	0.000380	1.043

TABLE 2.10.2.A: T-statistic for the effective half spread. This table reports the t-values resulting when testing two adjacent means against each other within successive intraday periods of 5 minutes for the effective half spread (EHS). The t- values consider the first period under study (December 1, 1999 - March 31, 2000). (*) means that results are significant at 5% level of significance, whereas (**) results are significant at 1% level.

TIME	EHS	T VALUE OF DIFF		TIME	EHS	T VALUE OF DIFF	
905	3.918	1.146					
910	3.556	**3.863**	**	1305	-0.534	0.233	
915	2.766	**4.013**	**	1310	-0.564	0.476	
920	2.126	**3.115**	**	1315	-0.627	-0.266	
925	1.603	1.611		1320	-0.592	0.067	
930	1.343	0.085		1325	-0.601	0.314	
935	1.328	**3.188**	**	1330	-0.637	0.342	
940	0.775	0.496		1335	-0.678	1.423	
945	0.707	1.129		1340	-0.850	-1.024	
950	0.562	0.983		1345	-0.726	-1.710	
955	0.441	0.137		1350	-0.513	0.056	
1000	0.423	1.955		1355	-0.520	0.547	
1005	0.166	-0.754		1400	-0.589	0.605	
1010	0.261	0.887		1405	-0.660	-0.415	
1015	0.161	**2.192**	*	1410	-0.611	-1.211	
1020	-0.084	0.163		1415	-0.478	1.056	
1025	-0.103	-0.612		1420	-0.589	-0.700	
1030	-0.036	1.267		1425	-0.503	0.719	
1035	-0.181	-1.233		1430	-0.596	**-5.933**	**
1040	-0.037	-1.508		1435	0.141	1.521	
1045	0.141	**2.307**	*	1440	-0.060	1.325	
1050	-0.158	-0.040		1445	-0.226	0.114	
1055	-0.153	0.270		1450	-0.239	0.912	
1100	-0.181	-0.531		1455	-0.331	-0.661	
1105	-0.122	-0.503		1500	-0.268	0.080	
1110	-0.060	0.149		1505	-0.276	-0.664	
1115	-0.079	-0.634		1510	-0.192	0.851	
1120	0.005	1.716		1515	-0.302	-1.032	
1125	-0.206	-1.636		1520	-0.193	1.314	
1130	-0.026	1.955		1525	-0.330	-0.989	
1135	-0.236	1.672		1530	-0.204	0.232	
1140	-0.393	-1.430		1535	-0.235	0.372	
1145	-0.270	0.593		1540	-0.273	-0.992	
1150	-0.330	1.765		1545	-0.178	-0.188	
1155	-0.515	0.167		1550	-0.158	0.188	
1200	-0.530	**-2.638**	**	1555	-0.177	0.013	
1205	-0.251	0.139		1600	-0.178	1.113	
1210	-0.266	-0.916		1605	-0.281	-1.270	
1215	-0.179	1.707		1610	-0.151	-1.813	
1220	-0.344	1.873		1615	0.034	-1.232	
1225	-0.500	**-2.018**	*	1620	0.164	0.409	
1230	-0.307	0.470		1625	0.117	-0.518	
1235	-0.358	0.877		1630	0.180	-0.397	
1240	-0.460	0.889		1635	0.230	0.672	
1245	-0.568	0.821		1640	0.146	-1.124	
1250	-0.665	-1.585		1645	0.301	0.261	
1255	-0.485	0.163		1650	0.263	-1.051	
1300	-0.505	0.240		1655	0.407	**-6.209**	**
1305	-0.534			1700	1.441		

TABLE 2.10.2.B: T-statistic for the quoted half spread. This table reports the t-values resulting when testing two adjacent means against each other within successive intraday periods of 5 minutes for the quoted half spread (QHS). The t- values consider the first period under study (December 1, 1999 - March 31, 2000). (*) means that results are significant at 5% level of significance, whereas (**) results are significant at 1% level.

TIME	QHS	T VALUE OF DIFF		TIME	QHS	T VALUE OF DIFF	
905	3.883						
910	3.891	-0.030		1305	-0.495		
915	2.964	**4.991**	**	1310	-0.370	-1.006	
920	2.399	**3.785**	**	1315	-0.458	0.722	
925	1.787	**4.005**	**	1320	-0.435	-0.193	
930	1.543	1.559		1325	-0.278	-1.326	
935	1.421	0.814		1330	-0.469	1.465	
940	0.963	**3.276**	**	1335	-0.515	0.353	
945	0.817	1.116		1340	-0.655	1.305	
950	0.694	0.974		1345	-0.612	-0.380	
955	0.496	1.492		1350	-0.395	-1.884	
1000	0.460	0.252		1355	-0.433	0.326	
1005	0.086	**2.825**	**	1400	-0.515	0.614	
1010	0.229	-1.173		1405	-0.669	1.168	
1015	0.176	0.451		1410	-0.540	-1.087	
1020	-0.045	1.909		1415	-0.444	-0.858	
1025	-0.122	0.650		1420	-0.587	1.276	
1030	-0.006	-0.972		1425	-0.565	-0.194	
1035	-0.195	1.553		1430	-0.463	-0.849	
1040	-0.017	-1.473		1435	0.068	**-4.242**	**
1045	0.058	-0.599		1440	-0.025	0.790	
1050	-0.211	**2.159**	*	1445	-0.224	1.817	
1055	-0.175	-0.326		1450	-0.196	-0.275	
1100	-0.218	0.407		1455	-0.338	1.495	
1105	-0.229	0.091		1500	-0.278	-0.657	
1110	-0.133	-0.765		1505	-0.363	0.880	
1115	-0.147	0.112		1510	-0.245	-1.066	
1120	-0.109	-0.308		1515	-0.286	0.346	
1125	-0.298	1.672		1520	-0.226	-0.524	
1130	-0.076	**-2.122**	*	1525	-0.351	1.160	
1135	-0.298	**2.044**	*	1530	-0.325	-0.233	
1140	-0.432	1.288		1535	-0.360	0.300	
1145	-0.399	-0.382		1540	-0.331	-0.283	
1150	-0.452	0.579		1545	-0.290	-0.419	
1155	-0.588	1.345		1550	-0.182	-1.060	
1200	-0.619	0.367		1555	-0.219	0.372	
1205	-0.314	**-3.522**	**	1600	-0.236	0.162	
1210	-0.221	-0.996		1605	-0.381	1.406	
1215	-0.158	-0.609		1610	-0.296	-0.884	
1220	-0.302	1.314		1615	-0.006	**-3.012**	**
1225	-0.465	1.676		1620	-0.049	0.390	
1230	-0.352	-1.215		1625	0.005	-0.438	
1235	-0.332	-0.180		1630	0.112	-0.841	
1240	-0.330	-0.017		1635	0.027	0.676	
1245	-0.467	1.058		1640	0.030	-0.028	
1250	-0.505	0.332		1645	0.088	-0.437	
1255	-0.348	-1.518		1650	0.038	0.391	
1300	-0.359	0.105		1655	0.078	-0.333	
1305	-0.495	1.225		1700	0.715	**-4.662**	**

TABLE 2.10.2.C: T-statistic for the difference spread. This table reports the t-values resulting when testing two adjacent means against each other within successive intraday periods of 5 minutes for the difference spread (DSPR). The t- values consider the first period under study (December 1, 1999 - March 31, 2000). (*) means that results are significant at 5% level of significance, whereas (**) results are significant at 1% level.

TIME	DSPR	T VALUE OF DIFF		TIME	DSPR	T VALUE OF DIFF	
905	3.920						
910	3.893	0.103		1305	-0.512		
915	2.945	**5.152**	**	1310	-0.369	-1.093	
920	2.386	**3.833**	**	1315	-0.463	0.739	
925	1.772	**4.057**	**	1320	-0.420	-0.349	
930	1.538	1.503		1325	-0.249	-1.327	
935	1.397	0.943		1330	-0.442	1.385	
940	0.954	**3.226**	**	1335	-0.502	0.447	
945	0.823	0.986		1340	-0.632	1.188	
950	0.690	1.028		1345	-0.588	-0.389	
955	0.487	1.509		1350	-0.374	-1.859	
1000	0.482	0.033		1355	-0.449	0.638	
1005	0.080	**2.951**	**	1400	-0.499	0.381	
1010	0.230	-1.258		1405	-0.655	1.172	
1015	0.157	0.632		1410	-0.543	-0.916	
1020	-0.058	1.918		1415	-0.443	-0.870	
1025	-0.130	0.637		1420	-0.590	1.321	
1030	-0.007	-1.072		1425	-0.560	-0.279	
1035	-0.224	1.845		1430	-0.456	-0.910	
1040	-0.048	-1.465		1435	0.088	**-4.438**	**
1045	0.054	-0.810		1440	0.005	0.694	
1050	-0.214	**2.139**	*	1445	-0.207	1.917	
1055	-0.179	-0.321		1450	-0.198	-0.090	
1100	-0.234	0.512		1455	-0.338	1.447	
1105	-0.230	-0.037		1500	-0.269	-0.749	
1110	-0.105	-0.973		1505	-0.332	0.643	
1115	-0.122	0.133		1510	-0.242	-0.797	
1120	-0.097	-0.209		1515	-0.272	0.258	
1125	-0.278	1.709		1520	-0.236	-0.313	
1130	-0.065	**-2.043**	*	1525	-0.356	1.071	
1135	-0.292	**2.091**	*	1530	-0.349	-0.061	
1140	-0.435	1.416		1535	-0.376	0.233	
1145	-0.383	-0.611		1540	-0.350	-0.244	
1150	-0.430	0.549		1545	-0.331	-0.209	
1155	-0.592	1.701		1550	-0.217	-1.206	
1200	-0.626	0.398		1555	-0.262	0.473	
1205	-0.331	**-3.450**	**	1600	-0.243	-0.190	
1210	-0.235	-1.037		1605	-0.385	1.373	
1215	-0.182	-0.496		1610	-0.303	-0.860	
1220	-0.310	1.138		1615	-0.029	**-2.882**	**
1225	-0.455	1.527		1620	-0.044	0.137	
1230	-0.370	-0.954		1625	0.019	-0.519	
1235	-0.357	-0.118		1630	0.135	-0.944	
1240	-0.330	-0.216		1635	0.065	0.578	
1245	-0.459	0.993		1640	0.010	0.436	
1250	-0.524	0.574		1645	0.098	-0.674	
1255	-0.357	-1.597		1650	0.071	0.208	
1300	-0.385	0.265		1655	0.101	-0.237	
1305	-0.512	1.115		1700	0.728	**-4.568**	**

TABLE 2.10.2.D: T-statistic for the midquote. This table reports the t-values resulting when testing two adjacent means against each other within successive intraday periods of 5 minutes for the midquote (MID). The t- values consider the first period under study (December 1, 1999 - March 31, 2000). (*) means that results are significant at 5% level of significance, whereas (**) results are significant at 1% level.

TIME	MID	T VALUE OF DIFF	TIME	MID	T VALUE OF DIFF
905	-0.056	-0.664			
910	0.177	0.457	1305	-0.360	1.744
915	0.070	-0.115	1310	-0.931	-0.620
920	0.095	-0.107	1315	-0.711	-0.458
925	0.116	-0.223	1320	-0.582	-0.834
930	0.157	-0.794	1325	-0.348	1.563
935	0.317	-0.376	1330	-0.860	-1.148
940	0.394	0.126	1335	-0.454	-0.102
945	0.369	0.391	1340	-0.421	-0.055
950	0.285	-0.155	1345	-0.405	-1.245
955	0.318	-0.363	1350	-0.134	0.916
1000	0.381	0.074	1355	-0.337	-0.113
1005	0.371	0.237	1400	-0.309	-0.513
1010	0.341	0.571	1405	-0.192	0.853
1015	0.266	-0.225	1410	-0.390	0.392
1020	0.299	1.002	1415	-0.496	-1.108
1025	0.111	-0.182	1420	-0.213	-0.862
1030	0.147	-0.026	1425	-0.052	0.896
1035	0.151	0.748	1430	-0.210	-0.863
1040	0.016	-0.738	1435	-0.045	-0.593
1045	0.144	-0.470	1440	0.065	1.054
1050	0.214	-0.564	1445	-0.251	-0.337
1055	0.284	0.218	1450	-0.136	-1.052
1100	0.257	1.561	1455	0.119	-0.200
1105	0.003	-0.039	1500	0.152	-0.110
1110	0.012	-0.504	1505	0.168	-0.017
1115	0.117	-1.426	1510	0.171	-0.491
1120	0.321	1.276	1515	0.243	1.403
1125	0.155	-0.144	1520	0.002	-0.208
1130	0.177	0.058	1525	0.044	-0.898
1135	0.168	-0.063	1530	0.206	-0.002
1140	0.177	0.475	1535	0.207	0.236
1145	0.103	-0.906	1540	0.171	0.702
1150	0.231	-0.043	1545	0.026	-0.576
1155	0.236	0.438	1550	0.146	0.273
1200	0.189	-0.544	1555	0.103	0.716
1205	0.248	1.164	1600	-0.024	-0.683
1210	0.094	-0.220	1605	0.101	0.634
1215	0.126	0.750	1610	-0.011	0.141
1220	0.019	-0.735	1615	-0.034	-0.052
1225	0.123	-0.009	1620	-0.026	0.314
1230	0.124	1.423	1625	-0.076	0.164
1235	-0.115	-0.521	1630	-0.109	-0.015
1240	-0.029	**2.087** *	1635	-0.106	-0.739
1245	-0.540	-1.911	1640	0.038	-0.210
1250	-0.066	1.730	1645	0.074	0.061
1255	-0.527	-0.249	1650	0.063	0.454
1300	-0.455	-0.414	1655	-0.037	-0.350
1305	-0.360		1700	0.047	

TABLE 2.10.3: T-statistic for the QHS_WAS. This table reports the t-values resulting when testing two adjacent means against each other within successive intraday periods of 5 minutes for the quoted spread from the WAS file (QHS_WAS). The t- values consider the first period under study (December 1, 1999 - March 31, 2000). (*) means that results are significant at 5% level of significance, whereas (**) results are significant at 1% level.

TIME	QHS_WAS	T VALUE OF DIFF		TIME	QHS_WAS	T VALUE OF DIFF	
905	4.014						
910	3.495	**4.851**	**	1305	-0.569		
915	2.988	**5.928**	**	1310	-0.624	1.015	
920	2.673	**5.120**	**	1315	-0.620	-0.057	
925	2.387	**5.364**	**	1320	-0.651	0.453	
930	2.097	**5.603**	**	1325	-0.581	-1.007	
935	1.888	**4.428**	**	1330	-0.576	-0.055	
940	1.658	**4.785**	**	1335	-0.495	-0.956	
945	1.591	1.240		1340	-0.527	0.403	
950	1.404	**3.373**	**	1345	-0.480	-0.704	
955	1.200	**3.506**	**	1350	-0.463	-0.288	
1000	1.113	1.513		1355	-0.465	0.025	
1005	0.963	**2.710**	**	1400	-0.457	-0.110	
1010	0.895	1.296		1405	-0.501	0.628	
1015	0.777	**2.303**	*	1410	-0.521	0.353	
1020	0.681	1.884		1415	-0.535	0.249	
1025	0.621	1.046		1420	-0.529	-0.100	
1030	0.492	**2.072**	*	1425	-0.519	-0.209	
1035	0.414	1.349		1430	-0.486	-0.646	
1040	0.347	1.237		1435	-0.360	**-2.716**	**
1045	0.284	1.137		1440	-0.408	1.064	
1050	0.190	1.631		1445	-0.429	0.417	
1055	0.129	1.117		1450	-0.440	0.207	
1100	0.124	0.087		1455	-0.446	0.130	
1105	0.066	1.000		1500	-0.455	0.223	
1110	0.020	0.787		1505	-0.488	0.746	
1115	-0.068	1.507		1510	-0.524	0.739	
1120	-0.119	0.799		1515	-0.560	0.737	
1125	-0.181	0.969		1520	-0.541	-0.428	
1130	-0.156	-0.409		1525	-0.583	0.880	
1135	-0.226	1.194		1530	-0.541	-0.890	
1140	-0.314	1.621		1535	-0.553	0.235	
1145	-0.304	-0.196		1540	-0.562	0.154	
1150	-0.349	0.887		1545	-0.527	-0.598	
1155	-0.376	0.570		1550	-0.549	0.381	
1200	-0.398	0.446		1555	-0.530	-0.323	
1205	-0.384	-0.277		1600	-0.512	-0.299	
1210	-0.414	0.627		1605	-0.546	0.589	
1215	-0.376	-0.847		1610	-0.496	-0.837	
1220	-0.448	1.520		1615	-0.507	0.185	
1225	-0.488	0.910		1620	-0.524	0.286	
1230	-0.498	0.239		1625	-0.471	-0.874	
1235	-0.526	0.634		1630	-0.461	-0.173	
1240	-0.534	0.153		1635	-0.505	0.682	
1245	-0.549	0.272		1640	-0.518	0.162	
1250	-0.544	-0.088		1645	-0.481	-0.461	
1255	-0.564	0.347		1650	-0.434	-0.628	
1300	-0.566	0.044		1655	-0.384	-0.651	
1305	-0.569	0.046		1700	-0.196	**-2.244**	*

TABLE 2.10.4.A: T-statistic for the cumulated traded volume. This table reports the t-values resulting when testing two adjacent means against each other within successive intraday periods of 5 minutes for the cumulated traded volume (SUMVOL). The t- values consider the first period under study (December 1, 1999 - March 31, 2000). (*) means that results are significant at 5% level of significance, whereas (**) results are significant at 1% level.

TIME	SUMVOL	T VALUE OF DIFF		TIME	SUMVOL	T VALUE OF DIFF	
905	-0.871						
910	0.022	**-5.813**	**	1305	-0.636		
915	-0.091	0.674		1310	-0.848	**2.053**	*
920	-0.267	1.127		1315	-0.962	1.620	
925	-0.455	1.499		1320	-0.955	-0.129	
930	-0.407	-0.489		1325	-0.936	-0.289	
935	-0.342	-0.614		1330	-0.794	**-2.011**	*
940	-0.337	-0.050		1335	-0.872	0.914	
945	-0.332	-0.042		1340	-0.945	0.805	
950	-0.397	0.664		1345	-0.858	-0.974	
955	-0.385	-0.144		1350	-0.735	-1.379	
1000	-0.293	-1.163		1355	-0.846	1.423	
1005	-0.031	**-2.753**	**	1400	-0.815	-0.371	
1010	-0.296	**2.487**	*	1405	-0.696	-1.359	
1015	-0.295	-0.011		1410	-0.780	1.170	
1020	-0.220	-0.790		1415	-0.733	-0.685	
1025	-0.208	-0.102		1420	-0.713	-0.261	
1030	-0.239	0.310		1425	-0.505	**-2.512**	*
1035	-0.114	-1.435		1430	-0.490	-0.172	
1040	-0.240	1.558		1435	0.746	**-11.468**	**
1045	-0.243	0.033		1440	0.057	**6.611**	**
1050	-0.003	**-2.359**	*	1445	-0.105	**2.092**	*
1055	-0.068	0.702		1450	-0.228	1.493	
1100	-0.101	0.388		1455	0.020	**-3.134**	**
1105	-0.170	0.836		1500	-0.008	0.340	
1110	-0.241	0.806		1505	0.114	-1.352	
1115	-0.170	-0.864		1510	-0.003	1.130	
1120	-0.095	-0.913		1515	-0.137	1.340	
1125	-0.161	0.804		1520	0.110	**-2.909**	**
1130	-0.319	1.930		1525	0.066	0.497	
1135	-0.067	**-2.704**	**	1530	0.174	-1.083	
1140	-0.068	0.013		1535	0.620	**-3.653**	**
1145	-0.124	0.593		1540	0.736	-0.930	
1150	-0.076	-0.440		1545	0.903	-1.505	
1155	-0.044	-0.288		1550	0.854	0.416	
1200	0.060	-0.876		1555	0.834	0.163	
1205	-0.213	**2.289**	*	1600	0.790	0.393	
1210	-0.433	**2.206**	*	1605	1.017	**-2.259**	*
1215	-0.390	-0.477		1610	1.118	-0.999	
1220	-0.402	0.143		1615	1.083	0.310	
1225	-0.467	0.852		1620	1.343	**-2.290**	*
1230	-0.281	**-2.150**	*	1625	1.452	-0.950	
1235	-0.573	**3.529**	**	1630	1.441	0.089	
1240	-0.695	1.817		1635	1.261	1.682	
1245	-0.627	-0.992		1640	1.840	**-6.022**	**
1250	-0.658	0.402		1645	2.104	**-2.312**	*
1255	-0.724	0.924		1650	2.289	-1.459	
1300	-0.725	0.012		1655	3.094	**-6.425**	**
1305	-0.636	-0.859		1700	4.409	**-9.890**	**

TABLE 2.10.4.B: T-statistic for the number of trades. This table reports the t-values resulting when testing two adjacent means against each other within successive intraday periods of 5 minutes for the number of trades (NBTR). The t- values consider the first period under study (December 1, 1999 - March 31, 2000). (*) means that results are significant at 5% level of significance, whereas (**) results are significant at 1% level.

TIME	NBTR	T VALUE OF DIFF		TIME	NBTR	T VALUE OF DIFF	
905	-0.233	**-7.609**	**	1305	-1.189	1.865	
910	1.519	1.685		1310	-1.393	1.268	
915	1.113	**2.397**	*	1315	-1.503	0.073	
920	0.591	1.015		1320	-1.509	0.286	
925	0.412	0.093		1325	-1.536	**-2.479**	*
930	0.399	-0.279		1330	-1.303	-0.494	
935	0.443	0.635		1335	-1.234	1.478	
940	0.343	-1.368		1340	-1.424	-1.716	
945	0.523	1.506		1345	-1.278	-1.883	
950	0.330	-1.166		1350	-1.092	1.172	
955	0.478	0.651		1355	-1.192	-1.853	
1000	0.404	-1.825		1400	-1.011	-0.683	
1005	0.642	**2.073**	*	1405	-0.944	-0.391	
1010	0.346	0.159		1410	-0.915	-0.858	
1015	0.328	1.644		1415	-0.840	0.547	
1020	0.142	-1.335		1420	-0.892	**-4.389**	**
1025	0.305	-0.530		1425	-0.419	**2.741**	**
1030	0.369	0.823		1430	-0.695	**-10.400**	**
1035	0.275	1.501		1435	0.780	**4.531**	**
1040	0.133	-0.844		1440	0.086	**2.434**	*
1045	0.217	-1.165		1445	-0.171	**2.644**	**
1050	0.356	1.299		1450	-0.407	**-3.961**	**
1055	0.210	-0.418		1455	-0.015	-0.886	
1100	0.252	1.603		1500	0.098	1.256	
1105	0.084	0.363		1505	-0.048	0.897	
1110	0.044	-0.237		1510	-0.136	1.187	
1115	0.067	**-2.852**	**	1515	-0.256	-1.473	
1120	0.316	**2.140**	*	1520	-0.121	-0.650	
1125	0.117	1.323		1525	-0.051	-0.755	
1130	-0.001	**-2.138**	*	1530	0.040	**-2.610**	**
1135	0.212	0.969		1535	0.403	-1.125	
1140	0.106	-0.400		1540	0.564	**-2.039**	*
1145	0.150	0.650		1545	0.840	1.111	
1150	0.076	-1.001		1550	0.679	-0.691	
1155	0.208	-0.649		1555	0.792	0.251	
1200	0.312	**2.998**	**	1600	0.753	0.737	
1205	-0.162	1.819		1605	0.651	-0.287	
1210	-0.369	0.259		1610	0.691	-0.656	
1215	-0.390	1.188		1615	0.786	-1.280	
1220	-0.503	0.212		1620	0.965	0.744	
1225	-0.525	-1.590		1625	0.876	1.588	
1230	-0.338	**4.390**	**	1630	0.683	0.231	
1235	-0.806	**3.600**	**	1635	0.656	**-3.014**	**
1240	-1.104	-0.488		1640	0.989	**-2.199**	*
1245	-1.064	1.201		1645	1.281	-0.700	
1250	-1.152	0.316		1650	1.381	**-3.229**	**
1255	-1.177	-0.414		1655	1.863	**-5.728**	**
1300	-1.129	0.456		1700	2.850		
1305	-1.189						

TABLE 2.10.4.C: T-statistic for the cumulated volume imbalance. This table reports the t-values resulting when testing two adjacent means against each other within successive intraday periods of 5 minutes for the cumulated volume imbalance (VIMB). The t- values consider the first period under study (December 1, 1999 - March 31, 2000). (*) means that results are significant at 5% level of significance, whereas (**) results are significant at 1% level.

TIME	VIMB	T VALUE OF DIFF		TIME	VIMB	T VALUE OF DIFF	
905	-0.105						
		-2.053	*				
910	0.299			1305	-0.302		
		0.734				-0.066	
915	0.098			1310	-0.292		
		0.109				-0.701	
920	0.069			1315	-0.196		
		-0.234				-0.983	
925	0.112			1320	-0.080		
		0.374				0.336	
930	0.048			1325	-0.126		
		-0.770				-0.145	
935	0.192			1330	-0.102		
		-0.342				0.800	
940	0.252			1335	-0.238		
		-0.058				-1.090	
945	0.263			1340	-0.066		
		0.693				-0.349	
950	0.124			1345	-0.013		
		0.011				0.021	
955	0.122			1350	-0.016		
		-0.674				0.254	
1000	0.303			1355	-0.057		
		0.988				0.412	
1005	0.045			1400	-0.119		
		0.570				-0.783	
1010	-0.064			1405	-0.009		
		-0.133				0.734	
1015	-0.039			1410	-0.103		
		-0.124				-0.012	
1020	-0.015			1415	-0.101		
		-0.130				0.693	
1025	0.013			1420	-0.211		
		-0.982				-0.250	
1030	0.207			1425	-0.167		
		2.014	*			-0.855	
1035	-0.193			1430	0.016		
		-0.569				-1.693	
1040	-0.066			1435	0.375		
		0.095				0.635	
1045	-0.087			1440	0.266		
		-0.213				0.010	
1050	-0.044			1445	0.264		
		-0.345				0.202	
1055	0.018			1450	0.226		
		-1.098				**2.534**	*
1100	0.178			1455	-0.487		
		1.494				**-2.034**	*
1105	-0.056			1500	0.076		
		0.451				-0.216	
1110	-0.132			1505	0.115		
		-1.991	*			0.243	
1115	0.229			1510	0.077		
		2.049	*			-1.098	
1120	-0.149			1515	0.267		
		-1.239				1.573	
1125	0.068			1520	-0.004		
		1.416				0.660	
1130	-0.335			1525	-0.107		
		-0.430				-0.488	
1135	-0.212			1530	-0.023		
		-1.379				-0.517	
1140	0.019			1535	0.074		
		0.311				0.576	
1145	-0.034			1540	-0.059		
		0.206				-0.620	
1150	-0.072			1545	0.091		
		0.585				-0.533	
1155	-0.172			1550	0.220		
		-0.573				-0.115	
1200	-0.080			1555	0.258		
		-0.914				1.262	
1205	0.074			1600	-0.161		
		0.503				-1.451	
1210	-0.016			1605	0.228		
		0.591				1.111	
1215	-0.125			1610	-0.041		
		-0.318				0.315	
1220	-0.072			1615	-0.108		
		0.657				-1.279	
1225	-0.177			1620	0.300		
		-0.367				1.904	
1230	-0.120			1625	-0.442		
		-0.375				**-2.545**	*
1235	-0.063			1630	0.531		
		-0.411				1.287	
1240	0.041			1635	0.141		
		1.105				**1.964**	*
1245	-0.229			1640	-0.321		
		-0.252				-0.997	
1250	-0.189			1645	-0.048		
		0.773				0.239	
1255	-0.320			1650	-0.114		
		-1.061				-1.811	
1300	-0.147			1655	0.348		
		1.004				-1.244	
1305	-0.302			1700	0.774		

TABLE 2.10.4.D: T-statistic for the cumulated volume imbalance in absolute terms. This table reports the t-values resulting when testing two adjacent means against each other within successive intraday periods of 5 minutes for the cumulated volume imbalance in absolute terms (SABSVIMB). The t- values consider the first period under study (December 1, 1999 - March 31, 2000). (*) means that results are significant at 5% level of significance, whereas (**) results are significant at 1% level.

TIME	SABSVIMB	T VALUE OF DIFF		TIME	SABSVIMB	T VALUE OF DIFF	
905	-0.222	**-3.583**	**				
910	0.689	1.449		1305	-0.975	1.044	
915	0.363	**2.364**	*	1310	-1.091	0.568	
920	-0.048	0.773		1315	-1.148	1.402	
925	-0.158	-1.264		1320	-1.257	-1.362	
930	0.022	0.242		1325	-1.130	-0.823	
935	-0.015	-0.069		1330	-1.031	-0.030	
940	-0.004	-1.144		1335	-1.027	0.874	
945	0.189	**2.235**	*	1340	-1.107	-1.239	
950	-0.147	-0.733		1345	-0.992	-1.304	
955	-0.047	-0.011		1350	-0.870	0.320	
1000	-0.046	**-2.800**	**	1355	-0.899	-0.142	
1005	0.324	**3.428**	**	1400	-0.886	**-2.590**	**
1010	-0.114	-0.206		1405	-0.657	0.017	
1015	-0.093	-0.160		1410	-0.658	-0.389	
1020	-0.075	-1.361		1415	-0.624	0.228	
1025	0.110	0.400		1420	-0.645	-1.601	
1030	0.060	0.290		1425	-0.454	0.545	
1035	0.023	-0.112		1430	-0.539	**-6.022**	**
1040	0.039	-0.096		1435	0.422	**3.017**	**
1045	0.050	-1.142		1440	0.042	1.359	
1050	0.187	0.960		1445	-0.099	1.204	
1055	0.073	0.752		1450	-0.227	**-2.462**	*
1100	-0.007	0.452		1455	0.311	0.809	
1105	-0.054	1.535		1500	0.134	-1.011	
1110	-0.209	**-2.053**	*	1505	0.247	**2.237**	*
1115	-0.023	-0.909		1510	-0.008	-0.163	
1120	0.068	0.823		1515	0.010	1.137	
1125	-0.026	-0.388		1520	-0.114	-1.316	
1130	0.070	0.538		1525	0.019	-0.276	
1135	-0.062	0.061		1530	0.044	**-3.701**	**
1140	-0.068	-0.438		1535	0.435	-1.736	
1145	-0.023	1.773		1540	0.672	-0.755	
1150	-0.180	**-3.248**	**	1545	0.779	-0.511	
1155	0.198	0.074		1550	0.854	-1.251	
1200	0.187	**3.442**	**	1555	1.159	**2.031**	*
1205	-0.235	1.006		1600	0.689	**-2.431**	*
1210	-0.343	1.423		1605	1.052	1.917	
1215	-0.480	-0.636		1610	0.744	-1.415	
1220	-0.423	0.323		1615	0.973	-0.522	
1225	-0.459	-0.234		1620	1.061	-0.700	
1230	-0.432	**2.755**	**	1625	1.168	1.064	
1235	-0.683	0.417		1630	1.013	0.119	
1240	-0.756	0.444		1635	0.997	**-2.726**	**
1245	-0.836	0.630		1640	1.415	-0.061	
1250	-0.900	0.834		1645	1.424	**-2.342**	*
1255	-0.987	-0.479		1650	1.819	**-2.700**	**
1300	-0.932	0.371		1655	2.326	**-3.344**	**
1305	-0.975			1700	3.063		

TABLE 2.10.5.A: T-statistic for the average return. This table reports the t-values resulting when testing two adjacent means against each other within successive intraday periods of 5 minutes for the average return (RET). The t- values consider the first period under study (December 1, 1999 - March 31, 2000). (*) means that results are significant at 5% level of significance, whereas (**) results are significant at 1% level.

TIME	RET	T VALUE OF DIFF		TIME	RET	T VALUE OF DIFF	
905	2.402	**3.417**	**				
910	-0.006	-0.825		1305	-0.469	**-3.144**	**
915	0.255	1.357		1310	0.169	0.395	
920	-0.081	-0.741		1315	0.091	-1.708	
925	0.104	-1.216		1320	0.411	1.513	
930	0.374	0.004		1325	0.058	1.394	
935	0.373	-0.116		1330	-0.280	-0.674	
940	0.393	**3.546**	**	1335	-0.132	-1.383	
945	-0.203	-0.538		1340	0.161	1.530	
950	-0.097	-0.640		1345	-0.143	-1.251	
955	0.029	-0.754		1350	0.126	0.892	
1000	0.160	**2.427**	*	1355	-0.075	1.327	
1005	-0.183	0.285		1400	-0.377	**-2.244**	*
1010	-0.223	-1.954		1405	0.091	1.701	
1015	0.063	-0.249		1410	-0.266	-1.481	
1020	0.097	1.063		1415	0.049	-0.641	
1025	-0.031	0.368		1420	0.162	0.660	
1030	-0.079	0.653		1425	0.060	0.186	
1035	-0.173	-0.835		1430	0.029	**-3.521**	**
1040	-0.042	1.788		1435	0.621	**3.741**	**
1045	-0.330	1.091		1440	-0.003	0.212	
1050	-0.504	**-3.365**	**	1445	-0.037	1.020	
1055	0.039	0.654		1450	-0.244	-0.614	
1100	-0.067	**-1.995**	*	1455	-0.113	-0.470	
1105	0.277	0.662		1500	-0.037	-1.373	
1110	0.164	-1.195		1505	0.183	-0.614	
1115	0.357	**5.694**	**	1510	0.276	**1.991**	*
1120	-0.547	**-2.068**	*	1515	-0.018	**2.211**	*
1125	-0.244	-1.043		1520	-0.352	**-2.131**	*
1130	-0.106	1.336		1525	-0.054	-0.342	
1135	-0.282	**-1.990**	*	1530	-0.006	0.885	
1140	-0.016	-1.617		1535	-0.167	-1.233	
1145	0.220	**2.476**	*	1540	0.074	**2.366**	*
1150	-0.164	**-4.291**	**	1545	-0.311	-0.614	
1155	0.378	1.854		1550	-0.223	1.708	
1200	0.134	-1.167		1555	-0.509	**-3.059**	**
1205	0.315	**2.190**	*	1600	-0.010	-1.098	
1210	-0.066	**2.842**	**	1605	0.175	**2.528**	*
1215	-0.592	**-4.572**	**	1610	-0.266	-0.874	
1220	0.235	0.836		1615	-0.132	0.367	
1225	0.066	0.820		1620	-0.194	-1.109	
1230	-0.101	0.401		1625	-0.019	**-2.265**	*
1235	-0.179	0.423		1630	0.288	1.571	
1240	-0.265	-1.702		1635	0.061	**2.024**	*
1245	0.130	0.437		1640	-0.225	**-2.247**	*
1250	0.006	0.682		1645	0.089	1.935	
1255	-0.183	0.509		1650	-0.170	-1.140	
1300	-0.297	0.862		1655	-0.019	-1.383	
1305	-0.469			1700	0.163		

TABLE 2.10.5.B: T-statistic for the return in absolute terms. This table reports the t-values resulting when testing two adjacent means against each other within successive intraday periods of 5 minutes for the return in absolute terms (ABSRET). The t- values consider the first period under study (December 1, 1999 - March 31, 2000). (*) means that results are significant at 5% level of significance, whereas (**) results are significant at 1% level.

TIME	ABSRET	T VALUE OF DIFF		TIME	ABSRET	T VALUE OF DIFF	
905	6.292	**12.838**	**				
910	2.566	**2.027**	*	1305	-0.429	0.498	
915	2.113	**3.053**	**	1310	-0.496	-0.347	
920	1.543	1.020		1315	-0.450	-0.079	
925	1.385	**2.134**	*	1320	-0.440	-0.391	
930	1.100	-0.101		1325	-0.389	0.308	
935	1.117	1.369		1330	-0.430	0.699	
940	0.879	**2.720**	**	1335	-0.515	-0.476	
945	0.533	-0.219		1340	-0.464	0.024	
950	0.558	1.584		1345	-0.467	-0.516	
955	0.366	0.132		1350	-0.411	-0.672	
1000	0.350	**2.019**	*	1355	-0.332	0.324	
1005	0.101	-0.468		1400	-0.370	1.062	
1010	0.156	-0.219		1405	-0.496	-1.624	
1015	0.180	1.739		1410	-0.307	0.613	
1020	-0.016	0.023		1415	-0.379	0.363	
1025	-0.019	1.545		1420	-0.427	-0.459	
1030	-0.160	-1.740		1425	-0.369	-0.645	
1035	0.023	-0.097		1430	-0.286	0.625	
1040	0.034	-1.241		1435	-0.366	**-2.152**	*
1045	0.162	**2.999**	**	1440	-0.121	0.244	
1050	-0.174	-0.939		1445	-0.149	0.538	
1055	-0.058	-0.176		1450	-0.202	0.516	
1100	-0.039	1.041		1455	-0.251	-0.228	
1105	-0.126	-0.713		1500	-0.224	0.070	
1110	-0.060	-0.378		1505	-0.233	-0.962	
1115	-0.020	-0.101		1510	-0.134	0.562	
1120	-0.008	0.421		1515	-0.196	-0.065	
1125	-0.059	-0.440		1520	-0.189	0.430	
1130	-0.017	0.850		1525	-0.238	0.269	
1135	-0.097	1.130		1530	-0.267	0.955	
1140	-0.211	0.324		1535	-0.368	-1.348	
1145	-0.243	0.165		1540	-0.225	**2.228**	*
1150	-0.258	-0.307		1545	-0.422	-1.221	
1155	-0.229	1.770		1550	-0.314	-0.905	
1200	-0.387	-1.720		1555	-0.226	-0.295	
1205	-0.232	-1.503		1600	-0.200	-0.212	
1210	-0.073	0.030		1605	-0.181	0.845	
1215	-0.077	1.933		1610	-0.257	-0.591	
1220	-0.270	1.586		1615	-0.206	-0.718	
1225	-0.428	0.068		1620	-0.138	-1.701	
1230	-0.435	-0.125		1625	0.038	-0.255	
1235	-0.422	-1.286		1630	0.065	1.832	
1240	-0.284	**2.362**	*	1635	-0.131	0.639	
1245	-0.550	1.053		1640	-0.196	-1.207	
1250	-0.662	**-2.209**	*	1645	-0.071	0.589	
1255	-0.424	-0.222		1650	-0.130	0.774	
1300	-0.398	0.255		1655	-0.198	**-3.536**	**
1305	-0.429			1700	0.162		

TABLE 2.10.5.C: T-statistic for the volatility of returns. This table reports the t-values resulting when testing two adjacent means against each other within successive intraday periods of 5 minutes for the volatility of returns (VARRET). The t- values consider the first period under study (December 1, 1999 - March 31, 2000). (*) means that results are significant at 5% level of significance, whereas (**) results are significant at 1% level.

TIME	VARRET	T VALUE OF DIFF		TIME	VARRET	T VALUE OF DIFF	
905	7.706						
910	2.032	**19.082**	**	1305	-0.285		
915	1.589	**2.239**	*	1310	-0.332	0.457	
920	1.217	**2.107**	*	1315	-0.321	-0.121	
925	1.071	0.807		1320	-0.408	0.980	
930	0.797	1.650		1325	-0.392	-0.189	
935	0.710	0.548		1330	-0.360	-0.380	
940	0.590	0.752		1335	-0.414	0.637	
945	0.244	**2.817**	**	1340	-0.448	0.431	
950	0.307	-0.590		1345	-0.401	-0.628	
955	0.099	**2.077**	*	1350	-0.300	-1.363	
1000	0.198	-0.902		1355	-0.367	0.871	
1005	0.090	0.860		1400	-0.329	-0.483	
1010	0.074	0.173		1405	-0.311	-0.232	
1015	0.003	1.061		1410	-0.272	-0.488	
1020	-0.077	0.878		1415	-0.329	0.888	
1025	-0.108	0.326		1420	-0.322	-0.093	
1030	-0.151	0.651		1425	-0.315	-0.083	
1035	-0.057	-1.349		1430	-0.260	-0.698	
1040	-0.030	-0.265		1435	-0.182	-0.931	
1045	0.184	-1.675		1440	-0.111	-0.941	
1050	-0.038	1.708		1445	-0.134	0.267	
1055	-0.064	0.250		1450	-0.205	0.901	
1100	-0.073	0.113		1455	-0.263	0.969	
1105	-0.162	1.101		1500	-0.236	-0.355	
1110	-0.126	-0.501		1505	-0.292	0.754	
1115	-0.062	-0.827		1510	-0.073	**-2.474**	*
1120	-0.052	-0.124		1515	-0.223	1.583	
1125	-0.146	1.240		1520	-0.215	-0.091	
1130	-0.060	-1.189		1525	-0.168	-0.521	
1135	-0.123	0.728		1530	-0.202	0.396	
1140	-0.184	0.714		1535	-0.272	1.031	
1145	-0.212	0.395		1540	-0.252	-0.317	
1150	-0.175	-0.485		1545	-0.291	0.623	
1155	-0.223	0.667		1550	-0.268	-0.382	
1200	-0.281	1.088		1555	-0.197	-0.825	
1205	-0.204	-1.246		1600	-0.199	0.023	
1210	-0.100	-1.244		1605	-0.168	-0.476	
1215	-0.070	-0.292		1610	-0.238	1.053	
1220	-0.251	**2.094**	*	1615	-0.194	-0.628	
1225	-0.333	1.222		1620	-0.122	-1.005	
1230	-0.281	-0.733		1625	-0.029	-1.270	
1235	-0.249	-0.321		1630	-0.023	-0.074	
1240	-0.302	0.518		1635	-0.102	0.934	
1245	-0.412	1.673		1640	-0.128	0.322	
1250	-0.425	0.237		1645	-0.089	-0.472	
1255	-0.325	-1.581		1650	-0.141	0.671	
1300	-0.299	-0.361		1655	-0.147	0.081	
1305	-0.285	-0.144		1700	0.072	**-2.708**	**

TABLE 2.10.5.D: T-statistic for the volatility as log range. This table reports the t-values resulting when testing two adjacent means against each other within successive intraday periods of 5 minutes for the volatility as log range (VOLA). The t- values consider the first period under study (December 1, 1999 - March 31, 2000). (*) means that results are significant at 5% level of significance, whereas (**) results are significant at 1% level.

TIME	VOLA	T VALUE OF DIFF		TIME	VOLA	T VALUE OF DIFF	
905	1.816						
		-5.494	**				
910	3.068			1305	-1.286		
		4.073	**			0.513	
915	2.293			1310	-1.326		
		2.775	**			0.087	
920	1.885			1315	-1.332		
		3.373	**			0.959	
925	1.464			1320	-1.401		
		1.285				0.017	
930	1.325			1325	-1.403		
		3.034	**			**-2.456**	*
935	1.014			1330	-1.245		
		2.259	*			-1.313	
940	0.777			1335	-1.151		
		0.204				1.400	
945	0.757			1340	-1.252		
		2.072	*			-0.792	
950	0.571			1345	-1.194		
		0.295				**-2.985**	**
955	0.546			1350	-0.978		
		0.236				0.640	
1000	0.522			1355	-1.027		
		-0.304				-0.025	
1005	0.553			1400	-1.025		
		1.864				**-2.595**	**
1010	0.393			1405	-0.838		
		1.573				0.236	
1015	0.255			1410	-0.854		
		0.472				0.734	
1020	0.215			1415	-0.902		
		0.718				-1.504	
1025	0.151			1420	-0.785		
		-0.080				-1.568	
1030	0.158			1425	-0.654		
		-1.226				0.779	
1035	0.260			1430	-0.711		
		2.312	*			**-10.283**	**
1040	0.063			1435	0.180		
		-1.013				**3.395**	**
1045	0.149			1440	-0.133		
		0.474				**2.123**	*
1050	0.110			1445	-0.294		
		-0.768				1.439	
1055	0.173			1450	-0.400		
		-0.176				-1.300	
1100	0.188			1455	-0.303		
		1.232				-1.490	
1105	0.066			1500	-0.191		
		0.146				1.589	
1110	0.051			1505	-0.297		
		0.538				-0.183	
1115	-0.004			1510	-0.283		
		-0.445				1.616	
1120	0.040			1515	-0.409		
		0.445				-0.983	
1125	0.000			1520	-0.334		
		0.187				-0.882	
1130	-0.018			1525	-0.267		
		0.438				**-2.599**	**
1135	-0.062			1530	-0.074		
		1.222				-0.991	
1140	-0.177			1535	0.005		
		-1.613				-1.788	
1145	-0.029			1540	0.169		
		1.826				**-3.472**	**
1150	-0.202			1545	0.525		
		-1.122				**2.058**	*
1155	-0.094			1550	0.316		
		1.355				-0.237	
1200	-0.224			1555	0.339		
		0.895				**-1.977**	*
1205	-0.298			1600	0.537		
		0.445				0.462	
1210	-0.332			1605	0.490		
		-0.814				-0.572	
1215	-0.269			1610	0.543		
		4.490	*			-0.224	
1220	-0.587			1615	0.562		
		1.740				-1.374	
1225	-0.702			1620	0.676		
		0.998				-0.839	
1230	-0.775			1625	0.762		
		0.557				0.786	
1235	-0.817			1630	0.683		
		2.174	*			0.608	
1240	-0.992			1635	0.627		
		0.438				-1.761	
1245	-1.026			1640	0.802		
		2.384	*			**-2.227**	*
1250	-1.196			1645	1.007		
		-0.491				-1.594	
1255	-1.161			1650	1.173		
		-0.381				**-2.387**	*
1300	-1.134			1655	1.481		
		1.963	*			**-7.674**	**
1305	-1.286			1700	2.712		

TABLE 2.10.6: T-statistic for the waiting time. This table reports the t-values resulting when testing two adjacent means against each other within successive intraday periods of 5 minutes for the waiting time between subsequent trades (WT). The t- values consider the first period under study (December 1, 1999 - March 31, 2000). (*) means that results are significant at 5% level of significance, whereas (**) results are significant at 1% level.

TIME	WT	T VALUE OF DIFF		TIME	WT	T VALUE OF DIFF	
905	-1.822						
910	-0.497	**-9.020**	**	1305	1.638		
915	-0.215	**-2.063**	*	1310	1.851	-1.341	
920	-0.155	-0.500		1315	2.172	**-2.043**	*
925	-0.196	0.353		1320	2.270	-0.629	
930	-0.289	0.962		1325	2.143	0.764	
935	-0.336	0.532		1330	1.889	1.457	
940	-0.317	-0.217		1335	1.944	-0.339	
945	-0.588	**3.421**	**	1340	2.037	-0.665	
950	-0.427	**-2.513**	*	1345	1.694	**2.656**	**
955	-0.431	0.046		1350	1.301	**3.339**	**
1000	-0.517	1.053		1355	1.375	-0.634	
1005	-0.612	1.380		1400	1.176	1.655	
1010	-0.457	**-2.355**	*	1405	0.750	**4.226**	**
1015	-0.514	0.862		1410	0.857	-1.078	
1020	-0.322	**-2.557**	*	1415	0.704	1.276	
1025	-0.462	1.795		1420	0.689	0.116	
1030	-0.580	1.610		1425	0.477	1.831	
1035	-0.499	-1.309		1430	0.323	1.443	
1040	-0.429	-1.277		1435	-0.090	**4.488**	**
1045	-0.550	**1.992**	*	1440	0.048	-1.555	
1050	-0.512	-0.563		1445	0.023	0.288	
1055	-0.494	-0.275		1450	-0.026	0.600	
1100	-0.484	-0.179		1455	-0.080	0.615	
1105	-0.445	-0.532		1500	-0.223	1.771	
1110	-0.345	-1.263		1505	-0.111	-1.556	
1115	-0.456	1.473		1510	-0.114	0.043	
1120	-0.470	0.225		1515	-0.093	-0.324	
1125	-0.484	0.245		1520	-0.043	-0.643	
1130	-0.435	-0.849		1525	-0.200	1.592	
1135	-0.394	-0.689		1530	-0.204	0.041	
1140	-0.386	-0.133		1535	-0.478	**3.116**	**
1145	-0.473	1.202		1540	-0.549	0.916	
1150	-0.446	-0.385		1545	-0.765	**3.095**	**
1155	-0.440	-0.106		1550	-0.707	-0.793	
1200	-0.556	1.839		1555	-0.704	-0.043	
1205	-0.261	**-4.847**	**	1600	-0.814	1.427	
1210	-0.174	-1.188		1605	-0.693	-1.334	
1215	-0.085	-1.056		1610	-0.766	0.792	
1220	0.250	**-4.126**	**	1615	-0.696	-0.860	
1225	0.387	-1.708		1620	-0.857	**2.068**	*
1230	0.502	-1.155		1625	-0.806	-0.614	
1235	0.670	-1.473		1630	-0.797	-0.108	
1240	1.249	**-5.395**	**	1635	-0.779	-0.229	
1245	1.122	1.085		1640	-0.864	1.191	
1250	1.244	-0.846		1645	-0.939	1.109	
1255	1.390	-1.049		1650	-1.106	**2.524**	*
1300	1.504	-0.790		1655	-1.235	1.669	
1305	1.638	-0.823		1700	-1.384	1.806	

TABLE 2.10.7.A: T-statistic for the liquidity ratio. This table reports the t-values resulting when testing two adjacent means against each other within successive intraday periods of 5 minutes for the liquidity ratio (LR). The t- values consider the first period under study (December 1, 1999 - March 31, 2000). (*) means that results are significant at 5% level of significance, whereas (**) results are significant at 1% level.

TIME	LR	T VALUE OF DIFF		TIME	LR	T VALUE OF DIFF	
905	-1.843	**-3.720**	**				
910	-1.430	-1.603		1305	0.424	-1.783	
915	-1.267	-1.650		1310	0.732	0.628	
920	-1.054	0.825		1315	0.610	0.190	
925	-1.159	-1.216		1320	0.571	0.547	
930	-1.046	-0.463		1325	0.476	0.085	
935	-1.004	0.132		1330	0.462	**2.548**	*
940	-1.018	0.265		1335	0.005	-1.051	
945	-1.044	-1.523		1340	0.223	1.238	
950	-0.880	-0.319		1345	-0.036	0.159	
955	-0.844	-0.378		1350	-0.062	0.322	
1000	-0.792	-0.544		1355	-0.113	0.017	
1005	-0.718	-0.178		1400	-0.116	-0.416	
1010	-0.698	0.226		1405	-0.041	0.956	
1015	-0.724	-1.657		1410	-0.203	-0.942	
1020	-0.551	0.367		1415	-0.047	-0.393	
1025	-0.591	1.362		1420	0.043	0.739	
1030	-0.751	**-2.193**	*	1425	-0.121	0.296	
1035	-0.460	0.681		1430	-0.164	-1.411	
1040	-0.553	0.326		1435	0.001	0.115	
1045	-0.592	-1.772		1440	-0.014	-1.240	
1050	-0.367	-0.116		1445	0.155	1.234	
1055	-0.352	0.822		1450	-0.005	-0.727	
1100	-0.437	-1.230		1455	0.173	0.962	
1105	-0.291	-0.145		1500	-0.057	**-3.046**	**
1110	-0.273	0.753		1505	0.304	1.063	
1115	-0.355	-0.380		1510	0.159	-0.052	
1120	-0.311	-0.850		1515	0.167	0.124	
1125	-0.194	-0.154		1520	0.148	-0.862	
1130	-0.166	0.231		1525	0.278	-0.191	
1135	-0.206	0.697		1530	0.308	-1.951	
1140	-0.297	-0.534		1535	0.600	0.743	
1145	-0.229	-0.378		1540	0.495	-0.382	
1150	-0.177	1.789		1545	0.568	0.869	
1155	-0.408	-1.888		1550	0.394	1.377	
1200	-0.129	-0.097		1555	0.184	-0.683	
1205	-0.114	0.617		1600	0.278	**-3.533**	**
1210	-0.187	-0.006		1605	0.813	-0.030	
1215	-0.186	-0.212		1610	0.818	0.921	
1220	-0.159	-0.248		1615	0.673	-1.653	
1225	-0.128	-0.254		1620	0.890	**-2.280**	*
1230	-0.098	-0.814		1625	1.209	0.379	
1235	0.017	-1.703		1630	1.154	0.176	
1240	0.359	0.457		1635	1.131	-1.937	
1245	0.268	0.101		1640	1.462	0.375	
1250	0.251	**-2.111**	*	1645	1.394	-1.469	
1255	0.616	0.643		1650	1.656	-1.475	
1300	0.496	0.388		1655	1.949	-0.912	
1305	0.424			1700	2.147		

TABLE 2.10.7.B: T-statistic for the flow ratio. This table reports the t-values resulting when testing two adjacent means against each other within successive intraday periods of 5 minutes for the flow ratio (FR). The t- values consider the first period under study (December 1, 1999 - March 31, 2000). (*) means that results are significant at 5% level of significance, whereas (**) results are significant at 1% level.

TIME	FR	T VALUE OF DIFF		TIME	FR	T VALUE OF DIFF	
905	0.239			1305	-0.240		
910	-0.630	**3.408**	**	1310	-0.508	1.142	
915	-0.528	-0.848		1315	-0.571	0.415	
920	-0.403	-1.037		1320	-0.735	1.231	
925	-0.566	1.361		1325	-0.762	0.209	
930	-0.430	-1.232		1330	-0.462	**-2.326**	*
935	-0.433	0.022		1335	-0.593	1.000	
940	-0.394	-0.297		1340	-0.713	0.864	
945	-0.392	-0.013		1345	-0.812	0.775	
950	-0.412	0.170		1350	-0.723	-0.789	
955	-0.483	0.632		1355	-0.812	0.739	
1000	-0.546	0.594		1400	-0.765	-0.400	
1005	-0.107	**-3.889**	**	1405	-0.539	**-2.141**	*
1010	-0.407	**2.899**	**	1410	-0.430	-0.877	
1015	-0.327	-0.757		1415	-0.788	**2.917**	**
1020	-0.242	-0.805		1420	-0.613	-1.463	
1025	-0.300	0.572		1425	-0.330	-1.910	
1030	-0.373	0.690		1430	-0.346	0.097	
1035	-0.031	**-2.994**	**	1435	1.156	**-8.900**	**
1040	-0.476	**4.137**	**	1440	0.131	**7.182**	**
1045	-0.353	-1.297		1445	0.113	0.146	
1050	0.014	**-2.853**	**	1450	0.135	-0.144	
1055	-0.042	0.414		1455	-0.009	0.955	
1100	-0.189	1.327		1500	-0.253	1.959	
1105	-0.031	-1.251		1505	0.287	**-3.694**	**
1110	-0.280	1.903		1510	0.060	1.571	
1115	-0.086	-1.321		1515	0.155	-0.724	
1120	-0.225	0.887		1520	0.252	-0.535	
1125	-0.212	-0.101		1525	0.065	1.054	
1130	-0.402	1.744		1530	0.023	0.312	
1135	-0.183	**-1.961**	*	1535	0.413	**-2.501**	*
1140	-0.312	1.083		1540	0.729	**-2.094**	*
1145	0.018	**-2.311**	*	1545	1.353	**-4.217**	**
1150	-0.226	1.720		1550	0.666	**4.779**	**
1155	-0.090	-1.210		1555	0.748	-0.678	
1200	-0.070	-0.205		1600	0.827	-0.482	
1205	-0.259	1.644		1605	1.109	-1.607	
1210	-0.417	1.396		1610	0.970	0.918	
1215	-0.347	-0.621		1615	0.989	-0.105	
1220	-0.409	0.520		1620	1.089	-0.500	
1225	-0.528	1.010		1625	1.171	-0.494	
1230	-0.332	-1.431		1630	1.256	-0.552	
1235	-0.574	1.773		1635	1.261	-0.030	
1240	-0.454	-0.831		1640	1.802	**-3.217**	**
1245	-0.363	-0.507		1645	1.554	1.340	
1250	-0.218	-0.751		1650	2.068	**-2.380**	*
1255	-0.485	1.560		1655	2.518	-1.893	
1300	-0.287	-1.134		1700	2.686	-0.764	
1305	-0.240	-0.191					

TABLE 2.10.8.A: The Pearsons correlation between 16 liquidity proxies during the first period. This Table shows the correlations among the 16 liquidity proxies defined in Appendix 2.12.2 during the period December 1, 1999 - March 31, 2000. The calculation is based on the French Stock Exchange, estimated from 43 stocks (weighted average of all the 43 stocks included in the CAC 40 index during the first period under study). All correlations are significant at the 0.01 level (two-tailed). The meaning of each acronyme is indicated in the list of abbreviations.

	EHS	QHS	DSPR	MID	QHS_WAS	SUMVOL	NBTR	VIMB	SABSVIMB	RET	ABSRET	VARRET	VOLA	WT	LR	FR
EHS	1	0.9852	0.9854	0.3334	0.8920	0.1962	0.5347	0.4522	0.3510	0.4671	0.9073	0.8185	0.8434	-0.4826	-0.4205	0.1312
QHS	0.9852	1	0.9998	0.2706	0.9258	0.0567	0.4167	0.3817	0.2178	0.4592	0.9122	0.8163	0.7674	-0.3649	-0.4999	-0.0015
DSPR	0.9854	0.9998	1	0.2661	0.9243	0.0577	0.4147	0.3854	0.2171	0.4662	0.9139	0.8188	0.7661	-0.3630	-0.4965	0.0001
MID	0.3334	0.2706	0.2661	1	0.3772	0.2679	0.6456	0.3531	0.4622	-0.0007	0.2401	0.1525	0.5651	-0.7626	-0.3750	0.1611
QHS_WAS	0.8920	0.9258	0.9243	0.3772	1	-0.1461	0.3258	0.2703	0.0661	0.4208	0.8676	0.7592	0.6759	-0.3352	-0.7252	-0.2177
SUMVOL	0.1962	0.0567	0.0577	0.2679	-0.1461	1	0.8177	0.5445	0.9435	-0.0710	-0.0488	-0.0665	0.6019	-0.6356	0.6448	0.9495
NBTR	0.5347	0.4167	0.4147	0.6456	0.3258	0.8177	1	0.6289	0.9336	0.0133	0.2774	0.1856	0.8914	-0.8844	0.1118	0.7111
VIMB	0.4522	0.3817	0.3854	0.3531	0.2703	0.5445	0.6289	1	0.5995	0.1737	0.2433	0.1693	0.6111	-0.4868	0.0619	0.4676
SABSVIMB	0.3510	0.2178	0.2171	0.4622	0.0661	0.9435	0.9336	0.5995	1	-0.0279	0.1167	0.0700	0.7598	-0.8094	0.4062	0.8847
RET	0.4671	0.4592	0.4662	-0.0007	0.4208	-0.0710	0.0133	0.1737	-0.0279	1	0.6446	0.7034	0.2327	-0.1517	-0.2540	0.0110
ABSRET	0.9073	0.9122	0.9139	0.2401	0.8676	-0.0488	0.2774	0.2433	0.1167	0.6446	1	0.9744	0.6327	-0.3807	-0.5396	-0.0380
VARRET	0.8185	0.8163	0.8188	0.1525	0.7592	-0.0665	0.1856	0.1693	0.0700	0.7034	0.9744	1	0.5199	-0.3367	-0.4687	-0.0105
VOLA	0.8434	0.7674	0.7661	0.5651	0.6759	0.6019	0.8914	0.6111	0.7598	0.2327	0.6327	0.5199	1	-0.7902	-0.1514	0.4971
WT	-0.4826	-0.3649	-0.3630	-0.7626	-0.3352	-0.6356	-0.8844	-0.4868	-0.8094	-0.1517	-0.3807	-0.3367	-0.7902	1	0.0712	-0.5878
LR	-0.4205	-0.4999	-0.4965	-0.3750	-0.7252	0.6448	0.1118	0.0619	0.4062	-0.2540	-0.5396	-0.4687	-0.1514	0.0712	1	0.6947
FR	0.1312	-0.0015	0.0001	0.1611	-0.2177	0.9495	0.7111	0.4676	0.8847	0.0110	-0.0380	-0.0105	0.4971	-0.5878	0.6947	1

TABLE 2.10.8.B: The Pearsons correlation between 16 liquidity proxies during the second period. This Table shows the correlations among the 16 liquidity proxies defined in Appendix 2.12.2 during the period April 1, 2000 - November 30, 2000. The calculation is based on the French Stock Exchange, estimated from 43 stocks (weighted average of all the 43 stocks included in the CAC 40 index during the second period under study). All correlations are significant at the 0.01 level (two-tailed). The meaning of each acronyme is indicated in the list of abbreviations.

	EHS	QHS	DSPR	MID	QHS_WAS	SUMVOL	NBTR	VIMB	SABSVIMB	RET	ABSRET	VARRET	VOLA	WT	LR	FR
EHS	1	0.9868	0.9879	0.4595	0.9103	-0.0066	0.2937	0.3038	0.1037	-0.2660	0.9487	0.7537	0.7646	-0.3845	-0.4991	-0.0132
QHS	0.9868	1	0.9996	0.3441	0.9364	-0.1393	0.1562	0.2308	-0.0254	-0.2711	0.9436	0.7387	0.6704	-0.2425	-0.5694	-0.1424
DSPR	0.9879	0.9996	1	0.3488	0.9299	-0.1242	0.1682	0.2397	-0.0122	-0.2722	0.9423	0.7379	0.6786	-0.2503	-0.5550	-0.1266
MID	0.4595	0.3441	0.3488	1	0.3429	0.5183	0.7174	0.3575	0.5322	-0.0816	0.3844	0.2817	0.7351	-0.8227	0.0174	0.4846
QHS_WAS	0.9103	0.9364	0.9299	0.3429	1	-0.3100	0.0507	0.1078	-0.1943	-0.2351	0.8758	0.6368	0.5723	-0.1795	-0.7505	-0.3258
SUMVOL	-0.0066	-0.1393	-0.1242	0.5183	-0.3100	1	0.8919	0.4096	0.9404	0.1367	-0.1316	-0.1205	0.5791	-0.7138	0.7463	0.9744
NBTR	0.2937	0.1562	0.1682	0.7174	0.0507	0.8919	1	0.5265	0.8671	0.0884	0.1394	0.0448	0.8310	-0.9017	0.3884	0.8650
VIMB	0.3038	0.2308	0.2397	0.3575	0.1078	0.4096	0.5265	1	0.4664	0.0793	0.2569	0.2472	0.5035	-0.5389	0.0614	0.4484
SABSVIMB	0.1037	-0.0254	-0.0122	0.5322	-0.1943	0.9404	0.8671	0.4664	1	0.0843	-0.0128	-0.0187	0.6234	-0.7018	0.6327	0.9046
RET	-0.2660	-0.2711	-0.2722	-0.0816	-0.2351	0.1367	0.0884	0.0793	0.0843	1	-0.3763	-0.4590	-0.0662	0.0403	0.1708	0.0827
ABSRET	0.9487	0.9436	0.9423	0.3844	0.8758	-0.1316	0.1394	0.2569	-0.0128	-0.3763	1	0.9116	0.6150	-0.3136	-0.5505	-0.1065
VARRET	0.7537	0.7387	0.7379	0.2817	0.6368	-0.1205	0.0448	0.2472	-0.0187	-0.4590	0.9116	1	0.4101	-0.2741	-0.4048	-0.0555
VOLA	0.7646	0.6704	0.6786	0.7351	0.5723	0.5791	0.8310	0.5035	0.6234	-0.0662	0.6150	0.4101	1	-0.8060	-0.0420	0.5504
WT	-0.3845	-0.2425	-0.2503	-0.8227	-0.1795	-0.7138	-0.9017	-0.5389	-0.7018	0.0403	-0.3136	-0.2741	-0.8060	1	-0.1702	-0.7195
LR	-0.4991	-0.5694	-0.5550	0.0174	-0.7505	0.7463	0.3884	0.0614	0.6327	0.1708	-0.5505	-0.4048	-0.0420	-0.1702	1	0.7529
FR	-0.0132	-0.1424	-0.1266	0.4846	-0.3258	0.9744	0.8650	0.4484	0.9046	0.0827	-0.1065	-0.0555	0.5504	-0.7195	0.7529	1

TABLE 2.10.9.A: Stocks ranked by different liquidity proxies during the first period. This table shows 43 stocks of the French Stock Exchange belonging to the CAC 40 index, ranked by 16 different liquidity proxies during the period December 1, 1999 - March 31, 2000. Stocks are ranked from the highest liquid stock to the lowest.

EHS	QHS	DSPR	MID	QHS_W	SUMVO	NBTR	VIMB	SABSVI	RET	ABSRET	VARRE	VOLA	WT	LR	FR
Bnp	Bnp	EADS	EADS	Accor	Alcatel	Vivendi	Alcatel	Vivendi	L'Oreal	Suez	Suez	Dexia	Vivendi	Bouygue	Bouygue
Suez	Suez	Michelin	Alstom	Suez	Cap	France	Total	France	Vivendi	Bnp	Alcatel	Bic	France	Tf1	Tf1
Alcatel	Alcatel	Alstom	Michelin	Agf	Lagarder	Alcatel	France	Aventis	Canal	Alcatel	Bnp	Agf	Alcatel	Legrand	Peugeot
Vivendi	Vivendi	Credit	Csf	Danone	Vivendi	Canal	Stm	Alcatel	Equant	Vivendi	Vivendi	Eridania	Carrefour	Lvmh	Cap
Total	Total	Aventis	Credit	Bnp	Canal	Carrefour	Carrefour	Total	**MEAN**	France	France	Sodexho	Total	Cap	L'Oreal
France	France	Renault	Bic	Pinault	Equant	Suez	Vivendi	Bnp	Suez	Carrefour	Total	Legrand	Suez	Peugeot	Legrand
Carrefour	Carrefour	Sanofi	Sanofi	Michelin	Lafarge	Stm	Lagarder	Suez	Air	Total	Carrefour	Bnp	Stm	L'Oreal	Lvmh
Axa	Stm	Bnp	Renault	Lafarge	Accor	Total	Equant	Credit	Lafarge	Stm	Stm	Peugeot	Bnp	Danone	Alcatel
Aventis	Danone	Agf	Agf	Valeo	Valeo	Credit	Valeo	Stm	Alcatel	Danone	Danone	Michelin	Canal	Société	Danone
Danone	Aventis	Csf	Aventis	Csf	Aventis	Bnp	Aventis	Axa	Carrefour	Aventis	Aventis	Suez	Aventis	Dexia	Canal
Stm	Axa	Valeo	Valeo	L'Oreal	Peugeot	Cap	Bnp	Carrefour	Bnp	Axa	Axa	Danone	Credit	Sodexho	Société
Lvmh	Société	Vivendi	Schneide	Alcatel	Suez	Aventis	Multi	Sanofi	Michelin	Société	Lvmh	Société	Danone	Pinault	Saint
Dexia	Lvmh	Accor	Lagarder	Vivendi	Saint	Danone	Accor	Equant	Casino	Lvmh	Société	Axa	Axa	Canal	Sodexho
Société	Pinault	Schneide	Multi	Axa	Michelin	Renault	Lafarge	**MEAN**	Total	Pinault	Dexia	Lvmh	Cap	**MEAN**	Dexia
Pinault	Accor	Lagarder	Bnp	Carrefour	Danone	Lagarder	Renault	Renault	France	Accor	Pinault	Pinault	Renault	Saint	**MEAN**
Agf	Renault	Total	Eridania	Aventis	Bouygue	**MEAN**	Canal	Lagarder	Société	Renault	L'Oreal	Casino	Air	Alcatel	Pinault
L'Oreal	L'Oreal	Bic	Accor	Sodexho	Stm	Accor	**MEAN**	EADS	Sanofi	Credit	Equant	L'Oreal	Accor	Eridania	Equant
Accor	Michelin	France	Lafarge	Air	Schneide	Lafarge	Alstom	Canal	Alstom	Dexia	Agf	Aventis	EADS	Casino	Stm
Michelin	Air	Suez	Casino	Bouygue	Legrand	Equant	Suez	Accor	Cap	Valeo	Renault	Total	Equant	Bic	Suez
Renault	Dexia	Lafarge	Vivendi	Peugeot	**MEAN**	Multi	Credit	Alstom	Schneide	Equant	Lafarge	Sanofi	Lafarge	Stm	Lagarder
Air	Valeo	Axa	Equant	Saint	Renault	Air	Danone	Michelin	Pinault	Michelin	Air	Valeo	Société	Suez	Casino
Saint	Equant	Carrefour	Axa	Tf1	Tf1	Axa	Pinault	Lafarge	Saint	Lafarge	Michelin	**MEAN**	Lagarder	Accor	Lafarge
MEAN	Saint	Equant	Total	Lvmh	Bnp	EADS	Société	Schneide	Credit	L'Oreal	Valeo	Credit	Pinault	Lagarder	Air
Credit	Credit	Stm	Dexia	Canal	Société	Pinault	Cap	Cap	Multi	Agf	Saint	Bouygue	Lvmh	Equant	Axa
Valeo	Agf	Casino	France	Eridania	Alstom	Valeo	Sanofi	Valeo	Aventis	Air	Credit	Schneide	Saint	Lafarge	Carrefour
Equant	Cap	Alcatel	Air	Casino	Sodexho	Société	Air	Csf	Danone	**MEAN**	Cap	Saint	Multi	Air	Eridania
Cap	**MEAN**	Multi	Saint	Legrand	Air	Saint	Axa	Multi	Stm	Cap	**MEAN**	Renault	L'Oreal	Michelin	Vivendi
Peugeot	Lafarge	Air	Sodexho	Total	Casino	Lvmh	Csf	Saint	Axa	Saint	Canal	Accor	Sanofi	Axa	Valeo
Lafarge	Peugeot	Dexia	Carrefour	**MEAN**	Pinault	Alstom	Casino	Agf	Lagarder	Sanofi	Peugeot	Csf	Valeo	Schneide	Accor
Sanofi	Lagarder	Danone	**MEAN**	Renault	Credit	Sanofi	Bouygue	Air	Renault	Canal	Lagarder	Lafarge	**MEAN**	Valeo	Schneide
Bouygue	Sanofi	Saint	Suez	Lagarder	Csf	L'Oreal	EADS	Danone	Valeo	Lagarder	Bouygue	Air	Michelin	Agf	Total
Sodexho	Canal	**MEAN**	Stm	Stm	Axa	Michelin	Peugeot	Société	Lvmh	EADS	Casino	Alcatel	Alstom	Renault	Bnp
Lagarder	EADS	Société	Canal	Schneide	Carrefour	Schneide	Saint	Pinault	Legrand	Peugeot	Schneide	Carrefour	Schneide	Csf	Multi
EADS	Bouygue	Eridania	Legrand	France	Multi	Tf1	Tf1	Lvmh	Agf	Bouygue	Sodexho	EADS	Tf1	Bnp	Bic
Casino	Schneide	Pinault	Société	Dexia	Lvmh	Bouygue	Agf	Casino	EADS	Schneide	Sanofi	Stm	Bouygue	Carrefour	Agf
Schneide	Casino	Sodexho	Peugeot	Sanofi	Total	Csf	Michelin	Peugeot	Csf	Sodexho	EADS	Alstom	Peugeot	Total	Aventis
Canal	Sodexho	Canal	Danone	Equant	France	Peugeot	Dexia	Dexia	Sodexho	Casino	Legrand	Vivendi	Csf	Sanofi	France
Legrand	Alstom	Peugeot	Pinault	Société	Dexia	Casino	Legrand	L'Oreal	Peugeot	Alstom	Alstom	Tf1	Casino	Alstom	Michelin
Csf	Csf	Cap	Alcatel	EADS	Bic	Sodexho	Bic	Bouygue	Accor	Legrand	Csf	Equant	Sodexho	Vivendi	Renault
Alstom	Legrand	Legrand	Cap	Alstom	Sanofi	Legrand	Sodexho	Sodexho	Dexia	Csf	Tf1	France	Legrand	Multi	Csf
Eridania	Tf1	Lvmh	Lvmh	Bic	Agf	Agf	Schneide	Legrand	Bouygue	Tf1	Eridania	Cap	Agf	Aventis	Alstom
Tf1	Multi	L'Oreal	Tf1	Cap	Eridania	Dexia	Eridania	Tf1	Tf1	Bic	Bic	Lagarder	Dexia	Credit	Credit
Bic	Eridania	Bouygue	Bouygue	Credit	L'Oreal	Eridania	L'Oreal	Bic	Bic	Eridania	Multi	Canal	Eridania	France	Sanofi
Multi	Bic	Tf1	L'Oreal	Multi	EADS	Bic	Lvmh	Eridania	Eridania	Multi	Accor	Multi	Bic	EADS	EADS

TABLE 2.10.9.B: Stocks ranked by different liquidity proxies during the second period. This table shows 43 stocks of the French Stock Exchange belonging to the CAC 40 index, ranked by 16 different liquidity proxies during the period April 1, 2000 - November 30, 2000. Stocks are ranked from the highest value of liquidity indicator to the lowest.

EHS	QHS	DSPR	MID	QHS_W	SUMVO	NBTR	VIMB	SABSVI	RET	ABSRET	VARRE	VOLA	WT	LR	FR
Total	Vivendi	EADS	EADS	Dexia	Equant	Alcatel	France	France	Alstom	Alcatel	France	Eridania	Alcatel	EADS	EADS
Vivendi	Total	Alstom	Alstom	STM	Alcatel	France	Alcatel	Alcatel	Multi	France	Alcatel	Bic	France	France	Alstom
Alcatel	Alcatel	Michelin	Michelin	Suez	Cap	Vivendi	Vivendi	STM	France	Vivendi	Vivendi	Dexia	Vivendi	Carrefour	Credit
Bnp	France	Equant	Bic	Air	Vivendi	STM	Axa	Vivendi	Cap	Total	Total	Sodexho	STM	Sanofi	Csf
France	Bnp	Accor	Credit	Accor	Tf1	Cap	Carrefour	Aventis	Total	STM	Bnp	Legrand	Carrefour	Multi	Sanofi
Axa	STM	Aventis	Csf	Pinault	STM	Carrefour	Stm	Equant	Stm	Bnp	STM	Agf	Total	Alstom	Accor
Aventis	Axa	Credit	Accor	Axa	Valeo	Equant	Aventis	EADS	Vivendi	Carrefour	Carrefour	Casino	Cap	Aventis	Renault
Suez	Carrefour	Renault	Renault	Alcatel	Lagarder	Total	Suez	Carrefour	Sanofi	Aventis	Axa	Peugeot	Equant	Stm	Carrefour
STM	Aventis	Carrefour	Equant	Total	Canal	Multi	**MEAN**	Total	Suez	Axa	Aventis	Suez	Bnp	Credit	Michelin
Dexia	Suez	Sanofi	Sanofi	Société	Lafarge	Canal	Equant	Bnp	Accor	Suez	Suez	Pinault	Aventis	Vivendi	France
Carrefour	Cap	Vivendi	Valeo	Peugeot	Danone	EADS	Bnp	Axa	Casino	Cap	Dexia	Michelin	Axa	Agf	Multi
Canal	Canal	STM	Agf	Vivendi	Multi	Bnp	Société	**MEAN**	Pinault	Canal	Cap	Csf	Suez	Renault	Aventis
Pinault	Equant	Alcatel	Lagarder	Eridania	Bouygue	Aventis	Lagarder	Sanofi	Aventis	Dexia	Canal	Bnp	Société	Alcatel	Bic
Cap	Pinault	Bnp	Schneide	Carrefour	Bnp	**MEAN**	Cap	Société	Alcatel	Equant	Equant	Axa	Multi	Bnp	Agf
Danone	Lafarge	Valeo	Aventis	Danone	Axa	Axa	Total	Suez	Lagarder	Danone	Lafarge	Lafarge	EADS	Lagarder	Stm
Lvmh	Dexia	Agf	Multi	Casino	**MEAN**	Tf1	Sanofi	Multi	Carrefour	Lafarge	Pinault	Total	L'Oreal	Csf	Schneide
Lafarge	Danone	Lagarder	Carrefour	Bnp	Peugeot	Lagarder	Lvmh	Cap	Air	Pinault	Société	Schneide	Canal	Schneide	Equant
L'Oreal	Air	Csf	Eridania	Agf	Carrefour	Suez	Saint	Credit	Bnp	EADS	L'Oreal	Saint	Tf1	Total	Bnp
Société	Lvmh	Lafarge	STM	Michelin	Accor	Société	Accor	Lagarder	Valeo	Société	Air	Aventis	Danone	Michelin	Société
Saint	Société	Bic	Lafarge	Sodexho	Suez	Bouygue	Bouygue	Canal	Schneide	**MEAN**	Saint	Danone	Credit	Société	Alcatel
Peugeot	Saint	Schneide	Société	Lafarge	Saint	Danone	Schneide	Renault	Axa	L'Oreal	Peugeot	Valeo	Lvmh	Equant	Lagarder
Air	L'Oreal	France	Vivendi	Saint	Michelin	L'Oreal	Tf1	Accor	Csf	Lvmh	Sanofi	Alstom	Lagarder	Air	Vivendi
MEAN	**MEAN**	Société	Bnp	EADS	Société	Credit	Renault	L'Oreal	Dexia	Saint	Lagarder	**MEAN**	Bouygue	Valeo	Valeo
Equant	Lagarder	Multi	Casino	Equant	France	Renault	Valeo	Lvmh	Equant	Sanofi	EADS	Air	Renault	Axa	Total
Agf	Peugeot	Total	Alcatel	**MEAN**	Alstom	Lvmh	Credit	Alstom	Tf1	Air	Casino	Lvmh	Accor	Lafarge	Air
Sanofi	Renault	Axa	**MEAN**	Schneide	Aventis	Accor	Danone	Bouygue	Credit	Peugeot	Accor	Accor	Air	Casino	Lafarge
Schneide	Accor	Casino	France	L'Oreal	Schneide	Air	L'Oreal	Danone	Canal	Lagarder	Schneide	Sanofi	Lafarge	Bic	Eridania
Casino	Sanofi	**MEAN**	Saint	Csf	Casino	Lafarge	Agf	Lafarge	**MEAN**	Accor	Renault	Vivendi	Sanofi	L'Oreal	**MEAN**
Renault	Bouygue	Suez	Air	Alstom	Renault	Sanofi	Michelin	Tf1	Agf	Renault	Agf	Renault	Saint	Saint	Casino
Accor	EADS	Saint	Dexia	Cap	Total	Saint	Csf	Michelin	Renault	Credit	Valeo	L'Oreal	Pinault	Suez	Lvmh
Lagarder	Schneide	Air	Axa	Valeo	Legrand	Pinault	Alstom	Agf	Lafarge	Tf1	Tf1	Société	**MEAN**	Eridania	Saint
Bouygue	Tf1	Dexia	Total	Canal	Air	Valeo	Dexia	Schneide	Saint	Schneide	Michelin	Carrefour	Valeo	**MEAN**	Axa
Michelin	Michelin	Canal	Sodexho	France	EADS	Alstom	Bic	Valeo	EADS	Bouygue	Sodexho	EADS	Alstom	Cap	Pinault
EADS	Valeo	Eridania	Suez	Bic	Sodexho	Schneide	Air	Saint	Michelin	Michelin	Credit	Credit	Schneide	Tf1	Suez
Sodexho	Credit	Cap	Danone	Lagarder	Pinault	Michelin	Pinault	Air	Legrand	Valeo	Eridania	Canal	Michelin	Canal	L'Oreal
Valeo	Multi	Danone	Canal	Legrand	Agf	Peugeot	Canal	Pinault	Société	Agf	Bic	Lagarder	Peugeot	Pinault	Dexia
Credit	Casino	Pinault	Legrand	Bouygue	Credit	Casino	Casino	Csf	L'Oreal	Casino	Alstom	Bouygue	Casino	Danone	Danone
Eridania	Agf	Lvmh	Cap	Renault	Lvmh	Csf	EADS	Casino	Bouygue	Sodexho	Multi	Cap	Csf	Dexia	Cap
Alstom	Alstom	Peugeot	Pinault	Aventis	Sanofi	Agf	Multi	Dexia	Danone	Multi	**MEAN**	Tf1	Agf	Bouygue	Canal
Tf1	Sodexho	Sodexho	Lvmh	Lvmh	Bic	Sodexho	Sodexho	Peugeot	Peugeot	Alstom	Danone	Stm	Sodexho	Lvmh	Sodexho
Bic	Eridania	Bouygue	Peugeot	Sanofi	Dexia	Dexia	Peugeot	Sodexho	Sodexho	Bic	Legrand	France	Dexia	Sodexho	Tf1
Multi	Bic	L'Oreal	Bouygue	Tf1	L'Oreal	Legrand	Eridania	Bic	Lvmh	Eridania	Csf	Alcatel	Legrand	Peugeot	Legrand
Csf	Csf	Tf1	Tf1	Credit	Csf	Bic	Legrand	Legrand	Bic	Legrand	Lvmh	Multi	Bic	Legrand	Bouygue
Legrand	Legrand	Legrand	L'Oreal	Multi	Eridania	Eridania	Lafarge	Eridania	Eridania	Csf	Bouygue	Equant	Eridania	Accor	Peugeot

TABLE 2.10.10: Intraday market depth in terms of trading volume: This estimation is based on the average trading data between the 43 stocks belonging to the CAC 40 index during a one-year period. From this sample, I obtained 8352 observations of five minutes each for table 2.10.10.A and 17'238 for table 2.10.10.B. These tables represent the results of the regression between the ratio of cumulated traded volume (explained variable) and the following independent variables: ratio of waiting time (RWT), ratio of variance of return (RVARRET), ratio of cumulated volume imbalance in absolute terms (RSABSVIMB), a constant (C), and ARMA(2,1) in the first period and ARMA(2, 3) in the second period. The conditional variance equation of residuals follows a TARCH model in period 1 (explained in detail in Appendix 2.11.1) and includes two lagged residual coefficients, two for all residuals (ARCH(2)), the other only for negative residuals being a dummy variable (RESID<0)*ARCH(1)), lagged conditional variance (GARCH(1)) and a constant (C). In the second period the conditional variance equation follows a GARCH (1,1). In the Table 2.10.10.A. the value of parameters p, q, r, s and z are respectively: 2, 0, 0, 0 and 1. In the Table 2.10.10.B. the value of parameters p, q, r, s and z are respectively: 2, 0, 1, 1 and 3.

Table 2.10.10.A: Depth in terms of trading volume during the first period

	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.912	0.013	-68.707	0.000
RSABSVIMB	0.291	0.019	15.354	0.000
RVARRET	-0.109	0.009	-11.810	0.000
RWT	-1.158	0.013	-88.601	0.000
AR(1)	0.984	0.019	50.733	0.000
AR(2)	-0.034	0.016	-2.129	0.033
MA(1)	-0.749	0.015	-49.849	0.000
		Variance Equation		
C	0.004	0.002	2.070	0.038
ARCH(1)	0.140	0.034	4.133	0.000
ARCH(2)	-0.047	0.014	-3.470	0.001
(RESID< 0)*ARCH(1)	-0.088	0.033	-2.643	0.008
GARCH(1)	0.849	0.063	13.505	0.000

R-squared	0.834	**Mean dependent var**	-0.625
Adjusted R-squared	0.834	**S.D. dependent var**	0.480
S.E. of regression	0.196	**Akaike info criterion**	-0.451
Sum squared resid	318.833	**Schwarz criterion**	-0.441
Log likelihood	1894.070	**F-statistic**	3812.506
Durbin-Watson stat	1.930	**Prob(F-statistic)**	0.000

Inverted AR Roots	0.950	0.040
Inverted MA Roots	0.750	

Table 2.10.10.B: Depth in terms of trading volume during the second period

	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.442	0.033	-13.365	0.000
RSABSVIMB	0.628	0.019	33.688	0.000
RVARRET(-1)	-0.049	0.010	-4.785	0.000
RWT(-1)	0.032	0.018	1.803	0.071
AR(1)	1.811	0.014	133.861	0.000
AR(2)	-0.812	0.013	-60.724	0.000
MA(1)	-1.498	0.020	-74.256	0.000
MA(2)	0.449	0.023	19.335	0.000
MA(3)	0.067	0.009	7.465	0.000
		Variance Equation		
C	0.042	0.008	5.230	0.000
ARCH(1)	0.061	0.009	6.782	0.000
GARCH(1)	0.541	0.080	6.740	0.000

R-squared	0.456	**Mean dependent var**	-0.614
Adjusted R-squared	0.456	**S.D. dependent var**	0.438
S.E. of regression	0.323	**Akaike info criterion**	0.573
Sum squared resid	1799.140	**Schwarz criterion**	0.578
Log likelihood	-4924.470	**F-statistic**	1312.959
Durbin-Watson stat	1.988	**Prob(F-statistic)**	0.000

Inverted AR Roots	0.990	0.820	
Inverted MA Roots	0.950	0.650	-0.110

TABLE 2.10.11: Intraday market depth in terms of order volume imbalance: This estimation is based on the average trading data between the 43 stocks belonging to the CAC 40 index during a one-year period. From this sample I obtained 8352 observations of five minutes each for table 2.10.11.A and 17'238 for table 2.10.11.B. These tables represent the results of the regression between the ratio of cumulated order volume imbalance in absolute terms (explained variable) and the following independent variables: ratio of quoted half spread (RQHS), ratio of waiting time (RWT), a constant (C), and ARMA(3,2) in the first period and ARMA(3,1) in the second period. The conditional variance equation of residuals follows a GARCH model, including 3-lagged residuals coefficients, (ARCH(3)), 1-lagged conditional variance (GARCH(1)) and a constant (C). The conditional variance equation in the second period follows a GARCH(1,1) model. In the Table 2.10.11.A. the value of parameters p, q, r and z are respectively: 3, 0, 0 and 2. In the Table 2.10.11.B. the value of parameters p, q, r and z are respectively: 3, 0, 0 and 1.

Table 2.10.11.A: Depth in terms of volume imbalance during the first period

	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.341	0.020	-17.423	0.000
RQHS	-0.028	0.013	-2.149	0.032
RWT	-0.114	0.008	-13.856	0.000
AR(1)	1.864	0.096	19.356	0.000
AR(2)	-0.989	0.136	-7.262	0.000
AR(3)	0.123	0.041	3.000	0.003
MA(1)	-1.463	0.095	-15.386	0.000
MA(2)	0.485	0.089	5.423	0.000
		Variance Equation		
C	0.000	0.000	1.932	0.053
ARCH(1)	0.080	0.021	3.891	0.000
ARCH(2)	-0.054	0.024	-2.250	0.025
ARCH(3)	-0.019	0.012	-1.544	0.123
GARCH(1)	0.985	0.006	155.190	0.000

R-squared	0.499	**Mean dependent var**	-0.304
Adjusted R-squared	0.498	**S.D. dependent var**	0.186
S.E. of regression	0.132	**Akaike info criterion**	-1.235
Sum squared resid	144.696	**Schwarz criterion**	-1.224
Log likelihood	5167.856	**F-statistic**	692.342
Durbin-Watson stat	1.967	**Prob(F-statistic)**	0.000

Inverted AR Roots	0.990	0.690	0.180
Inverted MA Roots	0.950	0.510	

Table 2.10.11.B: Depth in terms of volume imbalance during the second period

	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.754	0.015	-51.833	0.000
RQHS	-0.137	0.018	-7.470	0.000
RWT	-0.897	0.007	-135.779	0.000
AR(1)	1.129	0.012	96.312	0.000
AR(2)	-0.107	0.013	-8.518	0.000
AR(3)	-0.038	0.010	-3.842	0.000
MA(1)	-0.864	0.008	-112.960	0.000
		Variance Equation		
C	0.009	0.001	7.225	0.000
ARCH(1)	0.092	0.012	7.657	0.000
GARCH(1)	0.700	0.035	20.233	0.000

R-squared	0.768	**Mean dependent var**	-0.540
Adjusted R-squared	0.768	**S.D. dependent var**	0.438
S.E. of regression	0.211	**Akaike info criterion**	-0.310
Sum squared resid	767.533	**Schwarz criterion**	-0.306
Log likelihood	2683.402	**F-statistic**	6329.128
Durbin-Watson stat	1.948	**Prob(F-statistic)**	0.000

Inverted AR Roots	0.980	0.280	-0.140
Inverted MA Roots	0.86		

TABLE 2.10.12: Time dimension of intraday market liquidity: This estimation is based on the average trading data between the 43 stocks belonging to the CAC 40 index during a one-year period. From this sample I obtain 8352 observations of five minutes each for table 2.10.12.A and 17'238 for table 2.10.12.B. These tables represent the results of the regression between the ratio of waiting time (explained variable) and the following independent variables: ratio of cumulated traded volume (RSUMVOL), ratio of return volatility (RVARRET), ratio of cumulated volume imbalance in absolute terms (RSABSVIMB), a constant (C), and ARMA (2,1) in the first period and ARMA (3,1) in the second. The conditional variance equation of residuals follows a GARCH model (explained in detail in Appendix 2.11.1), including 1-lagged residual coefficient, (ARCH (1)), 1-lagged conditional variance (GARCH (1)) and a constant (C). The conditional variance equation in the second period follows also a GARCH (1,1) model. In the Table 2.10.12.A. the value of parameters p, q, r, s and z are respectively: 2, 0, 0, 0 and 1. In the Table 2.10.12.B. the value of parameters p, q, r, s and z are respectively: 3, 0, 0, 0 and 1.

Table 2.10.12.A: Time dimension of intraday market liquidity during the first period

	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.577	0.011	-50.921	0.000
RSUMVOL	-0.378	0.011	-34.936	0.000
RSABSVIMB	-0.199	0.015	-13.510	0.000
RVARRET	0.035	0.007	4.933	0.000
AR(1)	1.040	0.020	52.442	0.000
AR(2)	-0.079	0.017	-4.602	0.000
MA(1)	-0.773	0.015	-51.807	0.000
	Variance Equation			
C	0.007	0.001	4.996	0.000
ARCH(1)	0.102	0.032	3.230	0.001
GARCH(1)	0.483	0.090	5.335	0.000
R-squared	0.839	**Mean dependent var**		-0.264
Adjusted R-squared	0.839	**S.D. dependent var**		0.312
S.E. of regression	0.125	**Akaike info criterion**		-1.334
Sum squared resid	131.113	**Schwarz criterion**		-1.325
Log likelihood	5577.493	**F-statistic**		4818.196
Durbin-Watson stat	1.928	**Prob(F-statistic)**		0.000
Inverted AR Roots	0.960	0.080		
Inverted MA Roots	0.770			

Table 2.10.12.B: Time dimension of intraday market liquidity during the second period

	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.520	0.012	-42.903	0.000
RSUMVOL	-0.040	0.005	-8.786	0.000
RSABSVIMB	-0.549	0.006	-98.832	0.000
RVARRET	0.062	0.005	12.150	0.000
AR(1)	1.047	0.012	84.527	0.000
AR(2)	-0.011	0.013	-0.909	0.364
AR(3)	-0.053	0.009	-5.550	0.000
MA(1)	-0.857	0.008	-113.335	0.000
	Variance Equation			
C	0.007	0.001	6.587	0.000
ARCH(1)	0.082	0.011	7.464	0.000
GARCH(1)	0.648	0.047	13.659	0.000
R-squared	0.744	**Mean dependent var**		-0.245
Adjusted R-squared	0.744	**S.D. dependent var**		0.324
S.E. of regression	0.164	**Akaike info criterion**		-0.804
Sum squared resid	462.015	**Schwarz criterion**		-0.799
Log likelihood	6935.192	**F-statistic**		5002.799
Durbin-Watson stat	1.959	**Prob(F-statistic)**		0.000
Inverted AR Roots	0.980	0.270	-0.200	
Inverted MA Roots	0.860			

TABLE 2.10.13: Tightness of intraday market liquidity: This estimation is based on the average trading data between the 43 stocks belonging to the CAC 40 index during a one-year period. From this sample I obtain 8352 observations of five minutes each for table 2.10.13.A and 17'238 for table 2.10.13.B. These tables represent the results of the regression between the ratio of quoted half spread (explained variable) and the following independent variables: ratio of cumulated volume imbalance in absolute terms (SABSVIMB), ratio of return volatility (VARRET), ratio of waiting time (WT), a constant (C), and ARMA (2,2) in the first period and ARMA (2,1) in the second period. The conditional variance equation of residuals follows, in the first and second period, a GARCH model, including 1-lagged residuals coefficients (ARCH (1)), 1-lagged conditional variance (GARCH (1)) and a constant (C). In the Table 2.10.13.A. the value of parameters p, q, r, s and z are respectively: 2, 0, 0, 0 and 2. In the Table 2.10.13.B. the value of parameters p, q, r, s and z are respectively: 2, 0, 1, 0 and 1.

Table 2.10.13.A: Tightness of intraday market liquidity during the first period

	Coefficient	Std. Error	z-Statistic	Prob.
C	0.052	0.007	7.733	0.000
RWT	-0.012	0.005	-2.560	0.011
RSABSVIMB	0.035	0.008	4.366	0.000
RVARRET	0.314	0.004	72.094	0.000
AR(1)	1.489	0.034	43.726	0.000
AR(2)	-0.496	0.033	-14.944	0.000
MA(1)	-1.152	0.037	-31.214	0.000
MA(2)	0.199	0.033	6.118	0.000
		Variance Equation		
C	0.002	0.001	3.113	0.002
ARCH(1)	0.053	0.014	3.651	0.000
GARCH(1)	0.635	0.106	5.966	0.000

R-squared	0.744	**Mean dependent var**	-0.186
Adjusted R-squared	0.744	**S.D. dependent var**	0.158
S.E. of regression	0.080	**Akaike info criterion**	-2.227
Sum squared resid	52.963	**Schwarz criterion**	-2.218
Log likelihood	9308.187	**F-statistic**	2427.886
Durbin-Watson stat	1.995	**Prob(F-statistic)**	0.000

Inverted AR Roots	0.990	0.500
Inverted MA Roots	0.940	0.210

Table 2.10.13.A: Tightness of intraday market liquidity during the second period

	Coefficient	Std. Error	z-Statistic	Prob.
C	0.076	0.003	24.559	0.000
RWT	-0.032	0.003	-9.777	0.000
RSABSVIMB(-1)	-0.021	0.005	-4.526	0.000
RVARRET	0.274	0.003	82.431	0.000
AR(1)	1.031	0.012	85.928	0.000
AR(2)	-0.057	0.011	-5.306	0.000
MA(1)	-0.912	0.007	-136.138	0.000
	Variance Equation			
C	0.003	0.002	1.570	0.116
ARCH(1)	0.013	0.008	1.673	0.094
GARCH(1)	0.605	0.248	2.436	0.015

R-squared	0.752	**Mean dependent var**	-0.125
Adjusted R-squared	0.752	**S.D. dependent var**	0.166
S.E. of regression	0.082	**Akaike info criterion**	-2.152
Sum squared resid	117.187	**Schwarz criterion**	-2.147
Log likelihood	18557.170	**F-statistic**	5236.189
Durbin-Watson stat	2.000	**Prob(F-statistic)**	0.000

Inverted AR Roots	0.970	0.060
Inverted MA Roots	0.910	

TABLE 2.10.14: Intraday volatility of return: This estimation is based on the average trading data between the 43 stocks belonging to the CAC 40 index during a one-year period. From this sample I obtain 8352 observations of five minutes each for table 2.10.14.A and 17'238 for table 2.10.14.B. These tables represent the results of the regression between the ratio of volatility of return (explained variable) and the following independent variables: ratio of quoted half spread (RQHS), ratio of cumulated volume imbalance in absolute terms (RSABSVIMB), ratio of waiting time (RWT), a constant (C), and ARMA (1,2) in the first period and ARMA (2,2) in the second period. The conditional variance equation of residuals follows, in the first and second period, a GARCH model, including 1-lagged residuals coefficients (ARCH (1)), 1-lagged conditional variance (GARCH (1)) and a constant (C). In the Table 2.10.14.A. the value of parameters p, q, r, s and z are respectively: 1, 0, 0, 0 and 2. In the Table 2.10.14.B. the value of parameters p, q, r, s and z are respectively: 2, 0, 1, 0 and 2.

Table 2.10.13.A: Tightness of intraday market liquidity during the first period

	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.590	0.024	-25.102	0.000
RQHS	0.708	0.031	22.580	0.000
RSABSVIMB	-0.098	0.014	-7.134	0.000
RWT	0.194	0.020	9.476	0.000
AR(1)	0.985	0.002	400.041	0.000
MA(1)	-0.789	0.015	-53.307	0.000
MA(2)	-0.096	0.013	-7.240	0.000
	Variance Equation			
C	0.004	0.003	1.619	0.105
ARCH(1)	0.015	0.007	2.263	0.024
GARCH(1)	0.908	0.052	17.457	0.000
R-squared	0.485	**Mean dependent var**		-0.724
Adjusted R-squared	0.485	**S.D. dependent var**		0.330
S.E. of regression	0.237	**Akaike info criterion**		-0.045
Sum squared resid	467.052	**Schwarz criterion**		-0.037
Log likelihood	198.495	**F-statistic**		873.461
Durbin-Watson stat	1.996	**Prob(F-statistic)**		0.000
Inverted AR Roots	0.990			
Inverted MA Roots	0.900	-0.110		

Table 2.10.13.B: Tightness of intraday market liquidity during the second period

	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.443	0.016	-27.692	0.000
RQHS	0.739	0.030	24.649	0.000
RSABSVIMB(-1)	0.048	0.009	5.276	0.000
RWT	0.234	0.011	20.591	0.000
AR(1)	1.323	0.109	12.084	0.000
AR(2)	-0.335	0.107	-3.120	0.002
MA(1)	-1.174	0.110	-10.711	0.000
MA(2)	0.248	0.097	2.570	0.010
	Variance Equation			
C	0.013	0.004	3.263	0.001
ARCH(1)	0.028	0.007	3.853	0.000
GARCH(1)	0.751	0.073	10.352	0.000
R-squared	0.517	**Mean dependent var**		-0.666
Adjusted R-squared	0.516	**S.D. dependent var**		0.347
S.E. of regression	0.241	**Akaike info criterion**		-0.010
Sum squared resid	1001.214	**Schwarz criterion**		-0.005
Log likelihood	95.424	**F-statistic**		1840.633
Durbin-Watson stat	1.995	Prob(F-statistic)		0.000
Inverted AR Roots	0.980	0.340		
Inverted MA Roots	0.900	0.280		

TABLE 2.10.15: Intraday relation between quoted half spread from the WAS file and volume imbalance: This estimation is based on the average trading data between the 43 stocks belonging to the CAC 40 index during a one-year period. From this sample I obtain 8352 observations of five minutes each for table 2.10.15.A and 17'238 for table 2.10.15.B. These tables represent the results of the regression between the ratio of quoted half spread from the weighted average spread file (explained variable) and the following independent variables: ratio of cumulated volume imbalance in absolute terms (RSABSVIMB), ratio of volatility of returns (RVARRET), ratio of waiting time (RWT), a constant (C), and ARMA (2,1) for the first period and an ARMA (2,2) in the second period. The conditional variance equation of residuals follows a GARCH model including 1-lagged residuals coefficients (ARCH (1)), 1-lagged conditional variance (GARCH (1)) and a constant (C). On the other hand, in the second period, the conditional variance equation of residuals follows a TARCH model (explained in detail in Appendix 2.11.1) including 2-lagged residuals coefficients, one for all the residuals (ARCH (1)), the other only for negative residuals being a dummy variable (RESID < 0)*ARCH(1), lagged conditional variance (GARCH (1)) and a constant (C). In the Table 2.10.15.A. the value of parameters p, q, r, s and z are respectively: 2, 0, 0, 0 and 1. In the Table 2.10.15.B. the value of parameters p, q, r, s and z are respectively: 2, 0, 0, 0 and 2.

Table 2.10.15.A: Relation betweenthe ratio of quoted spread from the WAS file (QHS_WAS) and the cumulated volume imbalance in absolute terms during the first period under study.

	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.031	0.019	-1.659	0.097
SABSVIMB	-0.063	0.002	-28.343	0.000
VARRET	0.040	0.001	30.680	0.000
WT	0.005	0.001	3.346	0.001
AR(1)	1.424	0.024	58.479	0.000
AR(2)	-0.430	0.024	-17.954	0.000
MA(1)	-0.732	0.019	-39.397	0.000
	Variance Equation			
C	0.000	0.000	12.638	0.000
ARCH(1)	0.086	0.006	13.441	0.000
GARCH(1)	0.607	0.029	21.270	0.000
R-squared	0.944	**Mean dependent var**		-0.044
Adjusted R-squared	0.944	**S.D. dependent var**		0.148
S.E. of regression	0.035	**Akaike info criterion**		-3.898
Sum squared resid	10.246	**Schwarz criterion**		-3.890
Log likelihood	16286.180	**F-statistic**		15520.430
Durbin-Watson stat	1.978	**Prob(F-statistic)**		0.000
Inverted AR Roots	0.990	0.430		
Inverted MA Roots	0.730			

Table 2.10.15.B: Relation betweenthe ratio of quoted spread from the WAS file (QHS_WAS) and the cumulated volume imbalance in absolute terms during the second period under study.

	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.062	0.011	-5.585	0.000
SABSVIMB	-0.074	0.002	-48.413	0.000
VARRET	-0.003	0.001	-3.034	0.002
WT	-0.015	0.001	-13.995	0.000
AR(1)	1.571	0.028	56.144	0.000
AR(2)	-0.575	0.028	-20.875	0.000
MA(1)	-0.919	0.030	-30.651	0.000
MA(2)	0.098	0.017	5.669	0.000
	Variance Equation			
C	0.001	0.000	38.805	0.000
ARCH(1)	0.276	0.010	27.168	0.000
(RESID< 0)*ARCH(1)	-0.042	0.012	-3.599	0.000
GARCH(1)	0.307	0.014	22.049	0.000
R-squared	0.885	**Mean dependent var**		-0.013
Adjusted R-squared	0.885	**S.D. dependent var**		0.117
S.E. of regression	0.040	**Akaike info criterion**		-3.728
Sum squared resid	27.398	**Schwarz criterion**		-3.723
Log likelihood	32139.830	**F-statistic**		12001.370
Durbin-Watson stat	1.914	**Prob(F-statistic)**		0.000
Inverted AR Roots	0.990	0.580		
Inverted MA Roots	0.800	0.120		

APPENDIX

APPENDIX 2.11.1: Analysis of a time series

After running the regression analysis I controlled that all the hypothesis concerning the model hold. In checking for the serial correlation, there are two limitations: the Durbin Watson statistics can only be used, if there is no lagged dependent variable on the right hand side of my regression. And, on the other hand, only the null hypothesis of no serial correlation against the alternative first order serial correlation can be tested. In order to overcome these limitations, I also performed the Q-statistics and the Breusch-Godfrey Lagrange multiplier test. The null hypothesis of this latter is that there is no serial correlation up to the specified order. The Q-statistics allows to perform autocorrelation and partial autocorrelation functions of the residuals, together with the Ljung-Box Q-statistics for high order serial correlation. If there is no serial correlation in the residuals, the autocorrelation and the partial autocorrelation (hereafter PAC) at all lags should be nearly zero, and all Q-statistics should be insignificant with large p-values. This was verified for all the regressions. The Marquardt algorithm was used to estimate the correct ARMA specification. For AR models, the R^2, the standard error of regression and the Durbin Watson statistic were based on the one-period forecast[38]. The general AR(p) process is represented by the following equation:

$$AR(p):\ y_t = \mu_t + \gamma_1 y_{t-1} + \gamma_2 y_{t-2} + \ldots + \gamma_\rho y_{t-\rho} + \varepsilon_t$$

For a stationary AR(1) model, the p lies between –1 and +1. The stationarity condition for general AR(p) processes is that the inverted roots of the log polynomial lies inside the unit circle. In my regression analysis, I report also these roots as inverted AR roots at the bottom of the regression. There is no particular problem if the roots are imaginary, but a stationary AR model should have all roots with a residual less than one.

The most widely used models for estimating AR models are the Cochrane-Orcutt, Prais-Winston, Hatanaka and Hildreth-Lu procedures. All these approaches suffer from important drawbacks, which occur when working with models containing lagged dependent variables as regressors, or with models using high order AR specifications. Instead, a non-linear regression technique is used. Note that non-linear least square estimates are asymptotically equivalent to maximum likelihood estimates, and are asymptotically efficient. The coefficients are estimated by the Marquardt non-linear least squares algorithm. In the ARMA model, the MA term corresponds to the moving average. A moving average forecasting model uses lagged values of the forecast error to improve the current forecast as reported by the following equation:

$$MA(q):\ y_t = \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \ldots + \theta_q \varepsilon_{t-q}$$

Therefore the general ARMA (ρ, q) model is expressed as follows:

$$\text{ARMA}(p,q):\ y_t = \mu_t + \gamma_1 y_{t-1} + \gamma_2 y_{t-2} + \ldots + \gamma_\rho y_{t-\rho} + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \ldots + \theta_q \varepsilon_{t-q}$$

In order to decide what kind of ARMA model to use, I looked at the autocorrelation and the PAC function. If the autocorrelation function dies off smoothly at a geometric rate and the PAC is zero after one lag, then a first order autoregressive model is appropriate. Alternatively, if the autocorrelations are zero after one lag and partial autocorrelation (PAC) declines geometrically, a first order moving average process would seem appropriate. If the autocorrelations appear like a wavy cyclical pattern, this would suggest the presence of a seasonal ARMA structure.

The Akaike Information criterion (smaller values of the AIC are preferred) and the Schwartz criterion (an alternative to the AIC imposing a larger penalty for additional coefficients) provide also a guideline for the appropriate lag order selection. The theory behind ARMA estimation is based on a stationary time series. A series is said to be stationary if the mean and the autocovariance of the series does not depend on time. I checked whether my series is stationary or not, before using it on regression. The formal method to test the stationarity of a series is the unit root test. I performed two tests: the Dickey-Fuller (and Augmented Dickey-Fuller) and the Phillips-Perron test (PP test).

The Dickey-Fuller (DF) test considers first an AR(1) process:

$$y_t = \mu + p y_{t-1} + \varepsilon_t$$

where μ and p are parameters and ε is assumed to be white noise. y_t is a stationary series, if $-1<p<1$. If $p=1$, it is a nonstationary series (a random walk with drift). From the point where the process is started, the variance of y increases steadily with time and goes to infinity. If the absolute value of ρ is greater than one, the series is explosive. Therefore, the hypothesis of a stationary series can be evaluated by testing whether the absolute value of p is strictly less than one. The DF test is valid only if the series is an AR(1) process. If the series is correlated in the presence of higher order lags, the assumption of white noise disturbances is violated. The ADF and PP tests use different methods to check for higher-order serial correlation in the series. The ADF test makes a parametric correction for higher order correlation by assuming that the y series follows an AR(p) process and adjusting the test methodology.

The PP test proposes a non-parametric method of controlling for higher order serial correlation series. While the ADF test corrects for higher order serial correlation by adding lagged differenced terms, the PP makes a correction to t-statistic of the y coefficient from the AR(1) regression in order to account for the serial correlation in ε. The correction is non-parametric, since an estimate of the spectrum of ε at frequency zero is used which is robust to heteroskedasticity and autocorrelation of unknown forms. This procedure uses the Newey-West heteroskedasticity autocorrelation consistent estimate.

[38] These residuals are the errors that you would observe if you made a prediction of the value of y_t using contemporaneous information, but ignoring the information contained in the lagged residual.

Both the Augmented Dickey-Fuller and the Phillips-Perron tests take the unit root as the null hypothesis H_0: p=1. Since explosive series do not make much economic sense, this null hypothesis is tested against the one-sided alternative H_0: p <1. The null hypothesis of a unit root (p=1) is rejected in favour of a one-sided alternative (p<1), if the t-statistic is significantly less than the critical value. Considering my series, the null hypothesis of a unit root is always rejected, i.e. my series are stationary. In fact, the statistics are largely below the MacKinnon critical value. It is therefore possible to use the ARMA models.I checked also for the multicollinearity, carrying out the collinearity test (Variance Inflation Test). The results were negative.

The Jarque-Bera statistic was used to test whether the standardized residuals are normally distributed. If the standardized residuals are normally distributed, the Jarque-Bera statistic should not be significant. In some cases, the distribution of the residuals is not normal according to the Jarque-Bera test, but my estimates are nevertheless consistent under quasi-maximum likelihood assumptions.

In order to model and forecast conditional variances, I specifically used the Autoregressive Conditional Heteroskedasticity (ARCH) models. In this case, the variance of the dependent variable is modeled as a function of past values of the dependent variable and of the independent or exogenous variable. ARCH models were introduced by Engle (1982), and generalized as GARCH by Bollersev (1986). For the ARCH model one has to consider two distinct specifications: one for the conditional mean and one for the conditional variance.

The GARCH equation is formed by a mean equation, written as a function of exogenous variables with an error term, and by a conditional variance equation which is a function of three terms: the mean, the news about volatility from the previous period, measured as the lag of the squared residual from the mean equation (ARCH term), and, finally, the forecast variance (GARCH term) of the last period. The representation of the GARCH (p,q) variance is:

$$\text{GARCH}(p,q):\ \sigma_t^2 = \omega + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2$$

where p is the order of the GARCH terms and q is the order of the ARCH term. In the standard GARCH (1,1) specification:

$$y_t = x_t \gamma + \varepsilon_t \qquad (1)$$

$$\sigma_t^2 = \omega + \alpha\, \varepsilon_{t-1}^2 + \beta\, \sigma_{t-1}^2 \qquad (2)$$

The mean equation given in (1) is written as a function of exogenous variables with an error term. Since σ_t^2 is the one period ahead forecast variance based on past information, it is called the conditional variance. The conditional variance equation, specified in (2) is a function of three terms:

1. the mean ω

2. News about volatility from the previous period, measured as the lag of the squared residual from the mean equation, i.e., ε^2_{t-i} (the ARCH term).

3. Last period's forecast variance σ^2_{t-j} (the GARCH term)

Furthermore, the quasi-maximum likelihood covariance and standard errors were computed, using the methods described by Bollersev and Wooldridge (1992), because my residuals were not conditionally normally distributed. The ARCH parameters are, however, still consistent. The sum of the ARCH and GARCH coefficients are very close to one, indicating that the volatility shocks are quite persistent.

The correlogram (autocorrelation and PAC) of the squared standardized residuals can be used to look for remaining ARCH in the variance equation and to check the specification of the variance equation. If the mean equation is correctly specified, all Q-statistics should be not significant. The Lagrange multiplier test (ARCH LM test) was used to test whether the standardized residuals exhibit additional ARCH. If the variance equation is correctly specified, there should be no ARCH left in the standardized residuals.

Engle and Ng (1993) developed two models in order to consider also asymmetric shocks to volatility: TARCH and EGARCH.

TARCH, or threshold ARCH, was introduced independently by Zakoian (1990) and Glosten, Jaganathan and Runkle (1993). The specification for the conditional variance is:

$$\sigma^2_t = \omega + \alpha\varepsilon^2_{t-1} + \gamma\varepsilon^2_{t-1}d_{t-1} + \beta\sigma^2_{t-1}$$

Where $d_t = 1$ if $\varepsilon_t<0$, and $d_t=0$ otherwise.

In this model, good news ($\varepsilon_t>0$) and bad news ($\varepsilon_t<0$) have differential effects on the conditional variance: good news has an impact of α, while bad news has an impact of $\alpha+\gamma$. If $\gamma>0$, one can say that the leverage effect exists. This is obtained by the means of the dummy variable d_{t-1}, which considers negative shocks in one of the two ARCH components. If $\gamma\neq 0$, the news impact is asymmetric. The conditional variance includes also one-lagged conditional variance, σ^2_{t-1} and a constant ω. The leverage effect term is represented by (RESID<0)*ARCH(1).

For higher order specifications of the TARCH model the following equation is estimated:

$$\mathrm{TARCH}(p,q):\ \sigma^2_t = \omega + \sum_{i=1}^{q}\alpha_i\varepsilon^2_{t-i} + \gamma\varepsilon^2_{t-1}d_{t-1} + \sum_{j=1}^{p}\beta_j\sigma^2_{t-j}$$

APPENDIX 2.11.2: Intraday market liquidity indicators: Sixteen market liquidity indicators were used, namely effective half spread (EHS), quoted half spread (QHS), difference spread (DSPR), midquote (MID), quoted half spread from the WAS file (QHS_WAS)[39], cumulated traded volume (SUMVOL), number of trades (NBTR), volume imbalance (VIMB), sum of volume imbalance in absolute terms (SABSVIMB), return (RET), return in absolute terms (ABSRET), volatility of return (VARRET), volatility measured as a log range (VOLA), waiting time (WT), liquidity ratio (LR), flow ratio (FR). Every proxy is measured on an intraday time period of 5 minutes. The ask price is labelled by $Ask_{i,j,t}$, the bid price $Bid_{i,j,t}$, the binary variable that equals one for customer buy orders and negative one for customer sell orders by $D_{i,j,t}$, the price by $p_{i,j,t}$, the quantity traded by $q_{i,j,t}$, the volume related to the best bid by $VBuy_{i,j,t}$, the volume related to the best ask by $VSell_{i,j,t}$, the maximum price within an intraday periods of five minutes by $sup_{i,j}$, the minimum price within an intraday period of five minutes by $inf_{i,j}$, the trade time during the day, i.e. the time when a transaction occur, by $time_{i,j,t}$, and each transaction, independently of the quantity traded, by $obs_{i,j,t}$. The intraday period of 5 minutes is labelled by i = 1,…,96, (in the first period, and i = 1,…,102 in the second period), the day is indexed by j = 1,…,J and the trade time during the i-5 minutes period by t = 1,…, n.

$$EHS_{i,j} = \frac{1}{n}\sum_{t=1}^{n} 100\, D_{i,j,t}\left(p_{i,j,t} - MID_{i,j,t}\right) \,/\, \left(MID_{i,j,t}\right) \quad (1)$$

$$QHS_{i,j} = \frac{1}{n}\sum_{t=1}^{n} 100\left(Ask_{i,j,t} - Bid_{i,j,t}\right) \,/\, \left(2 * MID_{i,j,t}\right) \quad (2)$$

$$DSPR_{i,j} = \frac{1}{n}\sum_{t=1}^{n}\left(Ask_{i,j,t} - Bid_{i,j,t}\right) \quad (3)$$

$$MID_{i,j} = \frac{1}{n}\sum_{t=1}^{n}\left(Ask_{i,j,t} + Bid_{i,j,t}\right) \,/\, 2 \quad (4)$$

$$QHS\_WAS_{i,j} = \frac{1}{n}\sum_{t=1}^{n} 100\left(Ask_{i,j,t} - Bid_{i,j,t}\right) \,/\, \left(2 * MID_{i,j,t}\right) \quad (5)$$

$$SUMVOL_{i,j} = \sum_{t=1}^{n} \frac{q_{i,j,t}}{\text{NB OF SHARES OUTSTANDING}} \quad (6)$$

$$NBTR_{i,j} = \sum_{t=1}^{n} obs_{i,j,t} \quad (7)$$

$$VIMB_{i,j} = \sum_{t=1}^{n}\left(VBuy_{i,j,t} - VSell_{i,j,t}\right) \quad (8)$$

$$SABSVIMB_{i,j} = \sum_{t=1}^{n}\left|VBuy_{i,j,t} - VSell_{i,j,t}\right| \quad (9)$$

[39] Note that QHS and QHS_WAS are calculated in the same manner, but QHS is obtained from the order data file, while QHS_WAS from the weighted average spread file.

$$RET_{i,j} = \frac{1}{n}\sum_{t=1}^{n}\left(\ln\left(p_{i,j,t}\right) - \ln\left(p_{i,j,t-1}\right)\right) \tag{10}$$

$$ABSRET_{i,j} = \left|RET_{i,j}\right| \tag{11}$$

$$VARRET_{i,j} = \left[\frac{\sum_{t=1}^{n}\left(\ln\left(\frac{p_{i,j,t}}{p_{i,j,t-1}}\right) - \frac{1}{n}\sum_{t=1}^{n}\ln\left(\frac{p_{i,j,t}}{p_{i,j,t-1}}\right)\right)^{2}}{n-1}\right] \tag{12}$$

$$VOLA_{i,j} = \ln\left(\sup_{i,j} - \inf_{i,j}\right) \tag{13}$$

$$WT_{i,j} = \frac{1}{n}\sum_{t=1}^{n}\left(time_{i,j,t} - time_{i,j,t-1}\right) \tag{14}$$

$$LR_{i,j} = \frac{\sum_{t=1}^{n}\left(q_{i,j,t} \cdot p_{i,j,t}\right)}{\left|\left[\frac{p_{i,j,n} - p_{i,j,1}}{p_{i,j,1}}\right]. 100\right|} \tag{15}$$

$$FR_{i,j} = \frac{\frac{1}{n}\sum_{t=1}^{n}\left(q_{i,j,t} \cdot p_{i,j,t}\right)}{\frac{1}{n}\sum_{t=1}^{n}\left(time_{i,j,t} - time_{i,j,t-1}\right)} \tag{16}$$

The standardization of each time series was based on the daily mean and the daily variance of each individual stock. Let the stock be s = 1, …, 43 and, as before, the intraday periods of five minutes i = 1, …, 96 for the first period and i = 1,…,102 in the second period, while the day is indexed by j = 1, …, J. So, for instance, standardized cumulated trading volume, say SSUMVOL, for the stock s and the day j is:

$$SSUMVOL_{i,j,s} = \frac{SUMVOL_{i,j,s} - \frac{1}{96}\sum_{i=1}^{96} SUMVOL_{i,j,s}}{\left[\frac{\sum_{i=1}^{96}\left(SUMVOL_{i,j,s} - \frac{1}{96}\sum_{i=1}^{96} SUMVOL_{i,j,s}\right)^{2}}{n-1}\right]^{1/2}} \tag{17}$$

The standardized market liquidity, i.e. the average for all the 43 index belonging to the CAC 40 index, in terms of cumulated trading volume for the intraday time i and the trading day j is:

$$TOT\_AVERAGE_{i,j} = \frac{1}{43}\sum_{s=1}^{43} SSUMVOL_{i,j,s} \tag{18}$$

The other 15 standardized proxies of intraday market liquidity are standardized and calculated following the same procedure.

APPENDIX 2.11.3: Intraday market variables. Six variables in the regression analysis of Section 2.6 and 2.7 are taken into account. These are the ratio of quoted bid-ask spread (RQHS), the ratio of the quoted bid-ask spread from the weighted average spread file (RQHS_WAS)[20], the ratio of cumulated trading volume (RSUMVOL), the ratio of sum of volume imbalance in absolute terms (RSABSVIMB), the ratio of return volatility (RVARRET) and the ratio of the waiting time between subsequent trades (RWT). Every proxy is measured on an intraday time of 5 minutes. Trading volume of each transaction is labelled by $q_{i,j,t}$, price by $p_{i,j,t}$, the ask price by $Ask_{i,j,t}$, the bid price by $Bid_{i,j,t}$, the volume related to the best ask by $VSell_{i,j,t}$, the volume related to the best bid by $VBuy_{i,j,t}$ and the trade time during the day, i.e. the time when a transaction occur, by $time_{i,j,t}$. The trading day is indexed by j = 1, ..., J, the intraday period of 5 minutes by i = 1, ..., 96 (during the first period and i = 1,…,102 in the second period) and the trade time during the i-5 minutes period by t = 1, ..., n.

$$RQHS_{i,j} = \ln\left[\frac{\frac{1}{n}\sum_{t=1}^{n}(100\left(Ask_{i,j,t} - Bid_{i,j,t}\right) / \left(2 * MID_{i,j,t}\right)}{\frac{1}{J}\sum_{j=1}^{J}\frac{1}{n}\sum_{t=1}^{n}(100\left(Ask_{i,j,t} - Bid_{i,j,t}\right) / \left(2 * MID_{i,j,t}\right)}\right]$$

$$RQHS\_WAS_{i,j} = \ln\left[\frac{\frac{1}{n}\sum_{t=1}^{n}(100\left(Ask_{i,j,t} - Bid_{i,j,t}\right) / \left(2 * MID_{i,j,t}\right)}{\frac{1}{J}\sum_{j=1}^{J}\frac{1}{n}\sum_{t=1}^{n}(100\left(Ask_{i,j,t} - Bid_{i,j,t}\right) / \left(2 * MID_{i,j,t}\right)}\right]$$

$$RSUMVOL_{i,j} = \ln\left[\frac{\sum_{t=1}^{n} q_{i,j,t}}{\frac{1}{J}\sum_{j=1}^{J}\sum_{t=1}^{n} q_{i,j,t}}\right]$$

$$RSABSVIMB_{i,j} = \ln\left[\frac{\sum_{t=1}^{n}\left|VBuy_{i,j,t} - VSell_{i,j,t}\right|}{\frac{1}{J}\sum_{j=1}^{J}\left(\sum_{t=1}^{n}\left|VBuy_{i,j,t} - VSell_{i,j,t}\right|\right)}\right]$$

$$RVARRET_{i,j} = \ln\left[\frac{\operatorname{var}_t\left[\ln(p_{i,j,t}) - \ln(p_{i,j,t-1})\right]}{\frac{1}{J}\sum_{j=1}^{J}\left(\operatorname{var}_t\left[\ln(p_{i,j,t}) - \ln(p_{i,j,t-1})\right]\right)}\right]$$

[20] cf. footnote 19.

$$\mathrm{RWT}_{i,j} = \ln\left[\frac{\frac{1}{n}\sum_{t=1}^{n}(\mathrm{time}_{i,j,t} - \mathrm{time}_{i,j,t-1})}{\frac{1}{J}\sum_{j=1}^{J}\frac{1}{n}\sum_{t=1}^{n}(\mathrm{time}_{i,j,t} - \mathrm{time}_{i,j,t-1})}\right]$$

CHAPTER 3

INTRADAY PUBLIC INFORMATION PATTERNS

3.1 Abstract

This chapter analyzes the intraday release of public information through one of the most important providers of economic and financial information: the Reuters News 2000 Alert System. All types of public information released by the Reuters Terminal has been considered. All news items has been then classified into one of eight categories according to their nature: All alerts, market news, economic news, political news, industrial news, general news, corporate news and firm-specific news. The patterns of information arrival has been documented in terms of the number of news releases per 5 minutes, with an emphasis on the intraday flows. All these information proxies display a distinct intraday pattern, similar to the inverted U-shaped pattern previously found by Berry and Howe (1994). The types of news items are also documented by day of the week (Friday has the fewest) and month of the year (February has most). Higher market capitalization does not necessarily correlate with higher news coverage.

3.2. Introduction and literature review

One of the most important issues in the efficiency market theory is the investors' reaction to news arrival. This reaction leads to a change of the asset price, reflecting investors' expectation of risk and return. The literature distinguishes between public information and private information (French and Roll, 1986). The former is related to the semi-strong form of the efficiency theory, and the latter to the strong form (Fama 1970). The semi-strong form considers the efficient adjustment to information that is publicly available (announcements of quarterly earnings, stock splits, dividends, and so on). In contrast, the strong form considers investors who have a monopolistic access to any information relevant for price formation. This chapter concentrates on public information, which corresponds to news that is publicly available to all market participants. This type of information is released mainly, but not exclusively, by the most important press agencies worldwide. The proliferation of Internet and of online brokers has made it possible, through different providers (Yahoo!, CBS market watch, Etrade, etc.), to get access to public information for all kind of investors, above all small investors. However, the interpretation, the quality (Veronesi 2000) and the timing of a news release play an important role in investment decisions, as investors assume increasingly more intraday positions instead of considering a longer investment horizon.

It seems to be evident that not all the released information leads to a revision of investors' expectations about the future payoffs of a stock. Investors are flooded every day, every minute and in some cases every few seconds with a variety of information: corporations earnings reports, revisions of macroeconomic indexes, statements by policy makers and political news. Investors, in order to update their projections of the future growth rate of the economy and interest rate, process these pieces of information. In turn, these changes in projections affect investment decisions. How is the behaviour of this news during the trading day, i.e. when is information mainly released during the day, the week and the year? Is it possible to differentiate news types by a specific category? Does an intraday pattern of news, like the one previously found for intraday market liquidity, exist? Which is most frequently news released? Do big companies receive greater coverage? These are only some of the questions I shall try to answer in this chapter by analysing public information. There are not many studies in the literature that found a distinct intraday news pattern, and I hope that my contribution to this extremely important issue in finance will shed new light on the behaviour of public information during the day.

Berry and Howe (1994), using intraday returns, trading volume calculated on the S&P 500 index and the overall flow of intraday public information obtained and estimated by the Reuter's News Service, during the period May 1990-April 1991, found an intraday news pattern. They studied an intraday periods of half an hour, which is probably too long, in order to establish a relation with market activity. In contrast to my approach, they mix macro news and firm-specific news, a solution which in my opinion may not be optimal. The authors develop a measure of public information flow to financial markets, and use it for documenting the patterns of information arrival. Their measure is the number of news released by Reuters's News Service per unit of time. They found that public information arrival is nonconstant, displaying seasonalities and distinct intraday patterns. In particular, they found that public information arrival exhibits an inverted U-shaped pattern across trading days.

Thompson, Olsen and Dietrich (1987) also focus on public information. Their database consists of announcements concerning firms quoted on the NYSE and on the AMEX. The period under investigation is the year 1983, and their provider is the Wall Street Journal. They found that larger firms and certain industries receive greater coverage, and that the number of announcements varies across days of the week and month of the year. Monday and December have the fewest announcements. Special types of news items (earnings and dividends) are also documented by the day of the week and month of the year. Earnings and dividends stories are much more present than other news, and they exhibit patterns related to quarterly announcements. This research has been considered important for its interday evolution of public information.

In a related article, Mitchell and Mulherin (1994) used a "distinctive proxy" for information: the number of announcements released daily by the Dow Jones & Company. Although they recognize that their source of information may be imperfect concerning of the overall information available to market participants, they nevertheless consider this measure more comprehensive that the one previously used. Via a sample of macroeconomic and firm-specific news announcements, they noted a seasonal pattern in the information flow by month, by day of the week and for holidays. For the full sample, April has the largest number of announcements per day, while December has the smallest number per day. They conclude that the variability across months is partially due to the financial reporting cycle. The average number of news announcements by day of the week shows an increase through Thursday and then tapers off sharply on Friday. They also found that the number of announcements is significantly lower on days before and after market holidays. The day-of-the-week behaviour of the Dow Jones announcements resembles the reported patterns in stock market trading activity (Jain and Joh 1988, Lakonishok and Maberly, 1990).

Similarities between intraday liquidity patterns and regularities of news release have also been reported in such early studies as Rozeff and Kinney (1976), who conjecture that the abnormal stock returns in January might stem from an above average amount of information production by firms at the turn of the year. Atkins and Basu (1991), Berry and Howe (1994), Niederhoffer (1971), Penman (1987), Thompson, Olsen and Dietrich (1987) and Change and Taylor (1995), among others, found the same. Patterns in intraday news release, such as big New York Times front page headlines, the daily number of stories in the Wall Street Journal, the number of news items that appear in Reuters News Service, and seasonalities in earnings announcements, mirror many of the observed regularities in financial markets. Macroeconomic and government announcements have been related to market volatility patterns, for example by Ederington and Lee (1993), Harvey and Huang (1991) and French, Leftwich and Uhrig (1989). In particular, Ederington and Lee (1993) gave a description of intraday news patterns, within a 5 minutes periods, for the most important monthly macroeconomic news announcements (unemployment, price producer index, consumer producer index, and so on). However, pattern in news announcements does not explain the day of the week seasonalities in market activity.

On the other hand, Damodaran (1989) found a day of the week pattern in the information content of dividend and earnings announcements, resembling that of stock return. Roll (1988) found a similar result, but he was using stories in the financial press.

Similar to Berry and Howe (1994), Gay and Mohorovic (1999), using the Reuters Business Briefing (hereafter RBB) provider for the Swiss market, found analogous weekly pattern in the sense that general macroeconomic and market news are significantly more numerous on Tuesdays and Thursdays. The behaviour of firm-specific news is different. Stories are most numerous on Mondays; their number gradually decreases through the week and rises again on Fridays. Firm-specific news shows the traditional intraday U-shaped pattern, whereas general news seems to follow an inverted U-shaped pattern across trading days. They also noted that cross-listed companies receive more attention and generate more news than firms listed on a single exchange, finding, in this manner, results similar to Baker, Nofsinger and Weaver (1998). Harvey and Huang (1991, 1992) observed that many macroeconomic announcements occur during the first hour of trading on Thursdays and Fridays. Ederington and Lee (1993) support this observation, based on nineteen announcements whose upcoming release is regularly covered in The Week Ahead section of Business Week.

Juergens (1999), during the period 1993-1996, compiled the date and time stamps from the Dow Jones News Wire (DJNW) articles in order to examine the impact of news announcements. Unlike Berry and Howe (1994), she found that intra-trading day patterns of news announcements exhibit the well-known U-shaped pattern for her sample. One possible explanation for the difference between her results and those of Berry and Howe (1994) is that she uses a different sample (DJNW vs. Reuters) and examines a later time period. She shows a similar U-shaped pattern for investment recommendations. Similar to the findings in Berry and Howe (1994), she noticed that a significant portion of news announcements occurs after the close of trading. Juergens (1999) explains by the tendency of firms to make announcements after the close of the market. The intraday trading hour patterns of recommendations and news announcements exhibit again the classical U-shaped pattern.

Atkins and Basu (1995), who had reported on news stories on the Dow Jones News Service (Broadtape) related to 400 randomly selected firms on the NYSE during 1984, made another study examining public information. They claim that this type of information is essentially the same as that on all the various news wire services, and is time stamped to the minute of the information release. Smirlock and Starks (1985, 1988) and Patell and Wolfson (1984) also used this data set. Atkins and Basu's (1995) patterns of intraday announcement show that before 08:00 a.m. and after 06:30 p.m. there are less than four announcements for any 15-minute periods, whereas during the trading day there is an average of more than 200 announcements per 15 minutes period. The maximum number is reached between 11:45 a.m. and noon, and, in contrast, the minimum number occurs between 01:15 p.m. and 01:30 p.m.. The most striking observation is made just after the market close, when the average number of announcements is nearly two and a half times the average number that occurs while the market is open. It seems that companies frequently prefer to make public announcements when the market is closed, and particularly right after the market closes (Atkins and Basu, 1995 and Juergens, 1999). This result seems to be evident for the US market. On the contrary, in Europe (Swiss, French and German markets), companies usually release, information such as earnings announcements before the market opens. In their firm-specific sample, Atkins and Basu (1995) also examine the time pattern of public announcements, focusing on time periods after the market closes. They conclude that, for firms making announcements after the close, trading in their shares exhibits an excess volume just before the close as well as on the following opening.

Nofsinger (2001), using firm-specific news releases in the Wall Street Journal and macroeconomic announcements during the period 1 November 1990 through 31 January 1991, found that the number of articles for each day is very similar for Monday through Thursday. The number then increases on Fridays. This is consistent with the end-of-the-week bias found by Thompson, Olsen and Dietrich (1987), although Mitchell and Mulherin (1994) saw the largest number of news releases to occur on Mondays. The number of articles published in Nofsinger's (2001) study, during November, December and January show the smallest number in December, which is consistent with Thompson et al. (1987).

Chang and Taylor (1996), in an approach similar to mine, divide news items into five categories according to their nature. They also count the number of headlines reported by Reuters within a fixed period of time and apply five intraday periods: one hour, 30 minutes, 15 minutes and 5 minutes across the businees week. Their news categories are as follows: first, they extract the US scheduled macroeconomic news following the Ederington and Lee (1993, 1995) approach. Second, through the utilization of key words they extract German macroeconomic news. Third and fourth, information related to the Bundesbank's monetary policy instruments, and, respectively, the US Federal Reserve's monetary policy are extracted. The last category corresponds to the global flow of information obtained through the 1st to the 4th subgroup. The authors found that US macroeconomic news and US Federal Reserve news items are higher than the German Bundesbank news. Monday has the lowest number of news releases, and Thursday the highest. The highest news activity is during the trading day, when also stocks are traded and not only currency.

Melvin and Yin (1998) measured the public information arrival using the Reuters Money-Market Headline News from December 1, 1993 to April 26, 1995. They considered the total news flow rather than selecting certain types of news. The basic unit of time used in their analysis is one hour. The average hourly number of reported news events on the Reuters screen for the business week shows a distinct intraday day seasonality where news events climb to a daily peak the morning in Europe and when the European and North American markets overlap. Clearly, public information largely arrives during business hours in each region.

Ranaldo (2002) also addresses the question of whether news arrivals have an intraday seasonality. He shows that index-related news occur mostly around openings and closings. For the firm-specific news, i.e. regarding companies quoted on the CAC 40 index, he does not find any clear patterns. The 01:30 p.m. to 02:00 p.m. interval seems, however, to be the period when the fewest news are released.

From the literature one cannot draw any congruent conclusion about intraday news patterns because of the heterogeneity or, in some cases, homogeneity of the news and of providers whom the authors considered in approaching the public information issue. They do not make any clear distinction between themes, or they limit themselves to few subjects. I shall try to overcome this lack of agreement among researchers by considering the whole flow of public information received by the market participants and dividing it into different categories according to its nature.

The data and methodology used in this study will be described in Section 3.3, whereas the results will be discussed in Section 3.4. The conclusions will be drawn in section 3.5. You will find the corresponding graphs and tables in section 3.6 and 3.7 respectively.

3.3 Data and methodology

The data used for this study was obtained from the Reuters News 2000 alert system. It consists of the most important news released during a one-year period (December 1, 1999 to November 30, 2000) over the full 24-hour day. All the subgroups (see Table 3.7.7), were then assigned to one of the following eight categories: All alerts, Political news, Market news, Economic news, Industrial news, Corporate news, Firm-specific news and General news.

All alerts represents the headlines of important news that is immediately released by the Reuters terminal without a detailed article, which usually follows a few minutes later. This category may correspond to the hot stories published by the Bloomberg terminal, but in reality Reuters considers a vaster range of news. Bloomberg publishes only those news items which may have an influence on market activity and are related to the most important blue chips worldwide as well as to macroeconomic indicators. Both Reuters and Bloomberg can be considered as a mix of the most significant news of each category and subgroup. But Reuters, is a news provider which had been considered also in previous studies as a data source for public information flow, because as Berry and Howe (1994) say, "it provides market participants with a timely source of information on news stories that impact financial markets". One criticism of Reuters is that it is not a completely public source of information, since access to it is not free. But considering its strength in the financial information field, it can be reasonably retained as a valid source of public information. Moreover, it can be assumed that the vast majority of market participants have this or a similar information system at their disposal. Berry and Howe (1994) also underline that market participants use this news service on a regular basis, along with the Dow Jones News Service and perhaps a few other news wires, as a prime source for economic decision-making.

Political news is a category where one can find all sorts of news related to political activities (politics, diplomatic affairs, elections and so on) worldwide. However, if one wants to know something about the general market activity (for example commodities, bonds and forex) one would check the market news category. All the macroeconomic indicators (gross domestic products, interest rates, central bank decisions, inflation, money supply and so on) of all countries in the world can be found in the economic news category. Industrial news include firms sectors such as automobiles, aerospace, chemicals and others, which can be found in detail in Table 3.7.7. The Corporate news category includes news about companies, earnings, dividends and ratings worldwide. In contrast to this last group, where all firms are covered, in the Firm-specific news category only such news items are considered which strictly concern firms belonging to the CAC 40 index during the one-year period under study. In the last group, the General news, the rest of public information is examined, which cannot be classified within the other seven categories. Sport, crime and religion are only few examples of items which belong to this category. For each category, I made different subgroups (see Table 3.7.7). Only All alerts does not have a subgroup.

I am aware that this classification may be a little subjective, but it has been established following some distinction already made by Reuters in their *Reuters Business Briefing 3000* (hereafter RBB) programme used for the daily news. But RBB proceeds to a categorization that is not suitable for intraday news, resulting, in some cases, in a subjective analysis. In order to find out into which category news item falls, I applied certain criteria concerning their importance. Reuters News Services have been used in previous studies and have proven their reliability. The RBB allows to distinguish different news categories (macroeconomic, corporate and so on) and stories released in French, English or German. I retain, in my intraday analysis, only public information released in English.

The release procedure by press and federal agencies is best explained by Ederington and Lee (1993, 1995), Thompson, Olsen and Dietrich (1987) and Patell and Wolfson (1982). The release is distributed to reporter (about 30 minutes prior to the scheduled release time) because of the "need for timely access". During that half hour, reporters have time to tape the headline and the news story they want to put into their computers or pick up the phone one minute before the deadline. However, until the scheduled release time the phone lines are dead. Then the stories hit the wires and are displayed on the boards on the floor of the exchanges within a few seconds.

As shown in Appendix 3.7.7, each category includes different subgroups. For these subgroups, a keyword combination exists in order to list all relevant news. The number of news items containing specified keyword combinations during each five minutes period is my measure of news arrival. The lists of news categories, the list of subgroups, the number of news items and examples for each news category are reported in Table 3.7.7, 3.7.1, 3.7.2 and 3.7.8. When repeats of news items occur, I keep only one and delete the subsequent, but only if time and date correspond to the original one. On the other hand, if the headlines are repeated but the release time is different, I keep both. This procedure is different from the one previously used by DeGennaro and Shrieves (1997), but in my view the release of the same news at different times may not just be an update, but a signal of the importance of a headline. In other aspects too, my approach is different from DeGennaro and Shrieves (1997). They classified news into one category only, so that no item appears more than once in the sample. In my sample, instead, one news item can fall into one or more categories. For example, if I consider a news item related to the Renault company, this headline will fall into the Firm-specific news category and into the Industrial news category (subgroup automobile).

A complete list of the news items is available from the author. To my knowledge, no other extant research has considered such a broad range of news.

By taping a key word for each news category (see Table 3.7.7 for some key words), I obtain the exact date and time of the headline release and of the history behind it (see Appendix 3.7.8 for some examples). This investigations like the one in Chapter 2, concerns the French market and in particular the 39 stocks belonging to the CAC40 index between December 1, 1999 and November 30, 2000. In contrast to Chapter 2 I left out 4 shares due to technical problems[40]. As my analysis focuses on the French market, also intraday news patterns related to that country are

[40] The Reuters terminal used to record one year of intraday news proved to be quite unstable. The terminal contained a maximum of 6 months of historical data until the end of the year 2000, when Reuters decided to reduce this period to 5 months without providing additional information to their customers. This caused a 1½ month lack of data collection depending on the news category considered. I show the results of this period, but I do not consider them for my general conclusions. Unlike in other studies, I did not replace the missing observations by the sample mean.

shown. The procedure is the same as previously explained, except for the addition of the abbreviation FR at the end of each keyword.

Reuters' news is recorded in Greenwich Mean Time (GMT). For the purpose of identifying regional business hours of the French market, I adjusted my sample by adding 1 hour to all news recorded in order to have public information expressed in Central European Time (CET).

I decided to show intraday news patterns by day of the week and month of the year, as well as the global flow of public information for news related or not to the French market for all the eight categories, within which the news items are grouped according to their nature. Also calculated, but not reported, is the intraday public information pattern for news relevant for business hours of trading only, and for the 256 business days. For this last pattern, all news before and after the trading hours were left out, i.e. before 9:00 o'clock and after 17:00 until March 31, 2000, and after 17:30 since April 1, 2000. The number of news headlines, as in previous studies (Melvin and Xin 1995, 1998, Chang and Taylor 1996, and Berry and Howe 1994) can be considered as a measure of the arrival of public information. The average number of observations per day (for a total of 366 days) is reported. I also checked for significant mean changes between two consecutive time periods, but this will be presented in the empirical results section 3.4.

For the Firm-specific news, only intraday patterns of purely Firm-specific news are documented, i.e. without the ones related to the CAC index. For this purpose, words such as CAC40, CAC or index in the headline were identified, and those items were not included into the Firm-specific category. This procedure is similar to that adopted by Ranaldo (2002). In particular Alcatel news (Figure 3.6.8), France Telecom (Figure 3.6.9), Vivendi (Figure 3.6.10) and Total Fina (Figure 3.6.11) are reported.

3.4 Empirical results

The eight categories selected provide an overview of the information flow, and their respective patterns highlight interesting results. Collecting each story per news item, per 5 minutes period, I collected 3'679'721 observations for the global flow of information, and 235'518 for French related news during one year.

Tables 3.7.1 and 3.7.2 display data organized by month of the year, by day of the week and the global flow of information. From Table 3.7.1 it is evident that information related to the French market is highest during the month of March in seven of eight categories. Only in the Economic news category it is highest in September. I left out the data for June, July and August from the analysis due to technical problems registered in the Reuters Terminal, because they do not allow a comparison with other months. Considering the remaining months, for the global flow of information of each category (not French related) it is very difficult to draw any conclusion. In three cases, namely Market, General and Corporate news, November shows the highest number of information, in two cases (All alerts and Industrial news) this happened in May, in other two cases in February (Political news and news concerning CAC40 stocks) and one in March (Economic news). It is difficult to explain such an irregular pattern, but one can say that the majority of news is reported two months after the end of a quarter. Considering the overall information flow, news release is highest in February and March for that related to France, which is different from what Mitchell and Mulherin (1994) found, namely most occur in April. The reason for this discrepancy may be the time period considered and, above all, the different provider. In contrast to their results, I found that public information is lowest in December for All alerts, Political, General and Corporate, in January for Industrial, in April for Market and Economic news and in December for the CAC 40 stocks. In my approach, one has to bear in mind that April has the fewest trading days (only 18 trading days), whereas March and August (not considered in general conclusion) have most (23 trading days each).

Overall, the total number of news (French related and non-) is smallest in December. This result is similar to that of Thompson et al. (1987) and Mitchell and Mulherin (1994). Table 3.7.2 shows the overall information flow by day of the week. Also in this case, interesting features emerge. First, during the business week, news is concentrated on Wednesday (All alerts, Political, General, Economic and Corporate news), with the exception of Market news (on Thursdays), and Industrial news (on Tuesday). For the French related news, public information is always much more concentrated on Thursdays, which also in other studies is the heaviest day. Among them are Mitchell and Mulherin (1994) and Gay and Mohorovic (1999) for macroeconomic and market news, and Harvey and Huang (1991, 1992) for macroeconomic news.

The information release is light on Friday (All alerts, Industrial, General, Economic and Corporate) and on Monday (Political news and Market news). This distribution between days of the week is also evident for the French market. The result is similar to Berry and Howe (1994) who found that Mondays and Fridays are light compared with the other trading days, especially, like in my case, with Wednesday for not French related news and Thursday for French related news (see also the total flow of information). Considering the whole week, the overall news flow is lowest on Sunday, and on Saturday for French related subjects. Chang and Taylor (1995) found results similar to mine. In fact, news is light on Monday and heavy on Thursday. But Gay and Mohorovic (1999) saw a decrease from Monday to Thursday, and then an increase on Friday for firm-specific news (U-shaped pattern). Table 3.7.10 to 3.7.16 report tests of equality (mean, median and variance) between days of the week and months of the year. The results show that the null hypothesis of equality between days of the week and months of the year can be rejected in most cases.

Tables 3.7.3 to 3.7.6 show various situations concerning the 39 stocks belonging to the CAC 40 index during the one-year period under study.

Table 3.7.4 ranks the companies according to the total number of news released about them. France Telecom received the greatest coverage, and news on them is particularly concentrated during the month of July, but less so in January. On the bottom side I found Bic, for which the total number of news was only 15. These tables also show the evolution of public information by month of the year. However in my general conclusion, I shall omit September and October (although they occur in the Tables), because of the above-mentioned problem related to the Reuters Terminal. Table 3.7.6 gives a classification by market capitalization. The results seems to show that there is no a strict relation between market capitalization and the number of news released, even if in some rare cases the opposite seems to be true as for France Telecom. The intraday evolution in each category provides further interesting results.

As already demonstrated by other studies (Atkins and Basu, 1995 and Ranaldo, 2002), news is much more concentrated, for each category, around the opening (1-2 hours before), at around 14:30, when the majority of US macroeconomic news is released, at the closing of European stock market and last at around 22:00, when also the US market closes. Information is light during the Asian trading hours, even though some peaks can occur. Intraday evolution is also calculated and showed, for All Alerts news, by month of the year, by day of the week and by business trading hours. The latter case is not shown. In all these cases, seasonalities are strictly correlated, and no major changes are seen. The inverted U-shaped pattern, shown in other studies, is much more pronounced for the French market, and the decrease after the market close is very sharp. Figures 3.6.1 to 3.6.20 show the intraday pattern of each category[41] of public information considered in this study (French related and non-). T-tests for each liquidity proxy are shown in Tables 3.7.9.A to 3.7.9.G.

Political news, which exhibit an inverted U-shape pattern, is almost constant during trading hours but show two big increases outside the trading hours: one at 07:30 a.m. and the other one hour later. On the contrary, French related news show three peaks after the market closure.

Market news exhibits an inverted U-shaped pattern only in the afternoon of trading hours when the news is highest, mainly between 14:30 and 16:00 o'clock. During this period, US macroeconomic indicators are made public and the pre-opening of the US market begins.

For the French Market news I observed an increasing trend until 17:30 when the market closes. This seems to be logical if one looks at the subgroups included in this category. These seasonalities of the French related news are always present also in the other categories, with the only exception of Economic news, where this trend is not so evident. Industrial news are light

[41] For the firm-specific news category, the graphs of Alcatel, France Telecom, Vivendi and Total Fina are shown.

compared to the other categories, mainly during the first hours of trading. General news is higher during the whole day, but a lull occurs in the early morning.

In conclusion one can say that investors are flooded with many news items, which may or may not have an impact on their expectations of the future payoff of a stock. Since this flow arrives continuously also before the beginning of the trading day, investors can include all these news items into their analysis.

3.5. Conclusions

In chapter 3 a measure of intraday public information flow was presented, which considers, always with respect to the French Stock exchange, the number of news items released by the Reuters 2000 Alert System during a one-year period. In the first part, each news item is categorized according to its nature. This procedure leads to the creation of eight major categories containing various subgroups. The categories are: All alerts, Political news, Market news, Industrial news, Economic news, Corporate news, Firm-specific news and General news. All alerts, which is a combination of the most important headlines for all categories, represents the vast majority of news per unit of time. Depending on the category chosen, the news flow varies by month of the year and by day of the week. Overall, the information release is mostly concentrated on February and March for the French related news items. For both, French news and non-, news flow is lightest in December.

The day with the lightest overall information flow is Friday, whereas the heaviest is Wednesday. Concerning the public information released for the French market, Monday is the lightest and Thursday the heaviest.

The coverage of the CAC 40 stocks, expressed as the number of firm-specific news, shows that market capitalization is not strictly related to this news flow. One of the few exceptions is the biggest blue chip, France Telecom, which during my period analysis released the highest number of news and is well positioned also in the analysis by month of the year. Most of the other stocks show no such a correlation between capitalization and news publication.

In the second part of chapter 3, intraday news patterns are presented by category, day of the week, month and business hour. My results show that the total public information flow follows an inverted U-shaped pattern, especially during the afternoon of trading days. For the France related news, I observed an increasing trend until the end of the exchange session, and afterwards a clear decrease, but similar to an inverted U-shape. In my opinion, it will be interesting for future research to deepen the analysis by considering contemporaneously also other providers, such as the Bloomberg terminal, which is much used by financial analysts and portfolio managers. My conclusions may stimulate a broader debate concerning the role of public information in investment decisions. In the next section I shall try to analyse whether there is any relation between the flow of public information and market liquidity.

FIGURES

FIGURE 3.6.1: Average number of All alerts news observations by time of the day: This figure shows the average intraday information flow of All alerts news during a one year period (December 1, 1999 – November 30, 2000) for all trading days by time of the day in five-minutes segments. On the horizontal axis there are 288 intervals of five minutes each (corresponding to one day) and on the vertical axis there are the average number of observations.

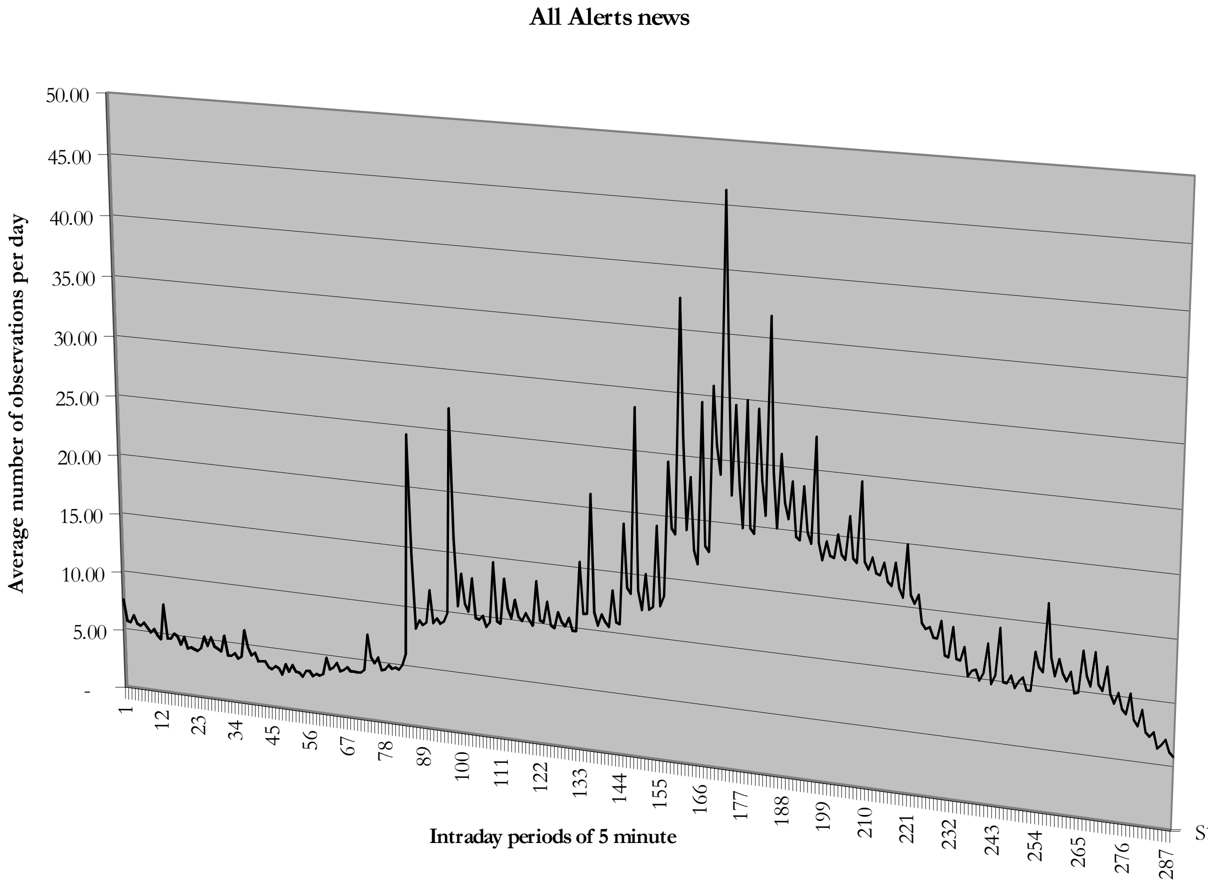


FIGURE 3.6.2: Average number of Political news observations by time of the day: This figure shows the average intraday information flow of Political news during a one year period (December 1, 1999 – November 30, 2000) for all trading days by time of the day in five-minutes segments. On the horizontal axis there are 288 intervals of five minutes each (corresponding to one day) and on the vertical axis there are the average number of observations.

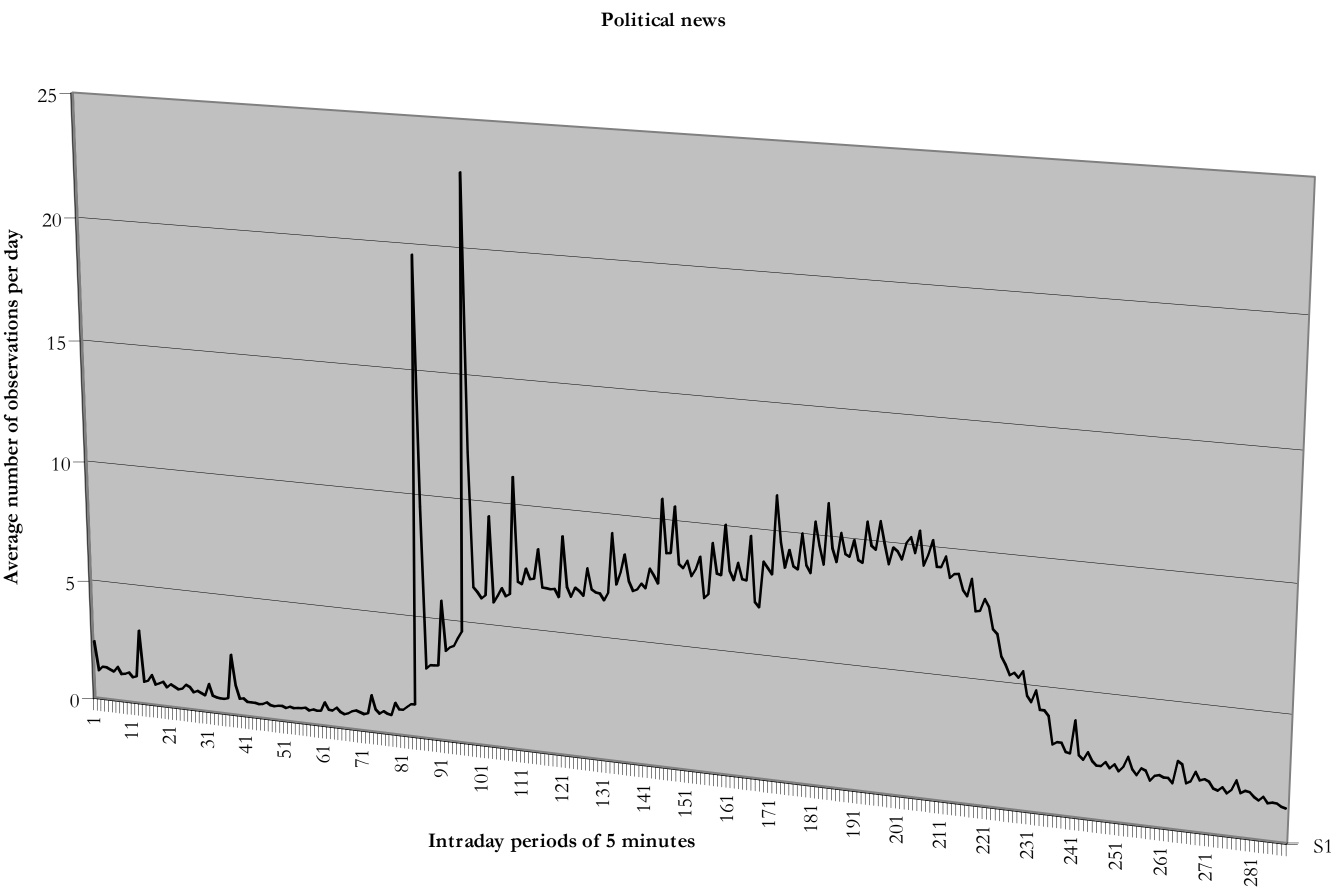


FIGURE 3.6.3: Average number of Market news observations by time of the day: This figure shows the average intraday information flow of Market news during a one year period (December 1, 1999 – November 30, 2000)) for all trading days by time of the day in five-minutes segments. On the horizontal axis there are 288 intervals of five minutes each (corresponding to one day) and on the vertical axis there are the average number of observations.

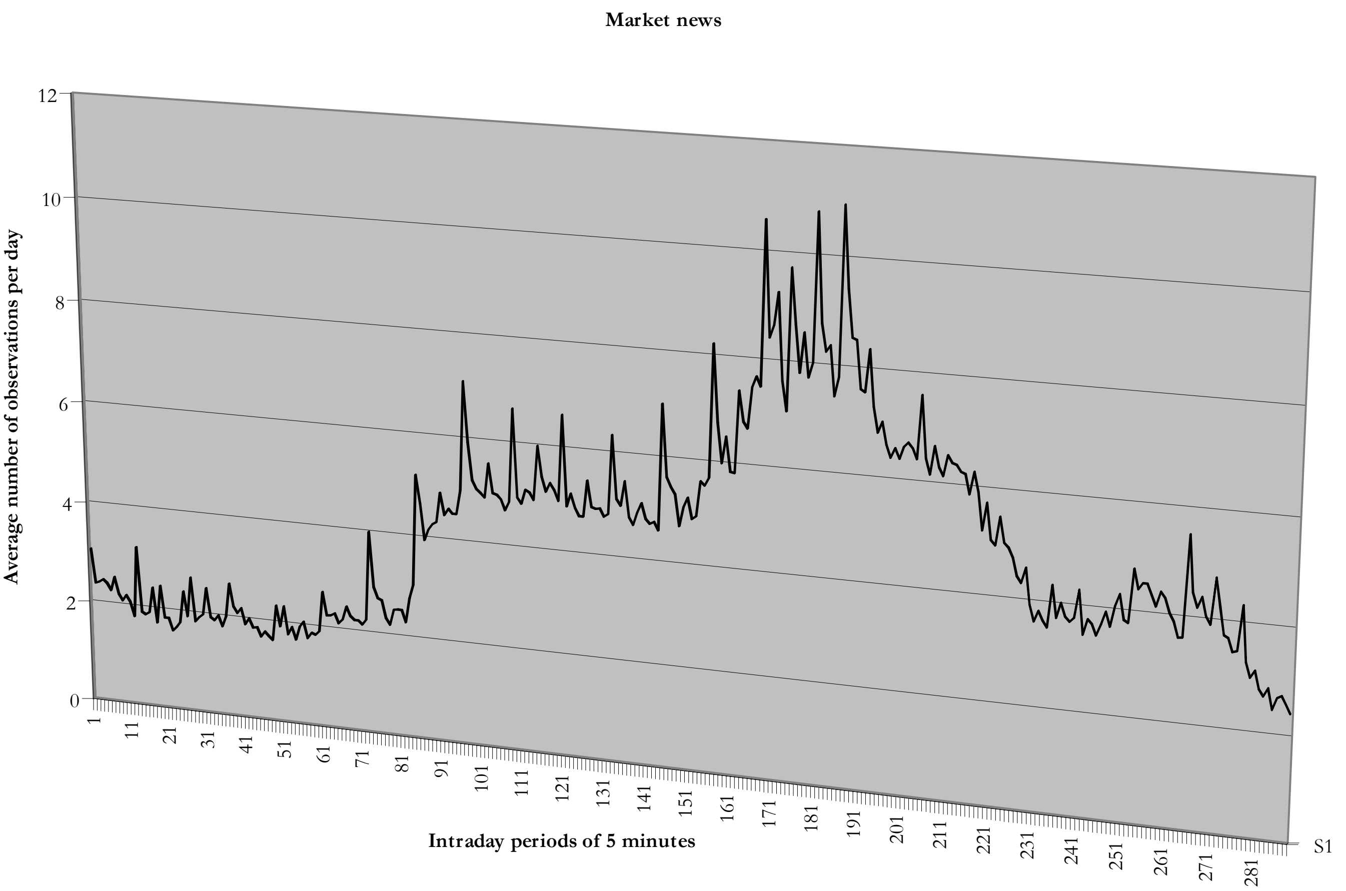


FIGURE 3.6.4: Average number of Industrial news observations by time of the day: This figure shows the average intraday information flow of Industrial news during a one year period (December 1, 1999 – November 30, 2000) for all trading days by time of the day in five-minutes segments. On the horizontal axis there are 288 intervals of five minutes each (corresponding to one day) and on the vertical axis there are the average number of observations.

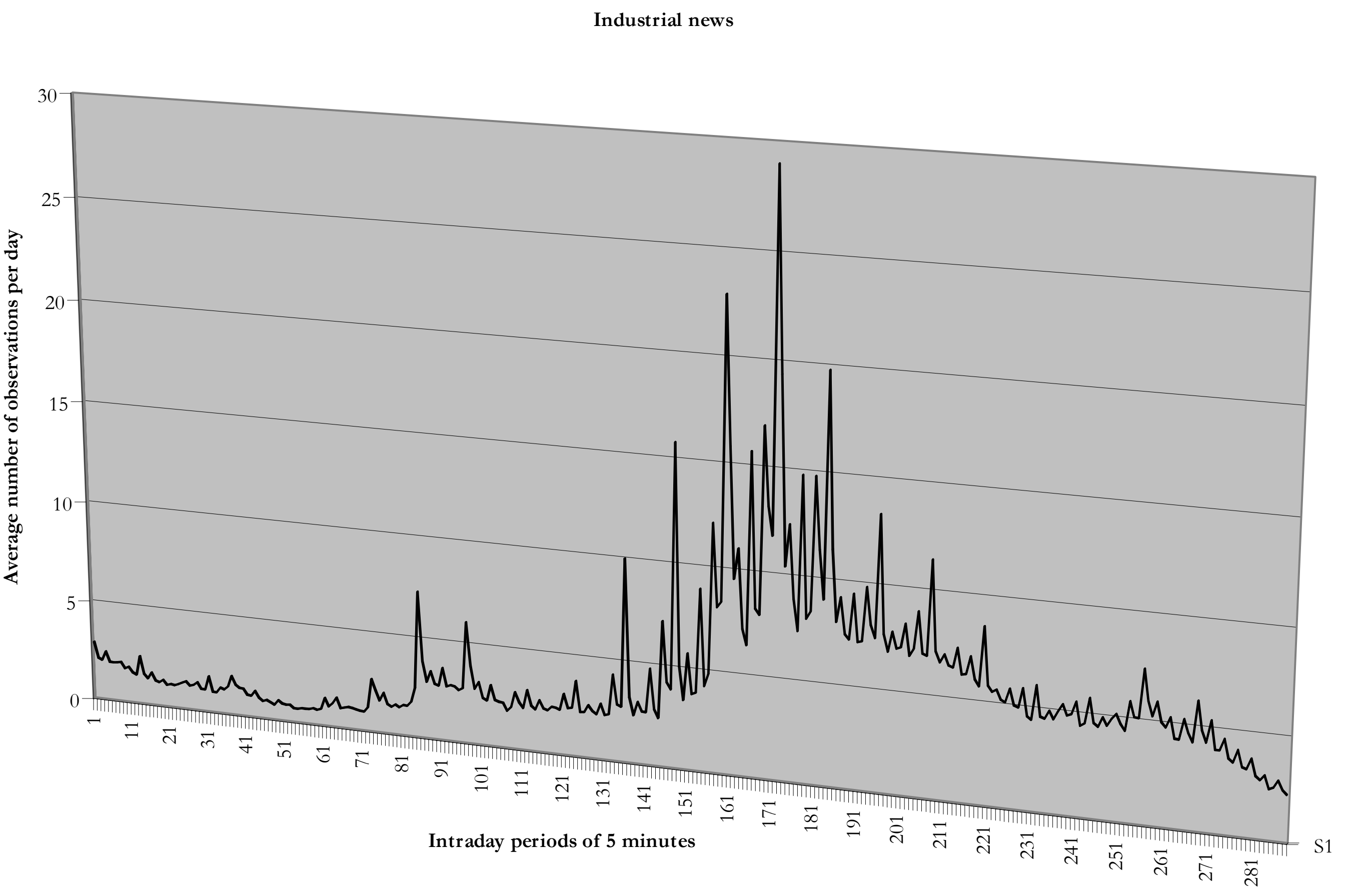


FIGURE 3.6.5: Average number of General news observations by time of the day: This figure shows the average intraday information flow of General news during a one year period (December 1, 1999 – November 30, 2000) for all trading days by time of the day in five-minutes segments. On the horizontal axis there are 288 intervals of five minutes each (corresponding to one day) and on the vertical axis there are the average number of observations.

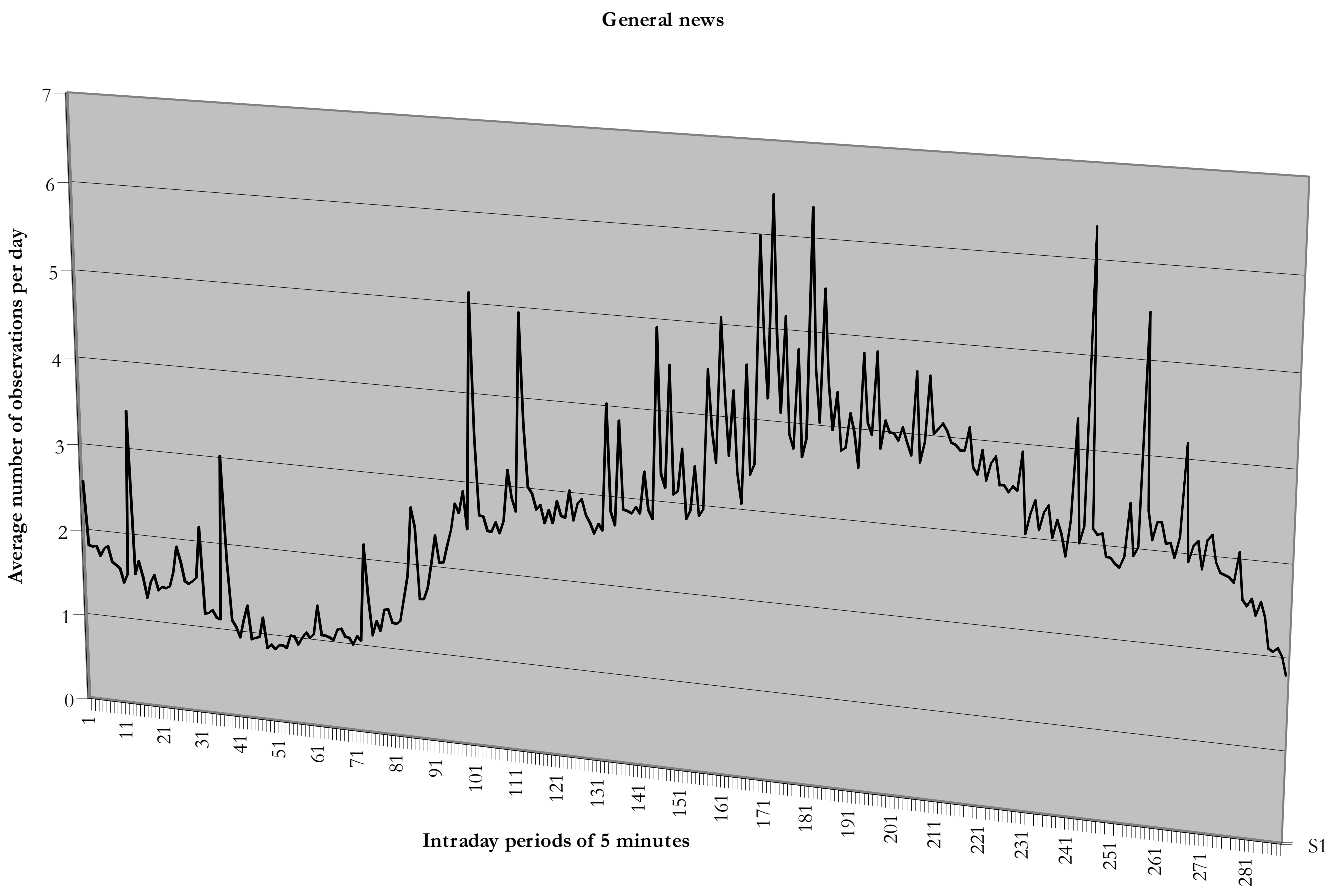


FIGURE 3.6.6: Average number of Economic news observations by time of the day: This figure shows the average intraday information flow of Economic news during a one year period (December 1, 1999 – November 30, 2000) for all trading days by time of the day in five-minutes segments. On the horizontal axis there are 288 intervals of five minutes each (corresponding to one day) and on the vertical axis there are the average number of observations.

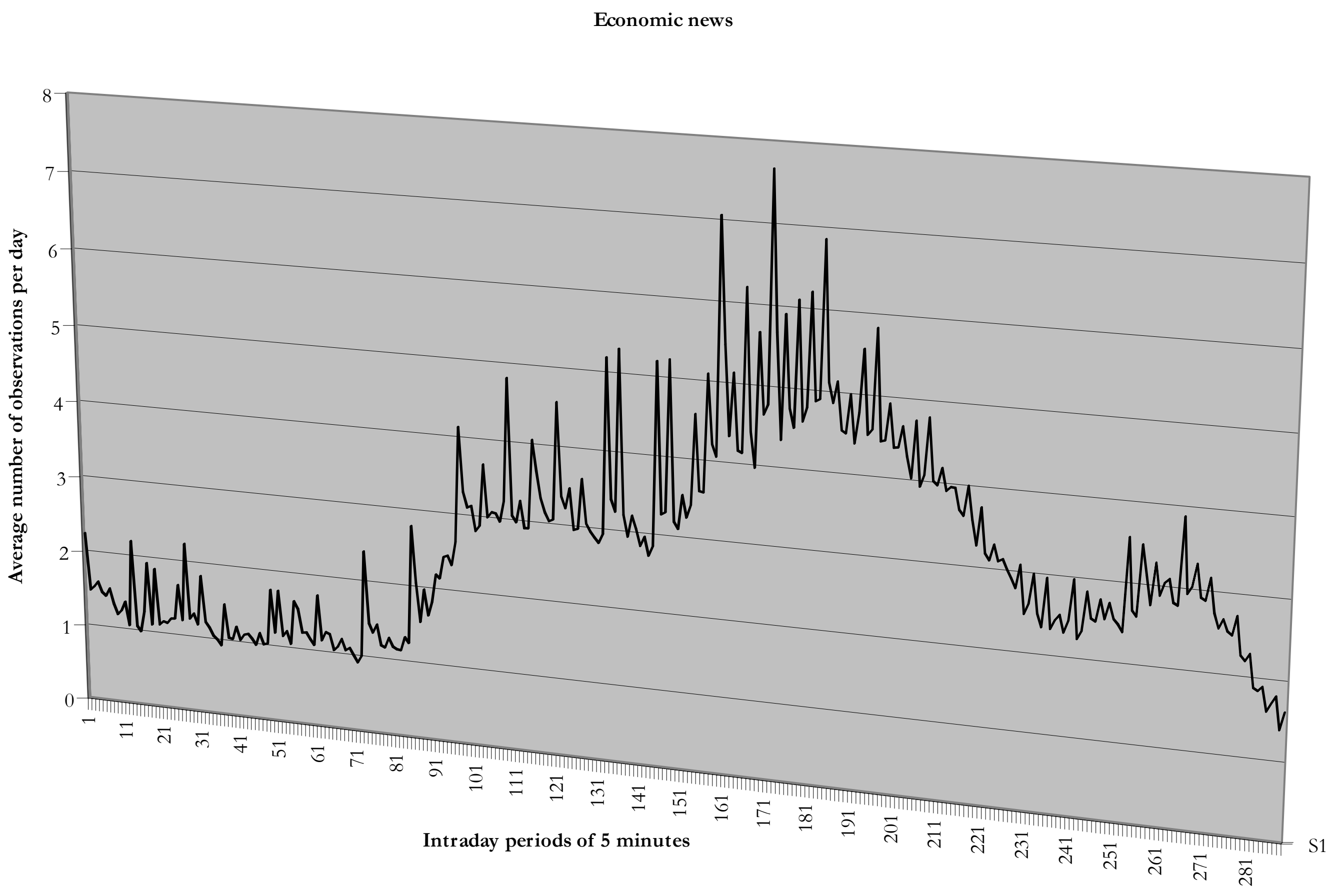


FIGURE 3.6.7: Average number of Corporate news observations by time of the day: This figure shows the average intraday information flow of Corporate news during a one year period (December 1, 1999 – November 30, 2000) for all trading days by time of the day in five-minutes segments. On the horizontal axis there are 288 intervals of five minutes each (corresponding to one day) and on the vertical axis there are the average number of observations.

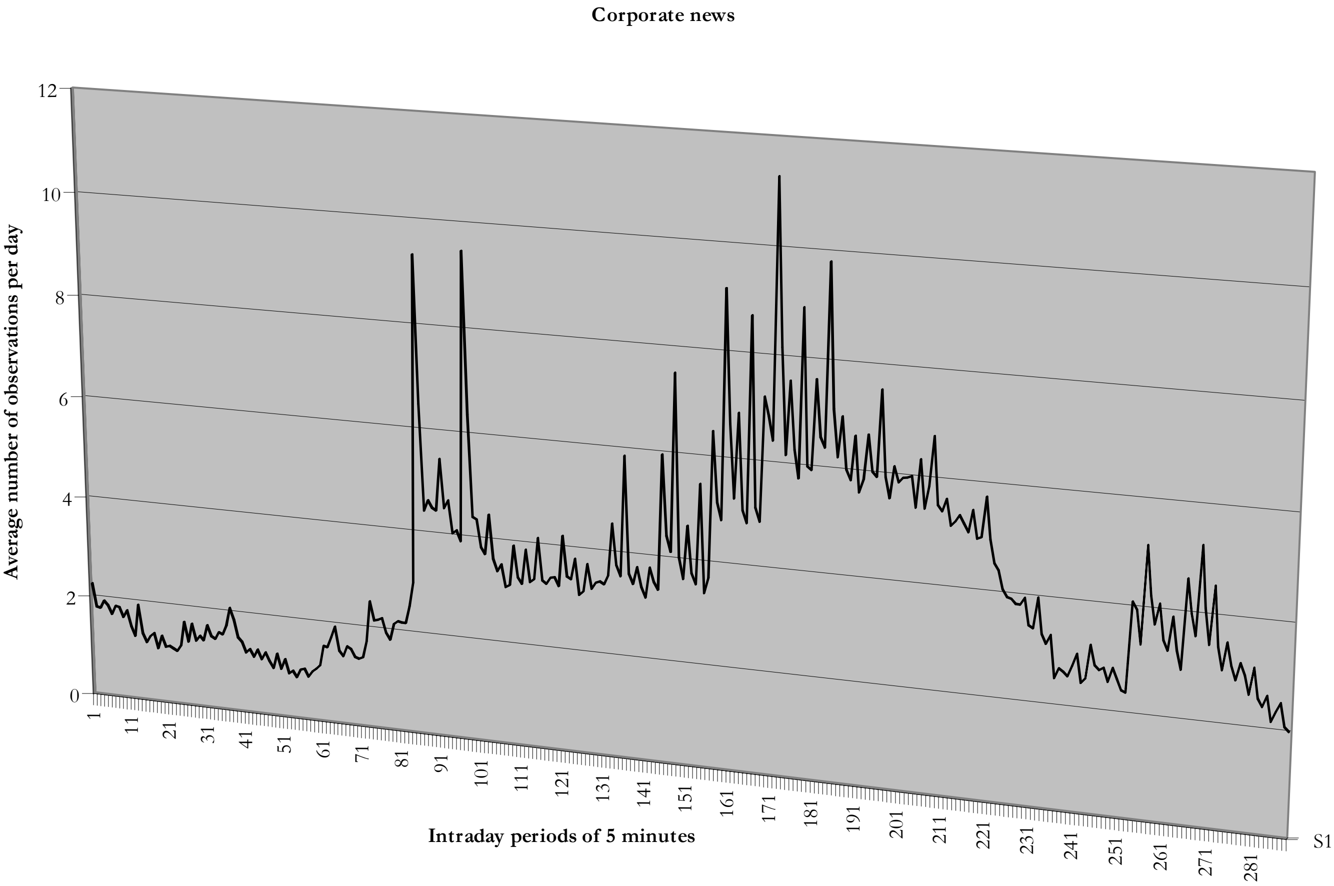


FIGURE 3.6.8: Average number of Alcatel news observations by time of the day: This figure shows the average intraday information flow of Alcatel news during a one year period (December 1, 1999 – November 30, 2000) for all trading days by time of the day in five-minutes segments. On the horizontal axis there are 288 intervals of five minutes each (corresponding to one day) and on the vertical axis there are the average number of observations.

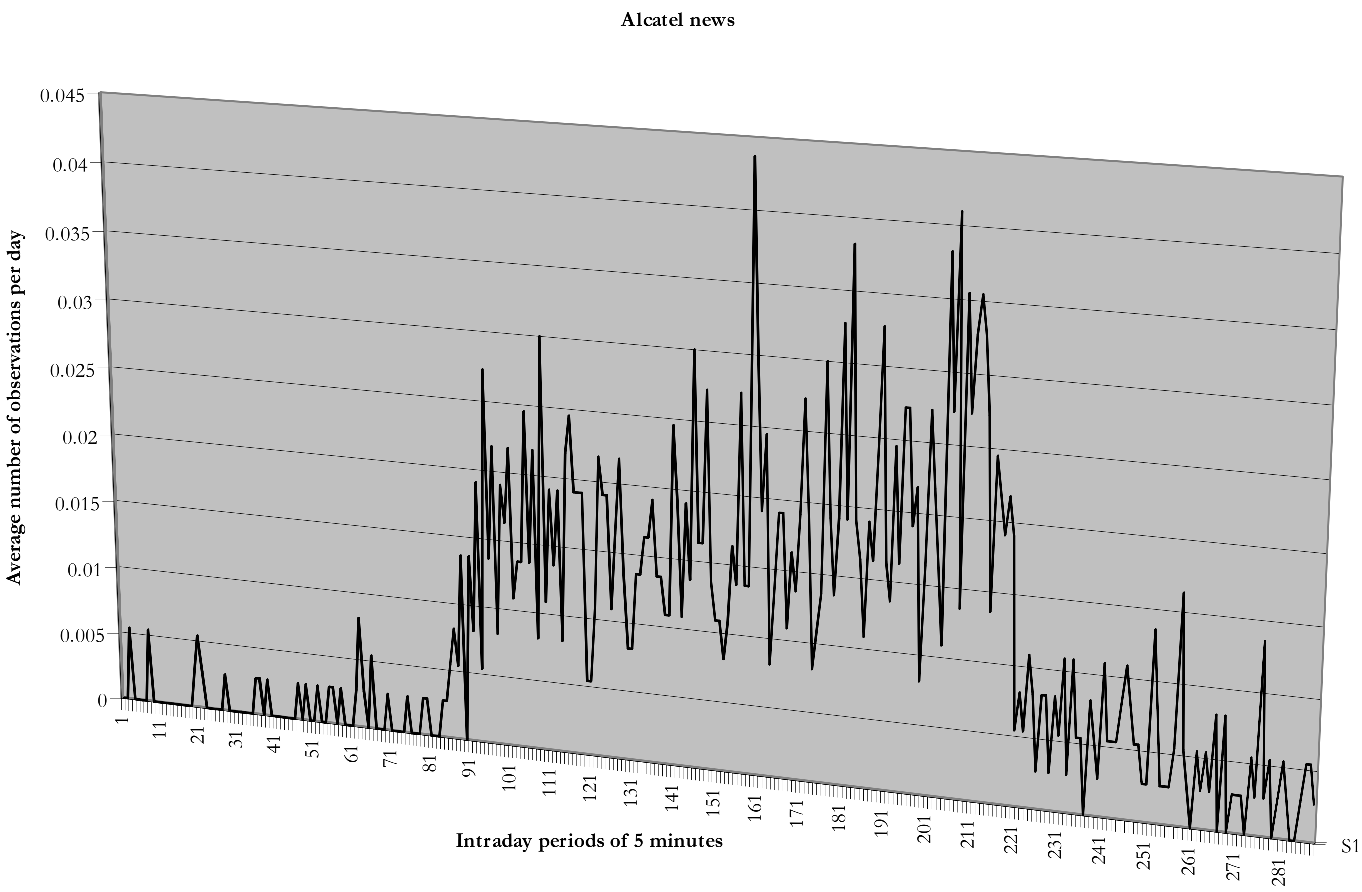


FIGURE 3.6.9: Average number of France Telecom news observations by time of the day: This figure shows the average intraday information flow of France Telecom news during a one year period (December 1, 1999 – November 30, 2000) for all trading days by time of the day in five-minutes segments. On the horizontal axis there are 288 intervals of five minutes each (corresponding to one day) and on the vertical axis there are the average number of observations.

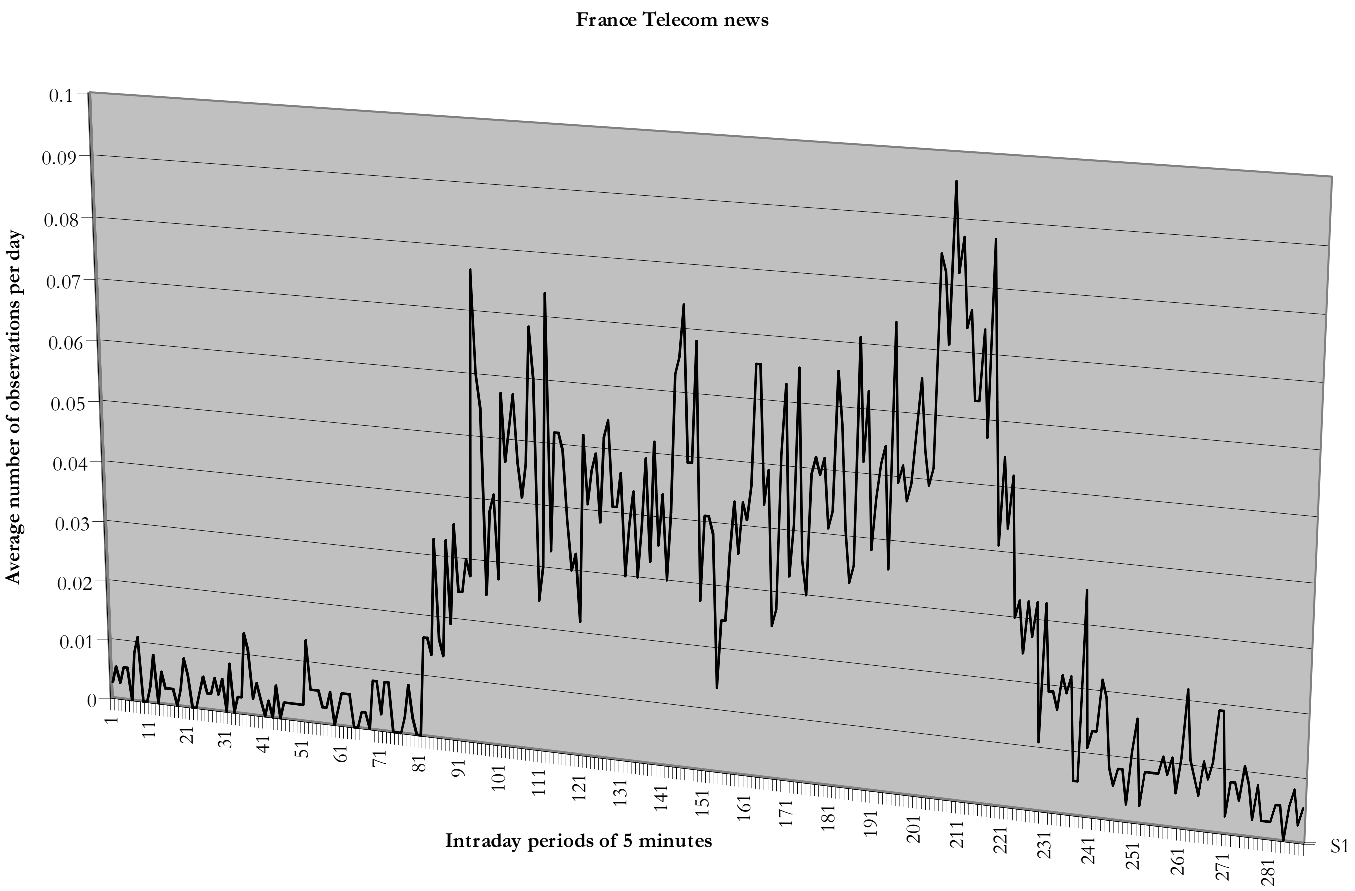


FIGURE 3.6.10: Average number of Vivendi news observations by time of the day: This figure shows the average intraday information flow of Vivendi news during a one year period (December 1, 1999 – November 30, 2000) for all trading days by time of the day in five-minutes segments. On the horizontal axis there are 288 intervals of five minutes each (corresponding to one day) and on the vertical axis there are the average number of observations.

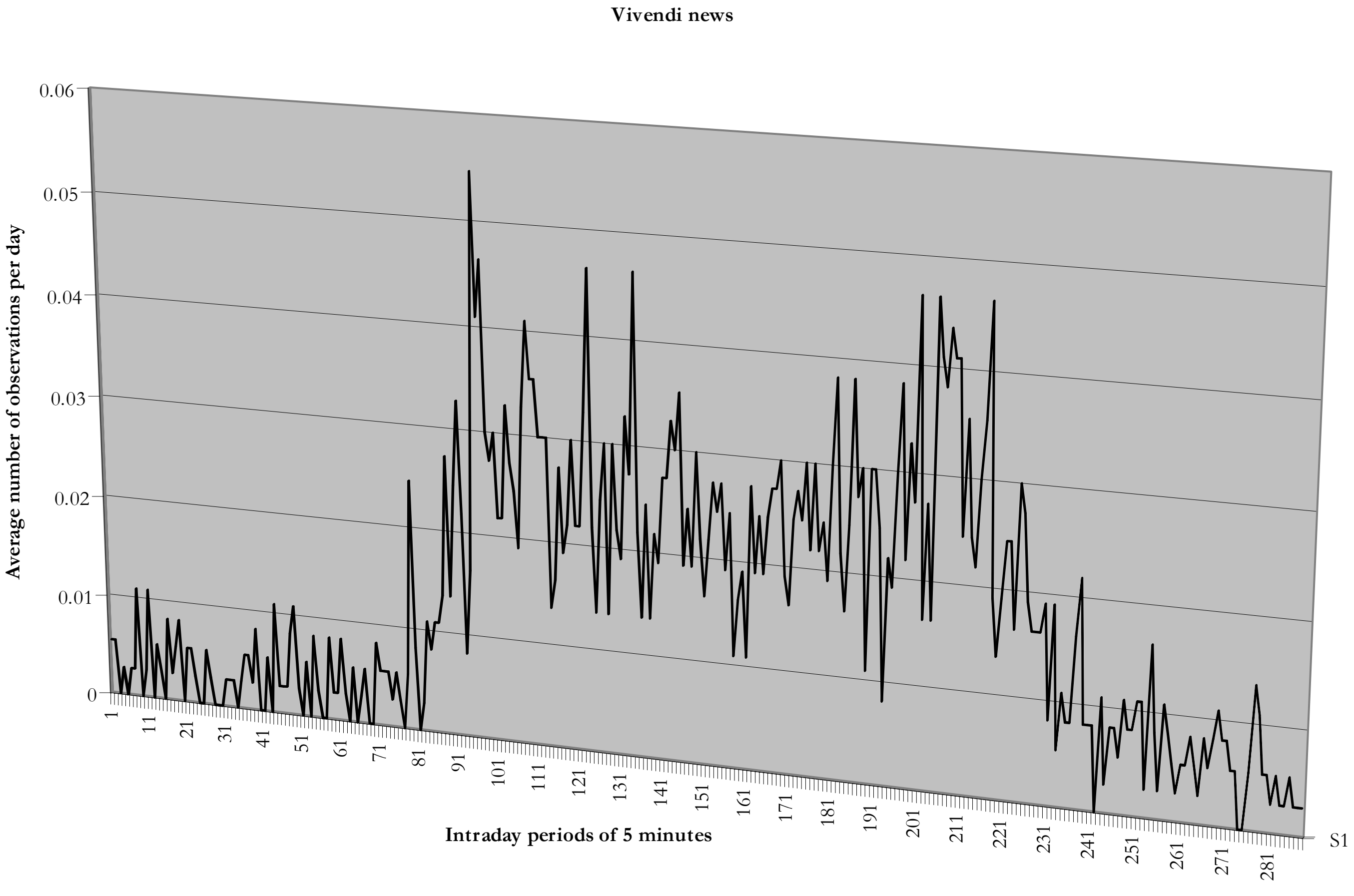


FIGURE 3.6.11: Average number of Total news observations by time of the day: This figure shows the average intraday information flow of Total news during a one year period (December 1, 1999 – November 30, 2000) for all trading days by time of the day in five-minutes segments. On the horizontal axis there are 288 intervals of five minutes each (corresponding to one day) and on the vertical axis there are the average number of observations.

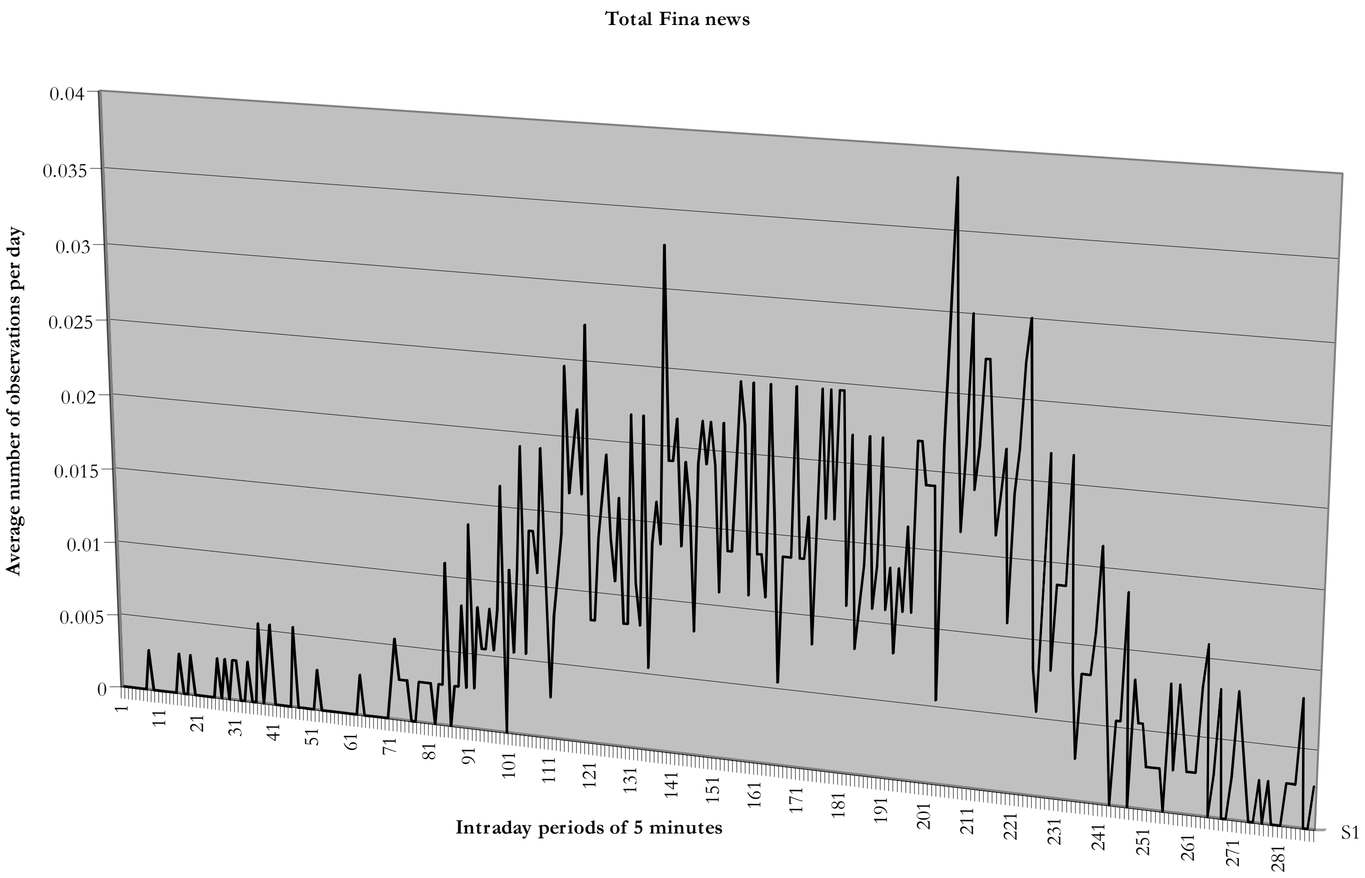


FIGURE 3.6.12: Average number of All Alerts news France observations by time of the day: This figure shows the average intraday information flow of All Alerts news France during a one year period (December 1, 1999 – November 30, 2000) for all trading days by time of the day in five-minutes segments. On the horizontal axis there are 288 intervals of five minutes each (corresponding to one day) and on the vertical axis there are the average number of observations.

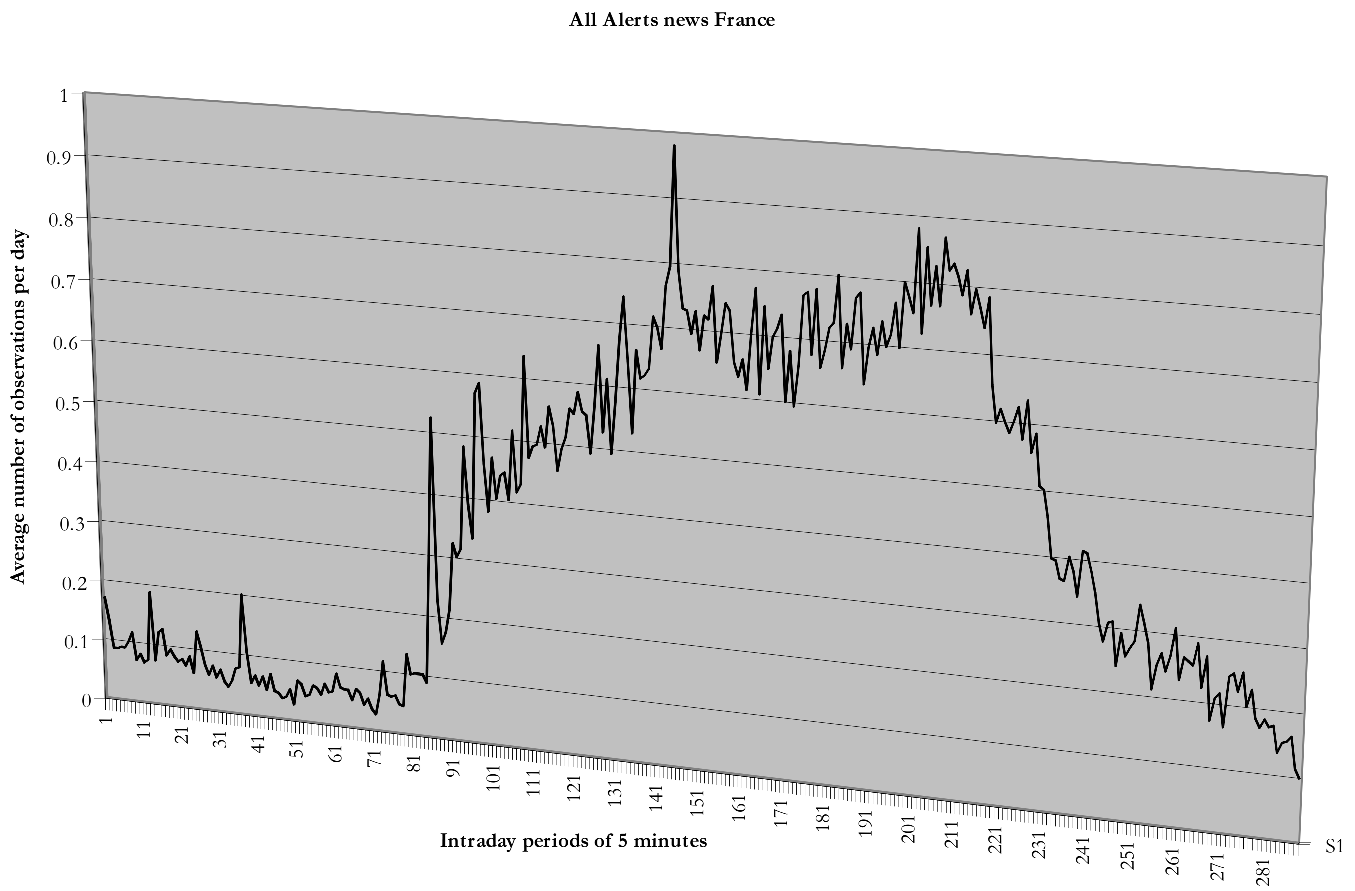


FIGURE 3.6.13: Average number of Political news France observations by time of the day: This figure shows the average intraday information flow of Political news France during a one year period (December 1, 1999 – November 30, 2000) for all trading days by time of the day in five-minutes segments. On the horizontal axis there are 288 intervals of five minutes each (corresponding to one day) and on the vertical axis there are the average number of observations.

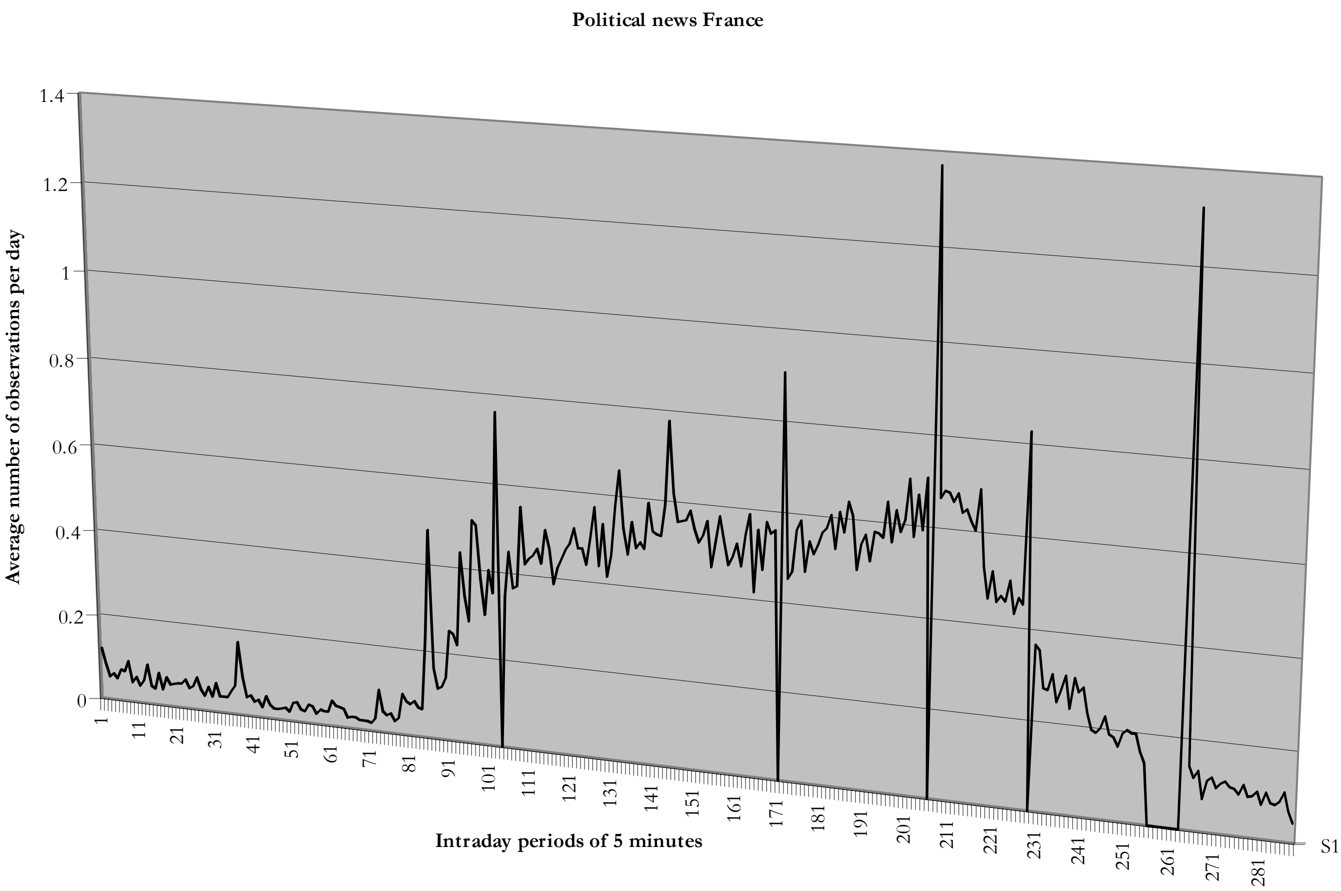


FIGURE 3.6.14: Average number of Market news France observations by time of the day: This figure shows the average intraday information flow of Market news France during a one year period (December 1, 1999 – November 30, 2000) for all trading days by time of the day in five-minutes segments. On the horizontal axis there are 288 intervals of five minutes each (corresponding to one day) and on the vertical axis there are the average number of observations.

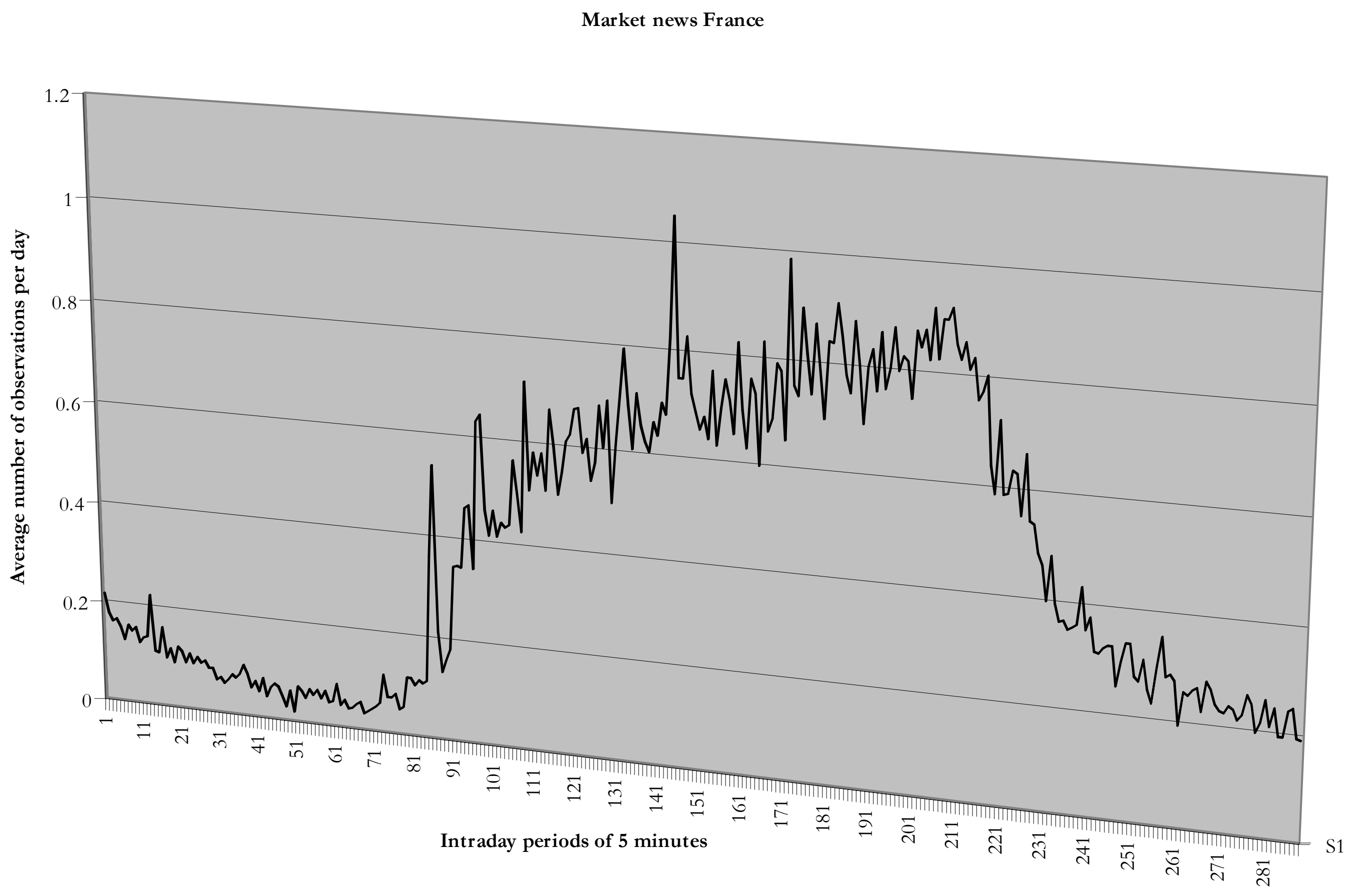


FIGURE 3.6.15: Average number of Industrial news France observations by time of the day: This figure shows the average intraday information flow of Industrial news France during a one year period (December 1, 1999 – November 30, 2000) for all trading days by time of the day in five-minutes segments. On the horizontal axis there are 288 intervals of five minutes each (corresponding to one day) and on the vertical axis there are the average number of observations.

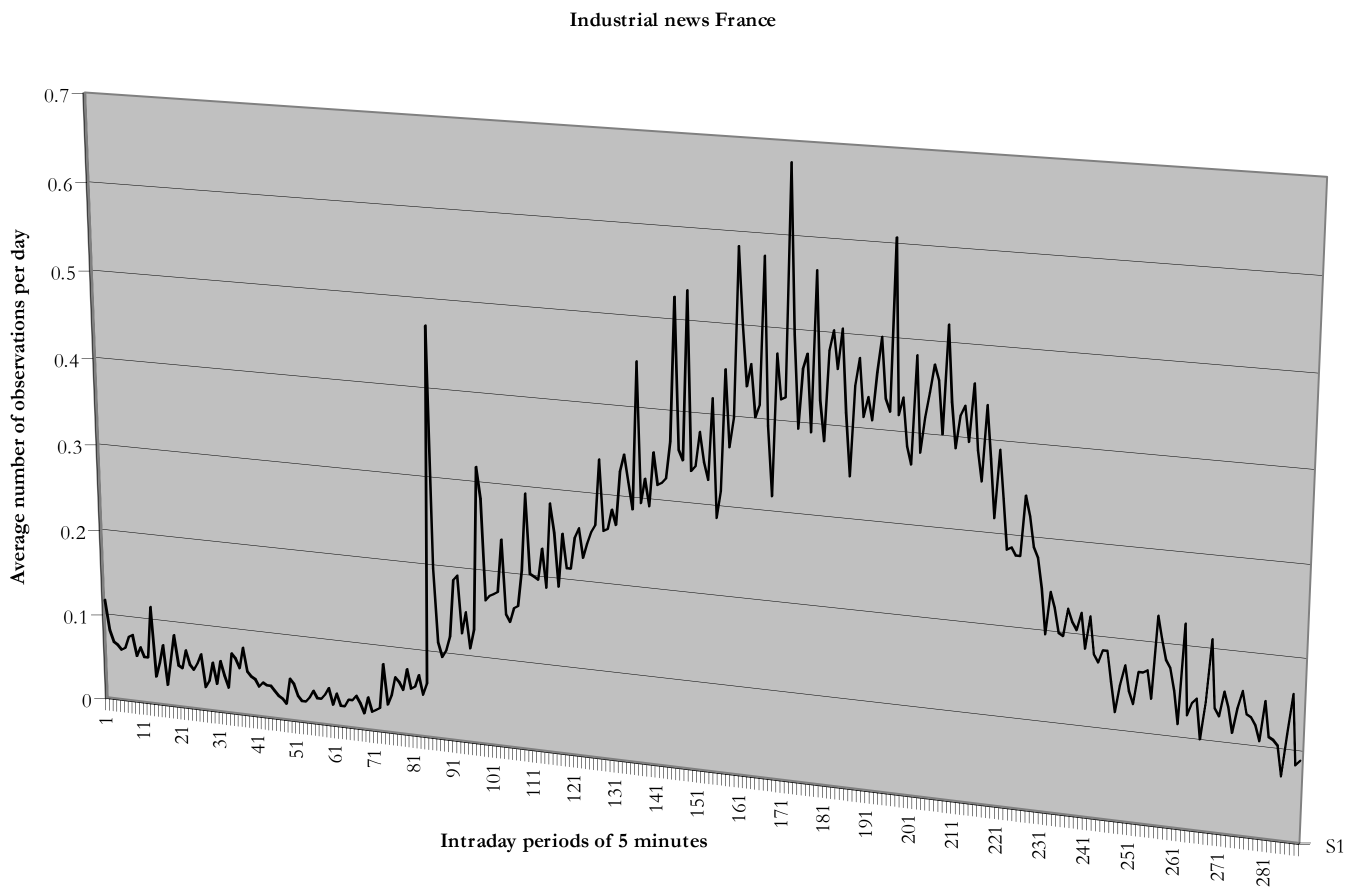


FIGURE 3.6.16: Average number of General news France observations by time of the day: This figure shows the average intraday information flow of General news France during a one year period (December 1, 1999 – November 30, 2000) for all trading days by time of the day in five-minutes segments. On the horizontal axis there are 288 intervals of five minutes each (corresponding to one day) and on the vertical axis there are the average number of observations.

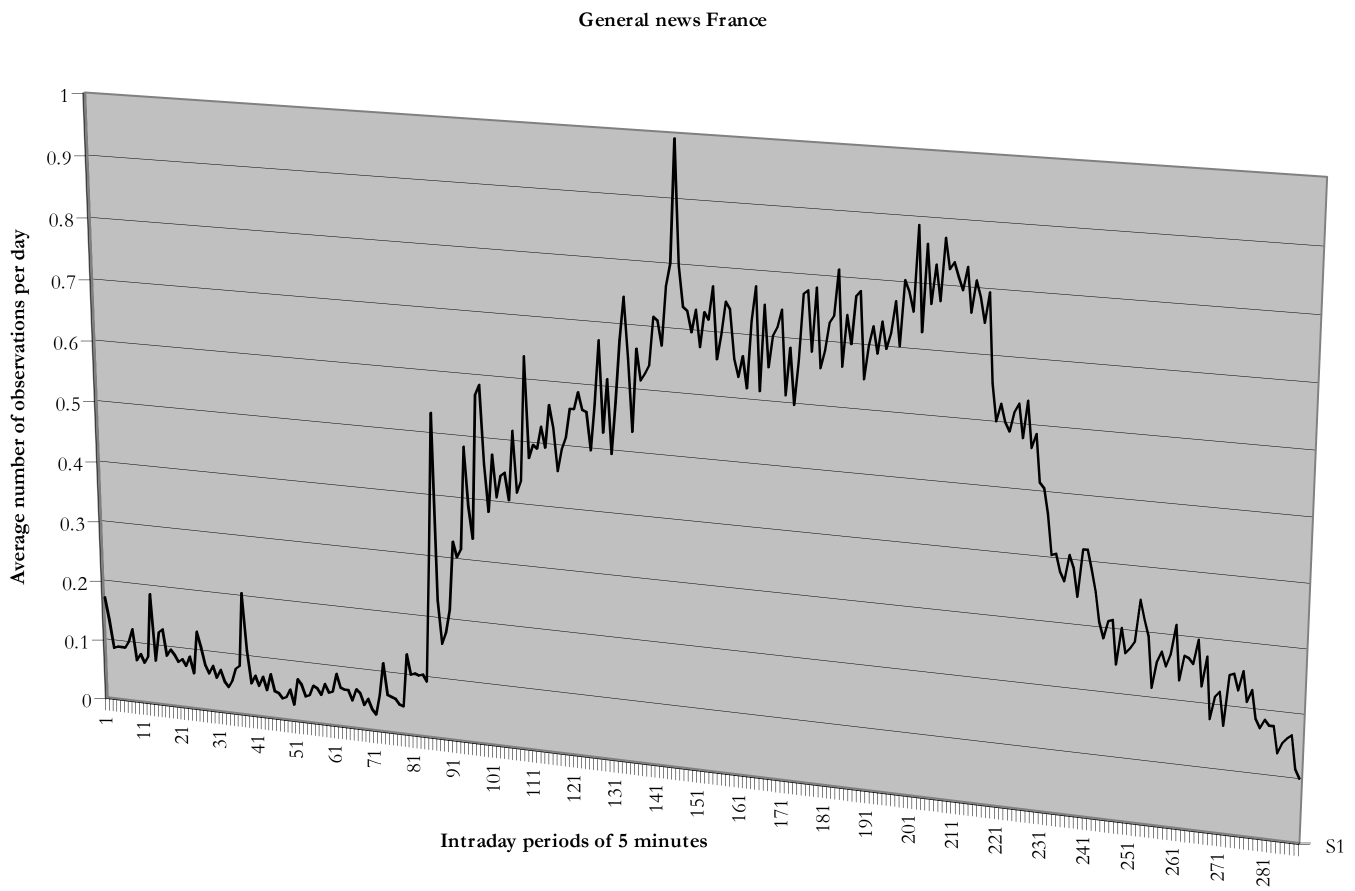


FIGURE 3.6.17: Average number of Economic news France observations by time of the day: This figure shows the average intraday information flow of Economic news France during a one year period (December 1, 1999 – November 30, 2000) for all trading days by time of the day in five-minutes segments. On the horizontal axis there are 288 intervals of five minutes each (corresponding to one day) and on the vertical axis there are the average number of observations.

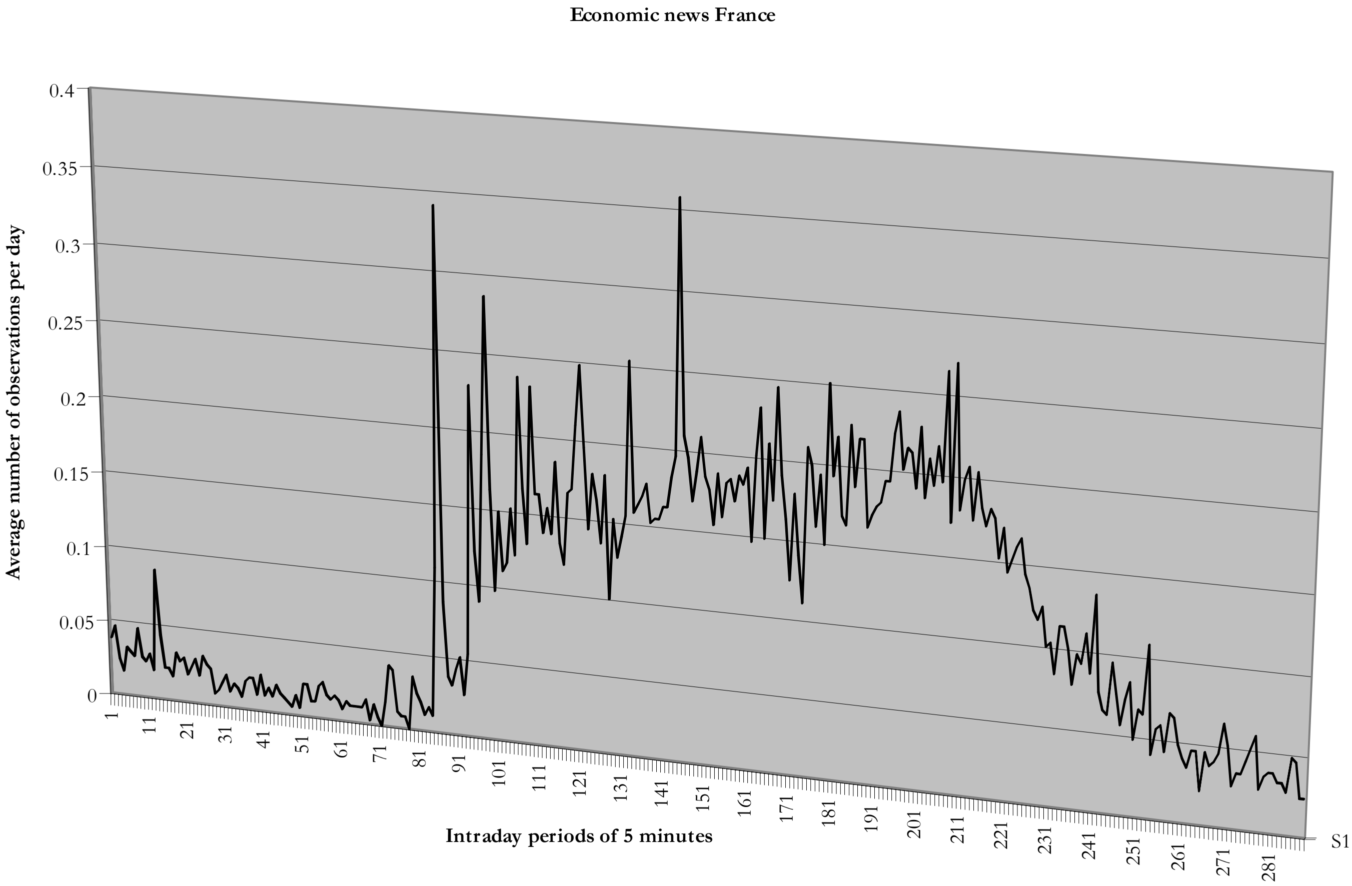


FIGURE 3.6.18: Average number of Corporate news France observations by time of the day: This figure shows the average intraday information flow of Corporate news France during a one year period (December 1, 1999 – November 30, 2000) for all trading days by time of the day in five-minutes segments. On the horizontal axis there are 288 intervals of five minutes each (corresponding to one day) and on the vertical axis there are the average number of observations.

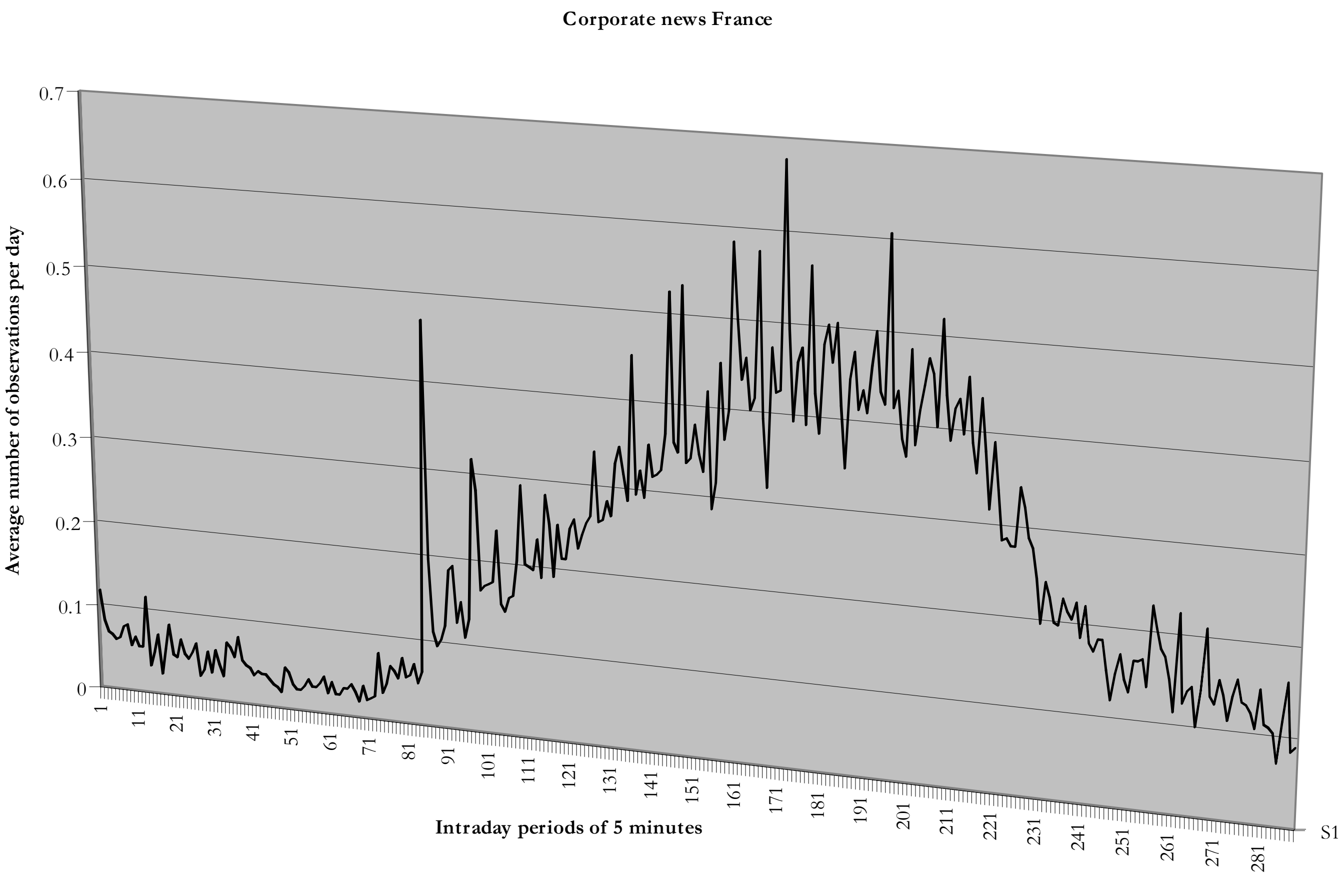


FIGURE 3.6.19: Average number of All alerts news observations by day of the week: This figure shows the average intraday information flow of All alerts news during a one year period (December 1, 1999 – November 30, 2000) for all trading days by time of the day in five-minutes segments. On the horizontal axis there are 288 intervals of five minutes each (corresponding to one day) and on the vertical axis there are the average number of observations.

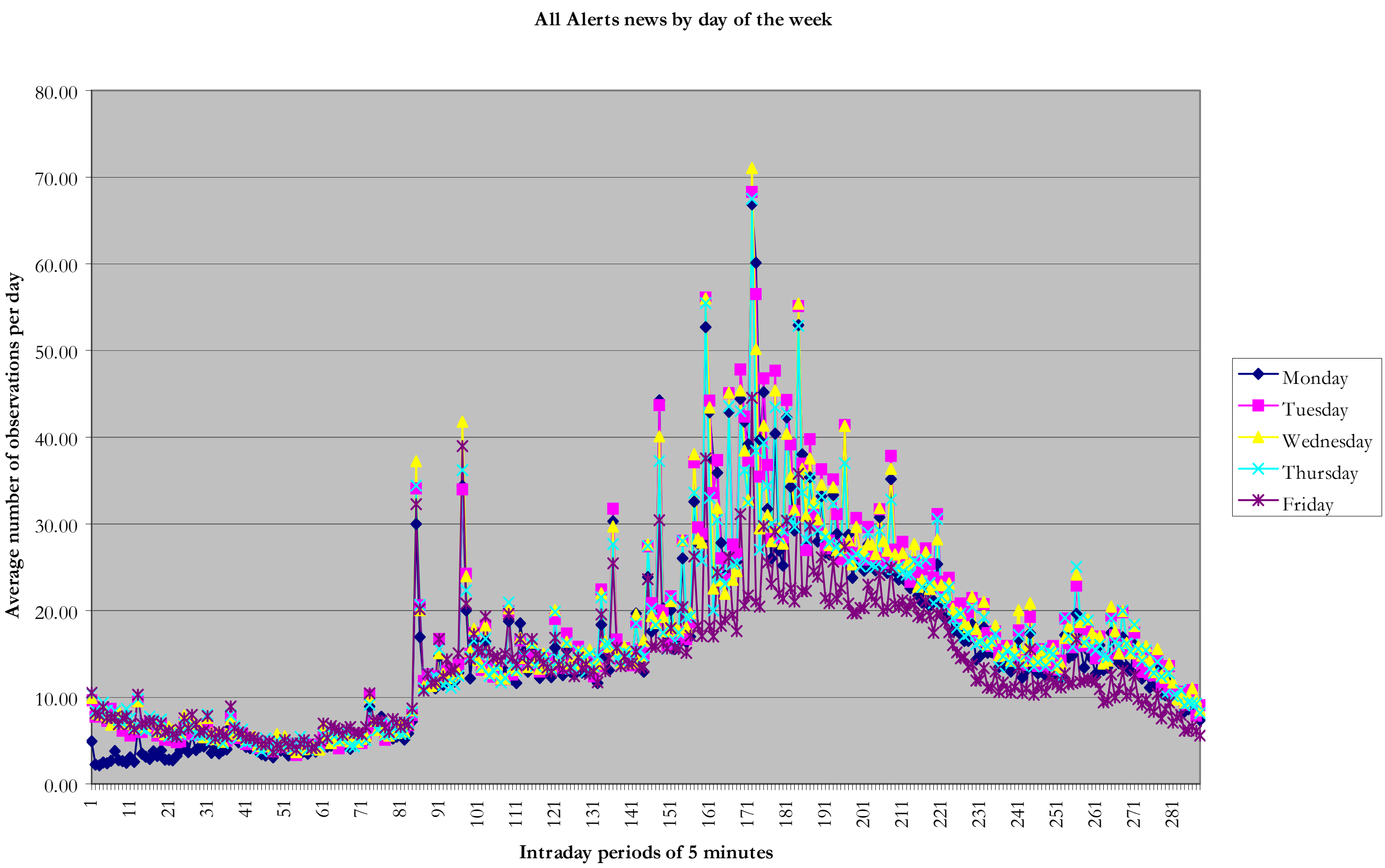
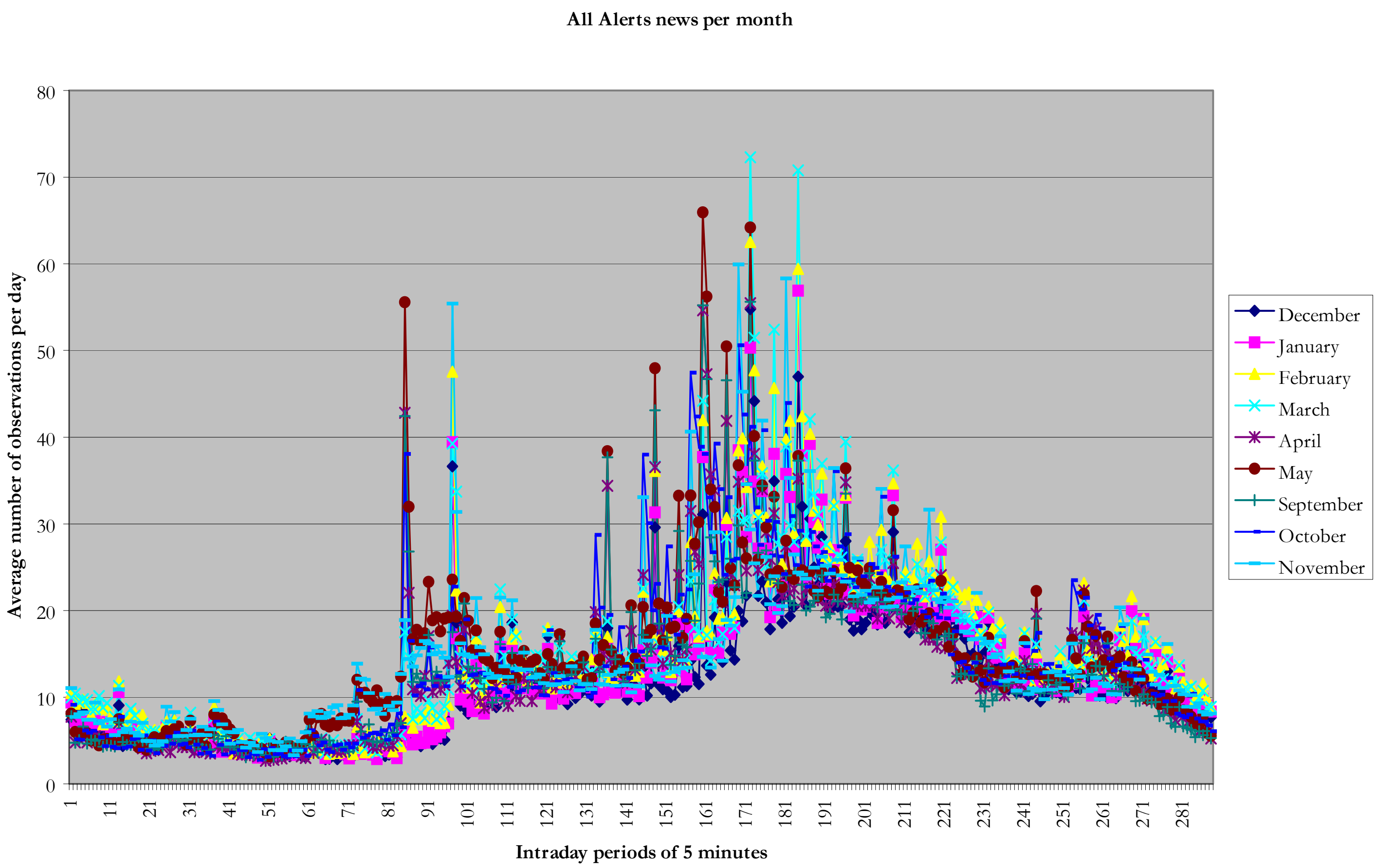


FIGURE 3.6.20: Average number of All alerts news observations by month of the year: This figure shows the average intraday information flow of All alerts news during a one year period (December 1, 1999 – November 30, 2000) for all trading days by time of the day in five-minutes segments. On the horizontal axis there are 288 intervals of five minutes each (corresponding to one day) and on the vertical axis there are the average number of observations.



TABLES

Table 3.7.1: Global information flow by month of the year. This table reports global information flow by month of the year from December 1, 1999 to November 30, 2000 for each of the eight categories considered in this study and released by the Reuters 2000 alert system.

News Category	December 1999	January 2000	February 2000	March 2000	April 2000	May 2000	June 2000
All alerts	105'276	117'028	126'267	135'358	114'961	136'155	89'296*
All alerts Fr	3'038	3'535	3'817	4'188	3'030	3'738	3'390
Political	39'623	41'193	68'130	51'977	42'008	49'256	43'601
Political Fr	2'463	2'704	2'870	3'123	2'472	2'881	2'317
market	55'455	59'576	62'845	58'857	41'618	1'972*	821*
market Fr	2'401	2'720	3'898	7'805	6'314	4'312	2'691
Industrial	37'493	28'344	48'322	48'581	43'406	50'788	37'378
Industrial fr	1'048	1'269	1'794	2'984	2'350	2'436	2'004
General	20'093	21'749	22'525	25'590	23'836	27'851	24'315
General Fr	3'039	3'535	3'818	4'187	3'187	3'732	3'393
Economic	24'600	26'123	26'093	27'664	22'899	26'443	23'303
Economic Fr	926	992	905	1'038	856	995	788
Corporate	30'052	36'463	40'356	37'528	34'002	34'702	25018*
Corporate Fr	1'048	1'269	1'794	2'984	2'350	2'436	2'004
Stocks CAC 40	1'439	1'668	1'945	1'871	1'517	1'735	1'462
Total	312'592	330'476	394'538	385'555	322'730	327'167	243'732
Total Fr	15'402	17'692	20'841	28'180	22'076	22'265	18'049

News Category	July 2000	August 2000	September	October 2000	November	TOTAL	MEAN	STD. DEV.
All alerts	229*	52'372*	114'537	130'348	125'955	1'247'78	122'876	40'160.96
All alerts Fr	3'510	2'580	3'611	3'682	3'487	41'606	3'570	421.83
Political	13'149*	20'463*	43'167	43'709	47'689	503'965	47'417	14'067.05
Political Fr	2'684	1'975	2'898	2'909	2'711	32'007	2'781	315.00
market	7*	228*	55'892	64'376	68'090	469'737	52'164	29'115.18
market Fr	2'927	2'230	3'214	3'145	2'757	44'414	4'063	1'704.42
Industrial	19'844*	25'823	42'708	48'719	46'343	477'749	43'856	10'226.13
Industrial fr	2'273	1'830	2'221	1'848	1'079	23'136	1'892	581.95
General	21'317	21'127	27'661	28'087	31'452	295'603	25'427	3'519.63
General Fr	3'511	2'585	3'666	3'719	3'486	41'858	3'597	411.37
Economic	25'708	21'758	24'528	26'486	25'557	301'162	25'599	1'724.94
Economic Fr	933	686	1'080	956	962	11'117	968	108.55
Corporate	19'174*	20'416*	26720*	35'657	43'635	383'723	35'457	7'742.83
Corporate Fr	2'273	1'830	2'221	1'848	1'079	23'136	1'892	581.95
Stocks CAC 40	1'666	1'226	674*	1224*	1'817	18'244	1'520	354.35
Total	99'428	162'187	335'213	377'382	388'721	3'679'72	43'806	32'081.30
Total Fr	19'777	14'942	19'585	19'331	17'378	235'518	2'453	1'193.37

* Due to technical problems with the Reuters 2000 News Alert System, the subgroup belonging to the corresponding category is not complete

Table 3.7.2: Global information flow by day of the week. This table reports global information flow by day of the week from December 1, 1999 to November 30, 2000 for each of the eight categories considered in this study and released by the Reuters 2000 alert system.

	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday	TOTAL	MEAN	STD. DEV.
All alerts	232'615	254'719	258'808	249'838	203'491	24'438	23'873	**1'247'782**	**178'255**	**106'883.8**
All alerts Fr	6'577	7'694	8'156	8'474	7'000	1'789	1'916	**41'606**	**5'944**	**2'868.25**
Political	86'147	101'399	104'243	103'382	88'086	10'166	10'542	**503'965**	**71'995**	**42'716.45**
Political Fr	5'143	6'115	6'454	6'712	5'589	1'012	982	**32'007**	**4'572**	**2'497.48**
Market	83'621	93'038	96'884	97'173	86'306	6'497	6'218	**469'737**	**67'219**	**41'900.19**
Market Fr	7'558	8'808	9'311	9'509	7'711	789	728	**44'414**	**6'345**	**3'886.55**
Industrial	97'525	105'570	101'992	94'890	69'057	4'849	3'866	**477'749**	**68'250**	**45'209.99**
Industrial Fr	3'997	4'624	4'770	5'094	3'923	347	381	**23'136**	**3'305**	**2'051.29**
General	48'636	52'912	56'170	54'780	45'622	17'975	19'508	**295'603**	**42'229**	**16'447.23**
General Fr	6'591	7'702	8'159	8'463	7'171	1'852	1'920	**41'858**	**5'980**	**2'863.40**
Economic	54'444	60'092	62'867	61'170	52'658	5'212	4'719	**301'162**	**43'023**	**26'250.68**
Economic Fr	1'875	2'088	2'145	2'243	2'133	333	300	**11'117**	**1'588**	**875.85**
Corporate	68'132	79'604	81'647	81'103	66'747	3'511	2'979	**383'723**	**54'818**	**35'740.49**
Corporate Fr	3'997	4'624	4'770	5'094	3'923	347	381	**23'136**	**3'305**	**2'051.29**
Total	671'120	747'334	762'611	742'336	611'967	72'648	71'705	**3'679'721**	**75'096**	**65'929**
Total Fr	35'738	41'655	43'765	45'589	37'450	6'469	6'608	**217'274**	**4'434**	**2'939**

*There were six market holidays: New Year's Eve (Friday 31.12.1999), Good Friday (Friday 21.04.2000), Easter Monday (Monday 24.04.2000), Labour day (Monday 01.05.2000), Whitmonday (Monday 12.06.2000) and National Holiday (14.07.2000).

Table 3.7.3: Firm-specific news. This table reports firm-specific news (without CAC40 news) by month of the year during the period December 1, 1999 and November 30, 2000 released by the Reuters 2000 alert system.

Company	December 1999	January 2000	February 2000	March 2000	April 2000	May 2000	June 2000	July 2000
Accor	21	6	15	15	7	15	9	12
Agf	12	10	11	13	9	8	5	1
Air	4	24	14	11	14	31	3	7
Alcatel	63	59	111	73	66	114	90	103
Alstom	23	15	40	35	19	33	14	24
Aventis	21	18	16	31	30	35	32	34
Axa	24	35	32	40	30	38	21	43
Bic	3	3	0	4	2	0	0	1
BNP	45	27	45	27	34	43	48	66
Bouygues	61	16	29	29	28	70	39	22
CAC40 Index	130	123	133	102	66	82	76	69
Canal	80	96	120	112	82	63	134	73
Cap Gemini	35	57	36	55	31	30	21	9
Carrefour	27	62	64	44	26	39	15	53
Casino	4	7	17	26	15	31	5	9
Credit Lyonnais	41	24	16	29	38	31	11	21
Thomson-csf	17	64	26	30	13	13	30	14
Danone	35	36	35	49	19	39	41	31
EADS	59	47	59	97	59	7	1	87
Equant	26	29	16	34	10	53	35	23
Eridania	1	4	23	7	0	4	12	2
France	210	155	158	250	242	316	260	340
Lafarge	7	47	67	35	44	44	24	25
Lagardere	16	69	75	56	39	19	12	8
Legrand	1	3	3	3	1	1	0	11
L'Oreal	6	6	10	4	13	6	7	14
LVMH	32	43	42	54	18	50	34	35
Michelin	3	7	5	14	10	8	7	21
Peugeot	35	34	80	47	27	24	15	23
Renault	60	95	84	112	139	91	60	61
Saint Gobain	7	15	19	11	24	25	4	12
Sanofi	2	10	9	11	17	3	7	6
Schneider	5	10	9	5	11	3	1	8
Société Générale	58	49	53	45	31	46	8	33
Sodexho	9	4	4	1	0	3	5	3
Stmicroelectronics	34	43	20	54	30	70	26	52
Suez Lyonnaise des	32	28	46	80	53	37	50	57
Total	87	94	90	82	87	94	55	64
Valeo	10	12	11	3	22	8	2	14
Vivendi	93	182	208	149	111	108	243	175

Company	August 2000	September 2000	October 2000	November 2000	TOTAL	MEAN	STD. DEV.	CAC40 News	Market Capital
Accor	6	1	20	8	135	6	6	143	8'504'448'767
Agf	3	2	4	10	88	7	4	90	9'881'148'945
Air	4	7	5	0	124	10	9	140	12'617'100'753
Alcatel	73	39	131	138	1060	88	31	1255	74'545'766'570
Alstom	19	5	4	35	266	22	12	296	5'940'658'878
Aventis	24	15	71	147	474	40	37	494	46'431'642'472
Axa	62	8	18	34	385	32	14	392	57'129'278'200
Bic	0	0	2	0	15	1	1	18	2'530'868'590
BNP	51	38	8	55	487	41	15	504	41'542'116'914
Bouygues	27	12	22	46	401	33	18	499	20'965'460'705
CAC40 Index	83	34	75	96	1069	89	29	1069	
Canal	19	18	39	39	875	73	39	1072	26'151'009'863
Cap Gemini	19	4	6	50	353	29	18	473	22'738'312'534
Carrefour	37	17	0	20	404	34	20	460	52'632'599'567
Casino	8	9	3	14	148	12	9	171	8'263'886'113
Credit Lyonnais	4	12	12	18	257	21	11	290	13'664'533'413
Thomson-csf	19	15	21	32	294	25	14	328	7'098'289'225
Danone	22	10	9	76	402	34	18	426	18'810'626'067
EADS	20	19	40	40	535	45	30	548	17'074'565'199
Equant	17	17	18	50	328	27	14	451	15'431'623'594
Eridania	3	3	1	12	72	6	7	73	2'530'062'421
France	276	111	266	247	2831	236	67	3146	145'948'601'889
Lafarge	9	10	19	17	348	29	19	365	9'208'521'841
Lagardere	5	2	5	6	312	26	27	417	9'577'283'774
Legrand	3	7	3	0	36	3	3	46	4'510'453'696
L'Oreal	3	10	4	15	98	8	4	116	51'449'339'578
LVMH	22	7	18	38	393	33	14	451	41'713'036'882
Michelin	33	10	11	8	137	11	8	147	4'767'243'799
Peugeot	11	26	28	18	368	31	18	398	9'978'589'909
Renault	35	24	59	72	892	74	32	922	11'490'044'369
Saint Gobain	6	1	11	12	147	12	7	159	12'563'648'185
Sanofi	2	15	5	17	104	9	5	125	35'199'269'636
Schneider	4	4	20	4	84	7	5	104	11'426'911'501
Société Générale	28	20	11	47	429	36	17	456	24'676'041'281
Sodexho	1	0	3	0	33	3	3	43	5'632'088'753
Stmicroelectronics	22	6	44	67	468	39	20	622	52'922'065'071
Suez Lyonnaise des Eaux	74	24	33	71	585	49	19	608	34'409'032'814
Total	77	75	43	115	963	80	19	1040	112'487'946'368
Valeo	6	1	11	23	123	10	7	139	4'666'916'391
Vivendi	89	46	121	120	1645	137	56	1812	60'685'848'634

Table 3.7.4: Rank of Firm-specific news. This table reports firm-specific news (without CAC40 news) by month of the year during the period December 1, 1999 and November 30, 2000 released by the Reuters 2000 alert system and ranked considering the total number of news (from lowest to highest).

Company	December 1999	January 2000	February 2000	March 2000	April 2000	May 2000	June 2000
Bic	3	3	0	4	2	0	0
Sodexho	9	4	4	1	0	3	5
Legrand	1	3	3	3	1	1	0
Eridania	1	4	23	7	0	4	12
Schneider	5	10	9	5	11	3	1
Agf	12	10	11	13	9	8	5
L'Oreal	6	6	10	4	13	6	7
Sanofi	2	10	9	11	17	3	7
Valeo	10	12	11	3	22	8	2
Air	4	24	14	11	14	31	3
Accor	21	6	15	15	7	15	9
Michelin	3	7	5	14	10	8	7
Saint Gobain	7	15	19	11	24	25	4
Casino	4	7	17	26	15	31	5
Credit Lyonnais	41	24	16	29	38	31	11
Alstom	23	15	40	35	19	33	14
Thomson-csf	17	64	26	30	13	13	30
Lagardere	16	69	75	56	39	19	12
Equant	26	29	16	34	10	53	35
Lafarge	7	47	67	35	44	44	24
Cap Gemini	35	57	36	55	31	30	21
Peugeot	35	34	80	47	27	24	15
Axa	24	35	32	40	30	38	21
LVMH	32	43	42	54	18	50	34
Bouygues	61	16	29	29	28	70	39
Danone	35	36	35	49	19	39	41
Carrefour	27	62	64	44	26	39	15
Société Générale	58	49	53	45	31	46	8
Stmicroelectronics	34	43	20	54	30	70	26
Aventis	21	18	16	31	30	35	32
BNP	45	27	45	27	34	43	48
EADS	59	47	59	97	59	7	1
Suez Lyonnaise des Eaux	32	28	46	80	53	37	50
Canal	80	96	120	112	82	63	134
Renault	60	95	84	112	139	91	60
Total	87	94	90	82	87	94	55
Alcatel	63	59	111	73	66	114	90
CAC40 Index	130	123	133	102	66	82	76
Vivendi	93	182	208	149	111	108	243
France	210	155	158	250	242	316	260

Company	July 2000	August 2000	September 2000	October 2000	November 2000	TOTAL	MEAN	STD. DEV.
Bic	1	0	0	2	0	15	1.25	1.48
Sodexho	3	1	0	3	0	33	2.75	2.63
Legrand	11	3	7	3	0	36	3.00	3.16
Eridania	2	3	3	1	12	72	6.00	6.67
Schneider	8	4	4	20	4	84	7.00	5.10
Agf	1	3	2	4	10	88	7.33	4.14
L'Oreal	14	3	10	4	15	98	8.17	4.13
Sanofi	6	2	15	5	17	104	8.67	5.48
Valeo	14	6	1	11	23	123	10.25	7.06
Air	7	4	7	5	0	124	10.33	9.21
Accor	12	6	1	20	8	135	6.09	6.09
Michelin	21	33	10	11	8	137	11.42	8.22
Saint Gobain	12	6	1	11	12	147	12.25	7.50
Casino	9	8	9	3	14	148	12.33	8.77
Credit Lyonnais	21	4	12	12	18	257	21.42	11.46
Alstom	24	19	5	4	35	266	22.17	11.80
Thomson-csf	14	19	15	21	32	294	24.50	14.28
Lagardere	8	5	2	5	6	312	26.00	26.71
Equant	23	17	17	18	50	328	27.33	13.58
Lafarge	25	9	10	19	17	348	29.00	18.55
Cap Gemini	9	19	4	6	50	353	29.42	18.36
Peugeot	23	11	26	28	18	368	30.67	18.26
Axa	43	62	8	18	34	385	32.08	13.80
LVMH	35	22	7	18	38	393	32.75	14.10
Bouygues	22	27	12	22	46	401	33.42	17.63
Danone	31	22	10	9	76	402	33.50	18.20
Carrefour	53	37	17	0	20	404	33.67	19.75
Société Générale	33	28	20	11	47	429	35.75	16.53
Stmicroelectronics	52	22	6	44	67	468	39.00	19.53
Aventis	34	24	15	71	147	474	39.50	36.95
BNP	66	51	38	8	55	487	40.58	15.20
EADS	87	20	19	40	40	535	44.58	29.83
Suez Lyonnaise des Eaux	57	74	24	33	71	585	48.75	18.86
Canal	73	19	18	39	39	875	72.92	38.69
Renault	61	35	24	59	72	892	74.33	32.06
Total	64	77	75	43	115	963	80.25	19.31
Alcatel	103	73	39	131	138	1060	88.33	31.02
CAC40 Index	69	83	34	75	96	1069	89.08	29.22
Vivendi	175	89	46	121	120	1645	137.08	55.98
France	340	276	111	266	247	2831	235.92	67.14

Table 3.7.5: Rank of Firm-specific news by month of the year. This table reports firm-specific news (without CAC40 news) by month of the year during the period December 1, 1999 and November 30, 2000 released by the Reuters 2000 alert system and ranked considering the total number of news (from lowest to highest).

Company	December	Company	January	Company	February	Company	March	Company	April	Company	May
Eridania	1	Bic	3	Bic	0	Sodexho	1	Eridania	0	Bic	0
Legrand	1	Legrand	3	Legrand	3	Legrand	3	Sodexho	0	Legrand	1
Sanofi	2	Eridania	4	Sodexho	4	Valeo	3	Legrand	1	Sanofi	3
Bic	3	Sodexho	4	Michelin	5	Bic	4	Bic	2	Schneider	3
Michelin	3	Accor	6	Sanofi	9	L'Oreal	4	Accor	7	Sodexho	3
Air	4	L'Oreal	6	Schneider	9	Schneider	5	Agf	9	Eridania	4
Casino	4	Casino	7	L'Oreal	10	Eridania	7	Equant	10	L'Oreal	6
Schneider	5	Michelin	7	Agf	11	Air	11	Michelin	10	EADS	7
L'Oreal	6	Agf	10	Valeo	11	Saint Gobain	11	Schneider	11	Agf	8
Lafarge	7	Sanofi	10	Air	14	Sanofi	11	L'Oreal	13	Michelin	8
Saint Gobain	7	Schneider	10	Accor	15	Agf	13	Thomson-csf	13	Valeo	8
Sodexho	9	Valeo	12	Aventis	16	Michelin	14	Air	14	Thomson-csf	13
Valeo	10	Alstom	15	Credit Lyonnais	16	Accor	15	Casino	15	Accor	15
Agf	12	Saint Gobain	15	Equant	16	Casino	26	Sanofi	17	Lagardere	19
Lagardere	16	Bouygues	16	Casino	17	BNP	27	LVMH	18	Peugeot	24
Thomson-csf	17	Aventis	18	Saint Gobain	19	Bouygues	29	Alstom	19	Saint Gobain	25
Accor	21	Air	24	Stmicroelectronics	20	Credit Lyonnais	29	Danone	19	Cap Gemini	30
Aventis	21	Credit Lyonnais	24	Eridania	23	Thomson-csf	30	Valeo	22	Air	31
Alstom	23	BNP	27	Thomson-csf	26	Aventis	31	Saint Gobain	24	Casino	31
Axa	24	Suez Lyonnaise des Eaux	28	Bouygues	29	Equant	34	Carrefour	26	Credit Lyonnais	31
Equant	26	Equant	29	Axa	32	Alstom	35	Peugeot	27	Alstom	33
Carrefour	27	Peugeot	34	Danone	35	Lafarge	35	Bouygues	28	Aventis	35
LVMH	32	Axa	35	Cap Gemini	36	Axa	40	Aventis	30	Suez Lyonnaise des Eaux	37
Suez Lyonnaise des Eaux	32	Danone	36	Alstom	40	Carrefour	44	Axa	30	Axa	38
Stmicroelectronics	34	LVMH	43	LVMH	42	Société Générale	45	Stmicroelectronics	30	Carrefour	39
Cap Gemini	35	Stmicroelectronics	43	BNP	45	Peugeot	47	Cap Gemini	31	Danone	39
Danone	35	EADS	47	Suez Lyonnaise des	46	Danone	49	Société Générale	31	BNP	43
Peugeot	35	Lafarge	47	Société Générale	53	LVMH	54	BNP	34	Lafarge	44
Credit Lyonnais	41	Société Générale	49	EADS	59	Stmicroelectronics	54	Credit Lyonnais	38	Société Générale	46
BNP	45	Cap Gemini	57	Carrefour	64	Cap Gemini	55	Lagardere	39	LVMH	50
Société Générale	58	Alcatel	59	Lafarge	67	Lagardere	56	Lafarge	44	Equant	53
EADS	59	Carrefour	62	Lagardere	75	Alcatel	73	Suez Lyonnaise des Eaux	53	Canal	63
Renault	60	Thomson-csf	64	Peugeot	80	Suez Lyonnaise des Eaux	80	EADS	59	Bouygues	70
Bouygues	61	Lagardere	69	Renault	84	Total	82	Alcatel	66	Stmicroelectronics	70
Alcatel	63	Total	94	Total	90	EADS	97	CAC40	66	CAC40	82
Canal	80	Renault	95	Alcatel	111	CAC40	102	Canal	82	Renault	91
Total	87	Canal	96	Canal	120	Canal	112	Total	87	Total	94
Vivendi	93	CAC40	123	CAC40	133	Renault	112	Vivendi	111	Vivendi	108
CAC40	130	France	155	France	158	Vivendi	149	Renault	139	Alcatel	114
France	210	Vivendi	182	Vivendi	208	France	250	France	242	France	316

Table 3.7.5: (cont.) Rank of Firm-specific news by month of the year.

Company	June	Company	July	Company	August	Company	September	Company	October	Company	November
Bic	0	Agf	1	Bic	0	Bic	0	Carrefour	0	Air	0
Legrand	0	Bic	1	Sodexho	1	Sodexho	0	Eridania	1	Bic	0
EADS	1	Eridania	2	Sanofi	2	Accor	1	Bic	2	Legrand	0
Schneider	1	Sodexho	3	Agf	3	Saint Gobain	1	Casino	3	Sodexho	0
Valeo	2	Sanofi	6	Eridania	3	Valeo	1	Legrand	3	Schneider	4
Air	3	Air	7	Legrand	3	Agf	2	Sodexho	3	Lagardere	6
Saint Gobain	4	Lagardere	8	L'Oreal	3	Lagardere	2	Agf	4	Accor	8
Agf	5	Schneider	8	Air	4	Eridania	3	Alstom	4	Michelin	8
Casino	5	Cap Gemini	9	Credit Lyonnais	4	Cap Gemini	4	L'Oreal	4	Agf	10
Sodexho	5	Casino	9	Schneider	4	Schneider	4	Air	5	Eridania	12
L'Oreal	7	Legrand	11	Lagardere	5	Alstom	5	Lagardere	5	Saint Gobain	12
Michelin	7	Accor	12	Accor	6	Stmicroelectronics	6	Sanofi	5	Casino	14
Sanofi	7	Saint Gobain	12	Saint Gobain	6	Air	7	Cap Gemini	6	L'Oreal	15
Société Générale	8	L'Oreal	14	Valeo	6	Legrand	7	BNP	8	Lafarge	17
Accor	9	Thomson-csf	14	Casino	8	LVMH	7	Danone	9	Sanofi	17
Credit Lyonnais	11	Valeo	14	Lafarge	9	Axa	8	Michelin	11	Credit Lyonnais	18
Eridania	12	Credit Lyonnais	21	Peugeot	11	Casino	9	Saint Gobain	11	Peugeot	18
Lagardere	12	Michelin	21	Equant	17	Danone	10	Société Générale	11	Carrefour	20
Alstom	14	Bouygues	22	Alstom	19	Lafarge	10	Valeo	11	Valeo	23
Carrefour	15	Equant	23	Canal	19	L'Oreal	10	Credit Lyonnais	12	Thomson-csf	32
Peugeot	15	Peugeot	23	Cap Gemini	19	Michelin	10	Axa	18	Axa	34
Axa	21	Alstom	24	Thomson-csf	19	Bouygues	12	Equant	18	Alstom	35
Cap Gemini	21	Lafarge	25	EADS	20	Credit Lyonnais	12	LVMH	18	LVMH	38
Lafarge	24	Danone	31	Danone	22	Aventis	15	Lafarge	19	Canal	39
Stmicroelectronics	26	Société Générale	33	LVMH	22	Sanofi	15	Accor	20	EADS	40
Thomson-csf	30	Aventis	34	Stmicroelectronics	22	Thomson-csf	15	Schneider	20	Bouygues	46
Aventis	32	LVMH	35	Aventis	24	Carrefour	17	Thomson-csf	21	Société Générale	47
LVMH	34	Axa	43	Bouygues	27	Equant	17	Bouygues	22	Cap Gemini	50
Equant	35	Stmicroelectronics	52	Société Générale	28	Canal	18	Peugeot	28	Equant	50
Bouygues	39	Carrefour	53	Michelin	33	EADS	19	Suez Lyonnaise des Eaux	33	BNP	55
Danone	41	Suez Lyonnaise des Eaux	57	Renault	35	Société Générale	20	Canal	39	Stmicroelectronics	67
BNP	48	Renault	61	Carrefour	37	Renault	24	EADS	40	Suez Lyonnaise des Eaux	71
Suez Lyonnaise des Eaux	50	Total	64	BNP	51	Suez Lyonnaise des Eaux	24	Total	43	Renault	72
Total	55	BNP	66	Axa	62	Peugeot	26	Stmicroelectronics	44	Danone	76
Renault	60	CAC40	69	Alcatel	73	CAC40	34	Renault	59	CAC40	96
CAC40	76	Canal	73	Suez Lyonnaise des Eaux	74	BNP	38	Aventis	71	Total	115
Alcatel	90	EADS	87	Total	77	Alcatel	39	CAC40	75	Vivendi	120
Canal	134	Alcatel	103	CAC40	83	Vivendi	46	Vivendi	121	Alcatel	138
Vivendi	243	Vivendi	175	Vivendi	89	Total	75	Alcatel	131	Aventis	147
France	260	France	340	France	276	France	111	France	266	France	247

Table 3.7.6: Rank of Firm-specific news by month of the year and by market capitalization. This table reports firm-specific news (without CAC40 news) by month of the year during the period December 1, 1999 and November 30, 2000 released by the Reuters 2000 alert system and ranked considering the market capitalization (from lowest to highest).

Company	December 1999	January 2000	February 2000	March 2000	April 2000	May 2000	June 2000	Market Cap
Eridania	1	4	23	7	0	4	12	2'530'062'421
Bic	3	3	0	4	2	0	0	2'530'868'590
Legrand	1	3	3	3	1	1	0	4'510'453'696
Valeo	10	12	11	3	22	8	2	4'666'916'391
Michelin	3	7	5	14	10	8	7	4'767'243'799
Sodexho	9	4	4	1	0	3	5	5'632'088'753
Alstom	23	15	40	35	19	33	14	5'940'658'878
Thomson-csf	17	64	26	30	13	13	30	7'098'289'225
Casino	4	7	17	26	15	31	5	8'263'886'113
Accor	21	6	15	15	7	15	9	8'504'448'767
Lafarge	7	47	67	35	44	44	24	9'208'521'841
Lagardere	16	69	75	56	39	19	12	9'577'283'774
Agf	12	10	11	13	9	8	5	9'881'148'945
Peugeot	35	34	80	47	27	24	15	9'978'589'909
Schneider	5	10	9	5	11	3	1	11'426'911'501
Renault	60	95	84	112	139	91	60	11'490'044'369
Saint Gobain	7	15	19	11	24	25	4	12'563'648'185
Air	4	24	14	11	14	31	3	12'617'100'753
Credit Lyonnais	41	24	16	29	38	31	11	13'664'533'413
Equant	26	29	16	34	10	53	35	15'431'623'594
EADS	59	47	59	97	59	7	1	17'074'565'199
Danone	35	36	35	49	19	39	41	18'810'626'067
Bouygues	61	16	29	29	28	70	39	20'965'460'705
Cap Gemini	35	57	36	55	31	30	21	22'738'312'534
Société Générale	58	49	53	45	31	46	8	24'676'041'281
Canal	80	96	120	112	82	63	134	26'151'009'863
Suez Lyonnaise des Eaux	32	28	46	80	53	37	50	34'409'032'814
Sanofi	2	10	9	11	17	3	7	35'199'269'636
BNP	45	27	45	27	34	43	48	41'542'116'914
LVMH	32	43	42	54	18	50	34	41'713'036'882
Aventis	21	18	16	31	30	35	32	46'431'642'472
L'Oreal	6	6	10	4	13	6	7	51'449'339'578
Carrefour	27	62	64	44	26	39	15	52'632'599'567
Stmicroelectronics	34	43	20	54	30	70	26	52'922'065'071
Axa	24	35	32	40	30	38	21	57'129'278'200
Vivendi	93	182	208	149	111	108	243	60'685'848'634
Alcatel	63	59	111	73	66	114	90	74'545'766'570
Total	87	94	90	82	87	94	55	112'487'946'368
France	210	155	158	250	242	316	260	145'948'601'889
CAC40 Index	130	123	133	102	66	82	76	
Total	1439	1668	1851	1879	1517	1735	1462	

Company	July 2000	August 2000	September 2000	October 2000	November 2000	TOTAL	MEAN	STD. DEV.	Market Cap
Eridania	2	3	3	1	12	72	6.00	6.67	2'530'062'421
Bic	1	0	0	2	0	15	1.25	1.48	2'530'868'590
Legrand	11	3	7	3	0	36	3.00	3.16	4'510'453'696
Valeo	14	6	1	11	23	123	10.25	7.06	4'666'916'391
Michelin	21	33	10	11	8	137	11.42	8.22	4'767'243'799
Sodexho	3	1	0	3	0	33	2.75	2.63	5'632'088'753
Alstom	24	19	5	4	35	266	22.17	11.80	5'940'658'878
Thomson-csf	14	19	15	21	32	294	24.50	14.28	7'098'289'225
Casino	9	8	9	3	14	148	12.33	8.77	8'263'886'113
Accor	12	6	1	20	8	135	6.09	6.09	8'504'448'767
Lafarge	25	9	10	19	17	348	29.00	18.55	9'208'521'841
Lagardere	8	5	2	5	6	312	26.00	26.71	9'577'283'774
Agf	1	3	2	4	10	88	7.33	4.14	9'881'148'945
Peugeot	23	11	26	28	18	368	30.67	18.26	9'978'589'909
Schneider	8	4	4	20	4	84	7.00	5.10	11'426'911'501
Renault	61	35	24	59	72	892	74.33	32.06	11'490'044'369
Saint Gobain	12	6	1	11	12	147	12.25	7.50	12'563'648'185
Air	7	4	7	5	0	124	10.33	9.21	12'617'100'753
Credit Lyonnais	21	4	12	12	18	257	21.42	11.46	13'664'533'413
Equant	23	17	17	18	50	328	27.33	13.58	15'431'623'594
EADS	87	20	19	40	40	535	44.58	29.83	17'074'565'199
Danone	31	22	10	9	76	402	33.50	18.20	18'810'626'067
Bouygues	22	27	12	22	46	401	33.42	17.63	20'965'460'705
Cap Gemini	9	19	4	6	50	353	29.42	18.36	22'738'312'534
Société Générale	33	28	20	11	47	429	35.75	16.53	24'676'041'281
Canal	73	19	18	39	39	875	72.92	38.69	26'151'009'863
Suez Lyonnaise des Eaux	57	74	24	33	71	585	48.75	18.86	34'409'032'814
Sanofi	6	2	15	5	17	104	8.67	5.48	35'199'269'636
BNP	66	51	38	8	55	487	40.58	15.20	41'542'116'914
LVMH	35	22	7	18	38	393	32.75	14.10	41'713'036'882
Aventis	34	24	15	71	147	474	39.50	36.95	46'431'642'472
L'Oreal	14	3	10	4	15	98	8.17	4.13	51'449'339'578
Carrefour	53	37	17	0	20	404	33.67	19.75	52'632'599'567
Stmicroelectronics	52	22	6	44	67	468	39.00	19.53	52'922'065'071
Axa	43	62	8	18	34	385	32.08	13.80	57'129'278'200
Vivendi	175	89	46	121	120	1645	137.08	55.98	60'685'848'634
Alcatel	103	73	39	131	138	1060	88.33	31.02	74'545'766'570
Total	64	77	75	43	115	963	80.25	19.31	112'487'946'368
France	340	276	111	266	247	2831	235.92	67.14	145'948'601'889
CAC40 Index	69	83	34	75	96	1069	89.08	29.22	
Total	1666	1226	684	1224	1817	18168	41.25	47.65	

Table 3.7.7.: News category: This table reports seven of the eight news categories considered. Firm-specific news are not reported. In each category, a keyword is given for every subgroup.

Category	Subgroup / Keyword	News
All Alerts	AA	All Alerts
Political news	DIP	Diplomatic affairs
	POL	Politics
	VOTE	Elections
Market news	C	All commodity news
	E	All Reuters international equity news
	E-DRV	Equity derivative news
	EQB	Equity linked bonds
	EUB/	Eurobonds
	EUR	Euro
	EUROPE-EUB	European Eurobond news
	FRX	Forex news
	FX/OPT	News on currency options
	M	Reuters money news
	MMT	Money markets
	T	Treasury news
	DRV	Derivatives
	MTG/	Mortgage-backed
	OPEC	OPEC
	OPTIONS	Option news
Industrial	AER	Aerospace & military technology
	APL	Appliances & household durables
	AUT	Automobiles
	BEV	Beverages & tobacco
	BLD	Building materials & components
	CHE	Chemicals
	CON	Construction & housing
	COT	Cotton & silk
	ELC	Electrical & electronics
	ELI	Electronic components / instruments
	FOD	Food & households products
	IND	Industrial components
	MAC	Machinery & engineering
	TIM	Forest products & paper
	TEX	Textiles & apparel
	WOO	Wool
	DPR	Data processing & reproduction
	GDM	Gold mines
	GRA	Grains
	GRO	All grains / oilseed news
	REC	Recreation, other consumer goods

TABLE 3.7.7 (cont.)

General	LIF	Lifestyle
	CRIM	Criminality
	DIS	General / manmade disasters
	ENT	Entertainment
	ENV	Environment
	G	General / human interest news
	ODD	Human interest
	REL	Religion
	SCI	Science technology
	SPO	Sports news
	WEA	Weather news
Economic	BNK	Banking
	CEN	Central banks
	D	Reuters news for debt market
	DBT	Debt news
	ECB	European central bank
	FED	Federal reserve news
	INSTANT	Fast analysis of economic data
	INT	Interest rates news
	MCE	Macroeconomics
	TRD	International debt issues
Corporate	AAA	Rating news
	DBT-ISU	New issue headlines
	DIV	Dividends
	EUB-ISU	Eurobond new issue news
	IPO	New equity issue
	GLANCE/RCH	Hot stocks research alert
	HOT	Most active shares
	IDEA	Trading idea & strategies
	MRG	Merger & acquisition
	RCH	Broker research
	RES	Company results
	RESF	Company results forecasts

TABLE 3.7.8: Samples of Reuters news. This table reports some news of each category during the month of December 1999 released by the Reuters 2000 News Alert System.

ALL ALERTS

Date	CET	GMT	News
03.12.1999	161500	151500	RTRS-London gold fix higher in PM, spot off lows
03.12.1999	161500	151500	RTRS-Moody's rates Kansai Electric < 9503.T> bonds Aa2
03.12.1999	161600	151600	BSW-Nunn, Wolfowitz to Head Special Hughes Task Force to Review Company's < GM.N>
03.12.1999	161600	151600	BSW-REMINDER/Holiday Retail Story and Photo Opportunity; Psychic Holiday Helper at
03.12.1999	161600	151600	BSW-TSIG.com Partners with Coca-Cola for Superbowl Promotion < TSIG.OB>
03.12.1999	161600	151600	PRN-GoCo-op Completes Successful Round of Financing
03.12.1999	161600	151600	RNS-RNS-SVB Holdings PLC < SVB.L> Directors' Shareholdings
03.12.1999	161600	151600	RNS-RNS-Text 100 Group PLC Doc reAdmission to OFL,etc
03.12.1999	161600	151600	RTRS-FOCUS-Schroeder slams Britain, lauds France
03.12.1999	161600	151600	RTRS-Greenspan to attend Commerce Dept. press briefing
03.12.1999	161700	151700	BSW-UCSD Extension to Offer New Certificate in Clinical Trials Administration
03.12.1999	161700	151700	PRN-Vanguard Health Care Fund to Reopen to New Accounts
03.12.1999	161700	151700	RNS-RNS-Hull Trading UK EMM Disclosure< NWB.L> < BSCT.L> < RBOS.L>
03.12.1999	161700	151700	RNS-RNS-Lon.&Manchester Gp Circ re Resolution Passed
03.12.1999	161700	151700	RTRS-Saudi highway robbers' hands, feet chopped off
03.12.1999	161700	151700	RTRS-TABLE-Venezuela 2000 economic forecasts from IESA
03.12.1999	161700	151700	RTRS-Telecom Developement sees sales doubling in 1999
03.12.1999	161800	151800	RNS-RNS-Salomon Brothers EMM Disclosure< CW.L>
03.12.1999	161800	151800	RNS-RNS-Total Fina S.A. Statement re Production
03.12.1999	161800	151800	RTRS-Essar Steel < ESRG.BO> notice to FRN holders
03.12.1999	161900	151900	RNS-RNS-British-BorneoOil&Gs < BBOR.L> Rule 8 Disclosure
03.12.1999	161900	151900	RTRS-***GLANCE - Brazil top stories at 1515 GMT***
03.12.1999	161900	151900	RTRS-EU could have say in Kirch-Murdoch deal-Germany

POLITICAL NEWS

Date	CET	GMT	News
01.12.1999	195500	185500	RTRS-Colombia sets jail terms for heinous crimes
01.12.1999	195900	185900	RTRS-FOCUS-Mozambique faces split vote in weekend polls
01.12.1999	200000	190000	BSW-ADVISORY/National Urban League Media Advisory
01.12.1999	200000	190000	RTRS-Insecticide from GM corn seeps into soil - study
01.12.1999	200000	190000	RTRS-U.S. ambassador to Haiti resigns
01.12.1999	200000	190000	RTRS-UK may be forced to close nuclear plants -report
01.12.1999	200100	190100	RTRS-Iran welcomes Gulf Arab stand on islands row
01.12.1999	200300	190300	RTRS-Reuters World News highlights 1900 GMT, Dec 1
01.12.1999	200400	190400	BSW-National Boston Medical, Inc. Reports First Quarter Financial Results < NBMX.OB>
01.12.1999	200400	190400	RTRS-FOCUS-Italy PM starts ground-breaking Libya trip
01.12.1999	200500	190500	RTRS-DepoMed, Elan to develop gastric drug technology
01.12.1999	200600	190600	RTRS-Brazil's UOL expands with Venezuela Internet portal
01.12.1999	200700	190700	RTRS-Momentous gene breakthrough heralded as milestone
01.12.1999	200700	190700	RTRS-Moody's issues mutual fund report for November
01.12.1999	200800	190800	RTRS-Rolimpex< ROLIs.WA> group H1 loss up to PLN 38 mln
01.12.1999	201100	191100	RTRS-Opposition veteran leads in Guinea-Bissau poll
01.12.1999	201300	191300	RTRS-Macedonia coalition may survive election row
01.12.1999	201400	191400	RTRS-Bass < BASS.L> buys Inter-Continental hotel lease
01.12.1999	201400	191400	RTRS-Vatican official urges WTO to listen to grassroots
01.12.1999	201500	191500	RTRS-California bus bank ads reach end of the line
01.12.1999	201600	191600	PRN-MDS Harris Names Ebi Kalahi Kimanani, Ph.D. to Newly Created Position of Vice
01.12.1999	201600	191600	PRN-Pharmacia & Upjohn Scientists Isolate Important Alzheimer's Disease < PNU.N>
01.12.1999	201800	191800	RTRS-FOCUS-U.S. FTC staff opposes BP Amoco-Arco merger

TABLE 3.7.8 (cont.)

MARKET NEWS

Date	CET	GMT	News
01.12.1999	104400	94400	RTRS-Indian Shipping-Bombay Port berths, vessels status
01.12.1999	104400	94400	RTRS-KepFELS < KFEI.SI> to buy 5.4 pct SPC stake
01.12.1999	104400	94400	RTRS-RESEARCH ALERT-ABN AMRO downgrades Allied < ALLD.L>
01.12.1999	104500	94500	RTRS-Finnish forestries gain on shift from techs
01.12.1999	104500	94500	RTRS-Hungary forint eases vs band on yr-end uncertainty
01.12.1999	104500	94500	RTRS-LIFFE March cocoa falls sharply in early trade
01.12.1999	104500	94500	RTRS-Swiss shares shrug off early losses
01.12.1999	104500	94500	RTRS-Telia-Telenor says Esat rejected bid outright
01.12.1999	104600	94600	RTRS-Jordan, Iraq open talks on renewal of oil deal
01.12.1999	104600	94600	RTRS-Korea Aluminium-Suppliers, buyers apart on premium
01.12.1999	104600	94600	RTRS-LIFFE coffee rockets above resistance
01.12.1999	104600	94600	RTRS-Mediator meets with Microsoft in Chicago - WSJ
01.12.1999	104600	94600	RTRS-Singapore stocks end lower, technology stocks hit
01.12.1999	104800	94800	RTRS-LIFFE white sugar falls to new contract low
01.12.1999	104800	94800	RTRS-S.Africa rand moves firmer at midday, bonds steady
01.12.1999	104900	94900	RTRS-Croatia soon to complete Privredna selloff -paper
01.12.1999	104900	94900	RTRS-Ericsson, Sprint in CDMA infrastructure deal
01.12.1999	104900	94900	RTRS-LME aluminium gains early, stocks fall
01.12.1999	104900	94900	RTRS-PRESS DIGEST - Ireland - Dec 1
01.12.1999	104900	94900	RTRS-UK's Prescott says air safety not compromised
01.12.1999	104900	94900	WSC-North America Energy Weather Summary
01.12.1999	105000	95000	RTRS-HKMA bought HK dlrs at convertibility rate in Oct
01.12.1999	105100	95100	RTRS-Latvia Ventspils port seen closed all day due wind

INDUSTRIAL NEWS

Date	CET	GMT	News
01.12.1999	41400	31400	RTRS-IBRA to tender Astra < ASII.JK> shares next week
01.12.1999	41700	31700	BSW-STREAMING VIDEO: December & January -- Important Times To Think About Your
01.12.1999	42200	32200	RTRS-TAKE A LOOK - Korean grain buying < GRAIN/TRD/KR1>
01.12.1999	42500	32500	BSW-STREAMING VIDEO: Sears Creates Handyman's Heaven Online
01.12.1999	42500	32500	RTRS-U.S. candidates go cyber for campaign fund-raising
01.12.1999	42600	32600	RTRS-CORRECTED-Olympus Optical to list sales unit in 2 yrs
01.12.1999	42600	32600	RTRS-PRESS DIGEST - British business press - December 1
01.12.1999	44200	34200	RTRS-Hatred of WTO spawns odd alliance in Seattle
01.12.1999	44600	34600	RTRS-Indonesian palm oil shipments Nov. 1-30
01.12.1999	44600	34600	RTRS-Philippines plans to buy 40,000 T U.S. soy, wheat
01.12.1999	45000	35000	RTRS-Canon< 7751.T> wins Samsung< 05930.KS> stepper order
01.12.1999	45300	35300	RTRS-CORRECTED - Profit-taking sends Toronto stocks spiraling down
01.12.1999	45500	35500	RTRS-Indonesia soymeal imports Nov. 1-30
01.12.1999	50000	40000	PRN-RateXchange Expands Finance Management < NAMI.OB>
01.12.1999	50100	40100	RTRS-Trifast < TRI.L> sees S$20 mln from S'pore centre
01.12.1999	50200	40200	RTRS-Income tax for Vietnamese at foreign co's may fall
01.12.1999	50400	40400	RTRS-TABLE-Hyundai Mtr Nov auto sales up 21.5 pct yr/yr
01.12.1999	50500	40500	RTRS-PRESS DIGEST - Financial Times - December 1
01.12.1999	50900	40900	RTRS-TABLE-Malaysia Powertek < PTEK.KL> 3-mth net rises
01.12.1999	50900	40900	RTRS-Timberline names senior vice presidents
01.12.1999	51500	41500	RTRS-HK exchange censures Q-tech < 0109.HK>
01.12.1999	51800	41800	RTRS-U.S. pushes Japan on giving up anti-dumping review
01.12.1999	52600	42600	RTRS-Japan says not protectionist despite rice tariff

TABLE 3.7.8 (cont.)

GENERAL NEWS

Date	CET	GMT	News
02.12.1999	170000	160000	RTRS-CSCE coffee eyes 150 cts/lb on Brazil crop fears
02.12.1999	170000	160000	RTRS-Libya vows to help stamp out terrorism
02.12.1999	170600	160600	RTRS-Dexia < DEXI.BR> bids for rest of Dexia France
02.12.1999	170600	160600	RTRS-EU grants free-market grain at weekly tender
02.12.1999	170600	160600	RTRS-Salzburg Festival names new artistic director
02.12.1999	170600	160600	RTRS-Soccer-Kenyan champions stripped of title for match-fixing
02.12.1999	170900	160900	RTRS-Euro Debt-Prices fall as euro nears dollar parity
02.12.1999	171200	161200	Reuters Sports Summary at 1545 GMT, Dec
02.12.1999	171200	161200	RTRS-ACNielsen< ART.N> buys UK media measurement firm MMS
02.12.1999	171200	161200	RTRS-INTERVIEW-Dexia sees no further merger with SocGen
02.12.1999	171300	161300	RTRS-Market Scrooges humbug European retailer rally
02.12.1999	171400	161400	RTRS-N.Ireland hopes peace will boost economy
02.12.1999	171500	161500	RTRS-Red Cross visits Algerian jails, first since 1992
02.12.1999	171500	161500	RTRS-S.African union to provide AZT for rape victims
02.12.1999	171600	161600	RTRS-EU sells intervention grain at weekly tender
02.12.1999	171600	161600	RTRS-Paris CAC ends in red, dragged by France Telecom
02.12.1999	171800	161800	RTRS-EU seen valuing French wheat around $90/tonne
02.12.1999	171800	161800	RTRS-Swiss Multimedia Co. Lysis Buys UK-Based Concision
02.12.1999	171900	161900	RTRS-Five killed in fighting near Somali airstrip
02.12.1999	171900	161900	RTRS-FOCUS-U.S. new home sales reach record in October
02.12.1999	171900	161900	RTRS-Gefco< PEUP.PA> eyes 14 bln franc turnover next year
02.12.1999	171900	161900	RTRS-Lagardere < LAGA.PA> rallies on Internet prospects
02.12.1999	172800	162800	RTRS-Canada trade sees big wheat and canola crops

ECONOMIC NEWS

Date	CET	GMT	News
09.12.1999	82200	72200	RTRS-DIARY - Today in Italy - December 9
09.12.1999	82200	72200	RTRS-INDICATORS-Czech Republic-Dec 9
09.12.1999	82600	72600	RTRS-INDICATORS - Latvia - Dec 8
09.12.1999	83000	73000	RTRS-India will be among fastest growing mkts-Deutsche
09.12.1999	83000	73000	RTRS-TABLE-Opinion polls on Swedish membership of EMU
09.12.1999	83000	73000	RTRS-TECHNICALS-Forex market outlook and key levels
09.12.1999	83500	73500	RTRS-Colt Telecom < CTM.L> sets 320 mln euro cnv note
09.12.1999	83600	73600	RTRS-TABLE-Russia's CPI 0.3 pct Nov 30-Dec 6
09.12.1999	83700	73700	RTRS-Swiss Nat Bank says Q3 GDP as expected
09.12.1999	83900	73900	RTRS-TECHNICALS-Debt market outlook and key levels
09.12.1999	84000	74000	RTRS-DIARY - Slovak Republic - to Dec 31
09.12.1999	84100	74100	RTRS-PRESS DIGEST- Spain - Dec 9
09.12.1999	84300	74300	RTRS-Dane Unidanmark's Tryg-Baltica buys Norway's Vesta
09.12.1999	84300	74300	RTRS-Euro drifts to day's lows against dollar in Europe
09.12.1999	84500	74500	RTRS-***INDICATORS - Slovak Republic - updated Dec 7***
09.12.1999	84600	74600	RTRS-S.Korea bonds end flat but sentiment better on won
09.12.1999	84700	74700	RTRS-Indonesia insists CPO exports roll on from Sumatra
09.12.1999	85300	75300	RTRS-French decision challenge to European Union-Byrne
09.12.1999	85400	75400	BSW-S&P Rates Intl Credit Recovery Japan One Y21 Bil. ABS
09.12.1999	85400	75400	RTRS-Duff&Phelps reaffirms S.Africa's currency ratings
09.12.1999	85600	75600	RTRS-Slovak November CPI up 0.4 pct mo/mo, 13.9 pct yr/yr
09.12.1999	85600	75600	RTRS-Slovak Q3 GDP up 0.6 pct yr/yr vs Q2 2.9 pct rise
09.12.1999	85700	75700	RTRS-German November steel output up 9.1 percent y/y

TABLE 3.7.8 (cont.)

CORPORATE NEWS

Date	CET	GMT	News
02.12.1999	172800	162800	RNS-RNS-Broadgate Investment < BGT.L> Net Asset Value
02.12.1999	172800	162800	RNS-RNS-First Ireland Inv. < FIC.L> Net Asset Value
02.12.1999	172900	162900	RTRS-CORRECTED - FACTBOX-Key data on Novartis< NOVZn.S> /AstraZeneca< AZN.ST>
02.12.1999	172900	162900	RTRS-Software, Internet shares slump on Danish bourse
02.12.1999	173000	163000	PRN-New York's Hottest Internet Executives Convene for First Ever Highland Capital
02.12.1999	173000	163000	RNS-RNS-Leveraged Inc Fd Ld < LIF.L> Net Asset Value
02.12.1999	173000	163000	RTRS-Irish private sector lending edges higher in Oct
02.12.1999	173100	163100	PRN-Burnham Pacific Announces Fourth Quarter 1999 Dividend < BPP.N>
02.12.1999	173100	163100	RTRS-Portugal's Colep surges on takeover talk
02.12.1999	173200	163200	RTRS-Suomi trustees okay sale of Pohjola< POHBS.HE> stake
02.12.1999	173300	163300	RNS-RNS-Goldman Sachs. EMM Disclosure< RBOS.L> < NWB.L> < BSCT.L> < BOC.L>
02.12.1999	173300	163300	RTRS-CORRECTED-AstraZeneca, Novartis did not discuss
02.12.1999	173300	163300	RTRS-Investors say "I do!" to the Knot Inc. IPO
02.12.1999	173400	163400	RTRS-U.S. mortgage-backeds lower amid lively dealings
02.12.1999	173500	163500	RTRS-Fitch IBCA cuts The Greenalls Group Plc ratings
02.12.1999	173700	163700	RTRS-RESEARCH ALERT - Brocade < BRCD.O> target raised
02.12.1999	173800	163800	RTRS-TABLE-World's largest crop protection producers
02.12.1999	174100	164100	RNS-RNS-Bank of Scotland Gov < BSCT.L> Rule 8 Disclosure
02.12.1999	174200	164200	RNS-RNS-Fidelity Jap. Values < FJV.L> Net Asset Value
02.12.1999	174200	164200	RTRS-Dexia seeks entry into pan-European stock indices
02.12.1999	174200	164200	RTRS-Misys< MSY.L> plays down meetings as stock surges
02.12.1999	174200	164200	RTRS-RESEARCH ALERT - Broadcom < BRCM.O> target raised
02.12.1999	174300	164300	PRN-National Discount Brokers Signs Marketing Agreement With Sandbox.com < NDB.N>

FIRM-SPECIFIC NEWS

Date	CET	GMT	News
02.12.1999	94100	84100	RTRS-Preussag< PRSG.DE> eyes link-ups with Club Med,Accor
02.12.1999	95300	85300	RTRS-Club Med < CMIP.PA> soars on Preussag link idea
02.12.1999	122200	112200	RTRS-Preussag partnership talk boosts Club Med< CMIP.PA>
02.12.1999	154800	144800	RTRS-FOCUS-Preussag eyes ties with French tourism firms
02.12.1999	163600	153600	RTRS-Preussag says open to anything on Club Med, Accor
03.12.1999	102400	92400	RTRS-PRESS DIGEST - Portugal – Dec 3
06.12.1999	133800	123800	RTRS-INTERVIEW-Accor< ACCP.PA> to exploit voucher boom
13.12.1999	95400	85400	RTRS-Accor < ACCP.PA> details investment plans - report
13.12.1999	145200	135200	RTRS-FOCUS-Preussag< PRSG.F> CEO eyes more acquisitions
15.12.1999	174300	164300	RTRS-Accor confirms 99 net attrib up about 10 percent
16.12.1999	81600	71600	RTRS-French bourse seen opening up in wake of U.S.
20.12.1999	175900	165900	RTRS-Abidjan bourse higher, assurers boost volume
20.12.1999	204200	194200	RTRS-Accor< ACCP.PA> adds 27 hotels to Australia chain
21.12.1999	90800	80800	RTRS-Accor< ACCP.PA> adds 27 hotels to its German network
21.12.1999	90800	80800	RTRS-Paris Bourse dips at open, but Bouygues jumps
21.12.1999	102700	92700	RTRS-Bass< BASS.L> wins SPHC bid in Australia--report
21.12.1999	113500	103500	RTRS-Paris Bourse lower early but Bouygues sparkles
21.12.1999	121800	111800	RTRS-Paris Bourse off at midday, Bouygues still sizzles
21.12.1999	130300	120300	RTRS-FOCUS-Bass< BASS.L> to win Australian hotels-source
22.12.1999	84300	74300	RTRS-Eurotunnel < ETL.L> < EUTL.PA> in Accor hotel deal
28.12.1999	95400	85400	RTRS-PRESS DIGEST - France - December 28
14.01.2000	125800	115800	RTRS-RESEARCH ALERT-Deutsche starts NH Hoteles as buy
17.01.2000	42500	32500	RTRS-Bass < BASS.L> continues Australian hotel buy talks

*Firm specific sample considers news related to the Accor stocks

**Reuters is not the only press agencies that publish its news on the Reuters terminal but also the Business Wire (BSW)

TABLE 3.7.9.A: T-statistic for All Alerts News. This table reports the t-values resulting when testing two adjacent means against each other within successive intraday periods of 5 minutes for All Alerts News. The t- values consider the period from December 1, 1999 to March 31, 2000). (*) means that results are significant at 5% level of significance, whereas (**) indicates significance at 1% level.

TIME	ALL ALERTS	VALUE OF DIFF.		TIME	ALL ALERTS	VALUE OF DIFF.	
905	0.437						
		2.986	**				
910	-0.245			1305	0.866		
		0.036				1.075	
915	-0.248			1310	0.567		
		-2.065	*			-0.437	
920	0.028			1315	0.662		
		1.300				**-3.096**	**
925	-0.159			1320	1.983		
		0.438				0.537	
930	-0.210			1325	1.656		
		-1.138				**2.134**	*
935	-0.079			1330	0.597		
		0.967				-1.393	
940	-0.191			1335	1.856		
		0.295				0.704	
945	-0.221			1340	1.096		
		-0.596				0.949	
950	-0.157			1345	0.502		
		0.409				**-2.649**	**
955	-0.202			1350	1.339		
		0.313				**2.817**	**
1000	-0.235			1355	0.410		
		-1.845				0.236	
1005	0.568			1400	0.363		
		1.733				**-3.023**	**
1010	-0.189			1405	1.335		
		0.220				0.978	
1015	-0.213			1410	0.964		
		-1.172				0.423	
1020	-0.069			1415	0.836		
		1.194				**-4.074**	**
1025	-0.216			1420	2.617		
		0.147				**2.221**	*
1030	-0.231			1425	1.534		
		-0.966				1.534	
1035	-0.126			1430	1.031		
		0.534				**-2.100**	*
1040	-0.186			1435	1.796		
		0.271				1.888	
1045	-0.215			1440	1.118		
		-0.566				**1.972**	*
1050	-0.153			1445	0.759		
		0.685				**-4.310**	**
1055	-0.229			1450	1.619		
		0.130				**4.427**	**
1100	-0.242			1455	0.757		
		-3.032	**			1.459	
1105	0.214			1500	0.618		
		2.048	*			**-2.261**	*
1110	-0.119			1505	1.240		
		-0.127				1.232	
1115	-0.102			1510	0.824		
		-2.913	**			-0.452	
1120	0.709			1515	0.943		
		2.883	**			**-2.169**	*
1125	-0.092			1520	1.834		
		0.652				0.146	
1130	-0.172			1525	1.721		
		-0.475				1.015	
1135	-0.116			1530	0.974		
		0.283				-0.008	
1140	-0.149			1535	0.977		
		0.192				0.917	
1145	-0.171			1540	0.710		
		-1.632				0.372	
1150	0.073			1545	0.623		
		1.472				-0.915	
1155	-0.146			1550	0.851		
		0.119				1.404	
1200	-0.160			1555	0.515		
		-3.050	**			0.075	
1205	0.451			1600	0.500		
		1.733				-1.305	
1210	0.063			1605	0.805		
		0.120				1.117	
1215	0.043			1610	0.540		
		-4.048	**			0.252	
1220	1.245			1615	0.489		
		3.887	**			**-2.637**	**
1225	0.077			1620	1.163		
		0.818				**2.570**	*
1230	-0.041			1625	0.502		
		-1.352				0.527	
1235	0.177			1630	0.402		
		1.233				-0.494	
1240	-0.030			1635	0.495		
		-0.173				-1.041	
1245	-0.005			1640	1.246		
		-2.483	*			0.539	
1250	0.525			1645	0.834		
		2.508	*			0.808	
1255	-0.003			1650	0.571		
		-0.475				0.669	
1300	0.071			1655	0.439		
		-2.997	**			-1.101	
1305	0.866			1700	1.459		

TABLE 3.7.9.B: T-statistic for Political News. This table reports the t-values resulting when testing two adjacent means against each other within successive intraday periods of 5 minutes for Political News. The t- values consider the period from December 1, 1999 to March 30, 2000). (*) means that results are significant at 5% level of significance, whereas (**) indicates significance at 1% level.

TIME	POLITICAL	VALUE OF DIFF.		TIME	POLITICAL	VALUE OF DIFF.	
905	1.213						
910	0.398	**6.271**	**	1305	0.882		
915	0.367	0.382		1310	0.634	**2.544**	*
920	0.543	**-2.155**	*	1315	0.621	0.161	
925	0.456	1.129		1320	1.087	**-4.938**	**
930	0.465	-0.131		1325	0.722	**3.854**	**
935	0.725	**-4.225**	**	1330	0.588	1.452	
940	0.394	**5.355**	**	1335	0.724	-1.252	
945	0.392	0.033		1340	0.576	1.282	
950	0.354	0.538		1345	0.592	-0.137	
955	0.387	-0.458		1350	1.024	**-3.752**	**
1000	0.338	0.815		1355	0.485	**5.719**	**
1005	0.821	**-5.054**	**	1400	0.440	0.717	
1010	0.431	**3.996**	**	1405	0.773	**-3.686**	**
1015	0.322	1.404		1410	0.778	-0.050	
1020	0.442	-1.712		1415	0.617	0.982	
1025	0.397	0.806		1420	1.501	**-3.413**	**
1030	0.356	0.682		1425	0.990	**2.334**	*
1035	0.610	**-4.230**	**	1430	0.789	**2.257**	*
1040	0.411	**3.942**	**	1435	0.938	**-2.076**	*
1045	0.395	0.317		1440	0.782	**2.192**	*
1050	0.399	-0.063		1445	0.800	-0.184	
1055	0.376	0.355		1450	1.062	**-2.643**	**
1100	0.410	-0.530		1455	0.843	**2.490**	*
1105	0.910	**-6.963**	**	1500	0.774	0.819	
1110	0.487	**5.413**	**	1505	1.202	**-3.191**	*
1115	0.604	-1.552		1510	1.000	1.395	
1120	0.812	-1.850		1515	0.867	1.293	
1125	0.560	**2.244**	*	1520	1.311	**-4.205**	**
1130	0.491	0.883		1525	0.978	**3.556**	**
1135	0.471	0.280		1530	0.865	1.426	
1140	0.520	-0.903		1535	1.089	**-2.714**	**
1145	0.498	0.317		1540	0.938	**2.145**	*
1150	0.682	-1.823		1545	0.916	0.326	
1155	0.628	0.552		1550	1.080	**-2.276**	*
1200	0.545	1.101		1555	0.876	**2.724**	**
1205	1.221	**-8.481**	**	1600	0.891	-0.201	
1210	0.781	**6.054**	**	1605	1.144	**-2.296**	*
1215	0.798	-0.300		1610	1.016	1.175	
1220	1.225	**-3.690**	**	1615	1.000	0.262	
1225	0.729	**3.946**	**	1620	1.269	**-3.825**	**
1230	0.692	0.533		1625	1.075	**2.370**	*
1235	0.750	-1.079		1630	0.906	**2.586**	**
1240	0.650	1.737		1635	1.010	**-2.205**	*
1245	0.703	-0.849		1640	0.998	0.177	
1250	0.810	-1.332		1645	0.964	0.464	
1255	0.419	**4.195**	**	1650	1.091	**-2.119**	*
1300	0.457	-0.467		1655	1.135	-0.784	
1305	0.882	**-4.724**	**	1700	1.014	1.907	

TABLE 3.7.9.C: T-statistic for Market News. This table reports the t-values resulting when testing two adjacent means against each other within successive intraday periods of 5 minutes for Market News. The t- values consider the period from December 1, 1999 to March 30, 2000). (*) means that results are significant at 5% level of significance, whereas (**) indicates significance at 1% level.

TIME	MARKET	VALUE OF DIFF.	TIME	MARKET	VALUE OF DIFF.
905	0.550				
		2.025 *			
910	-0.072		1305	0.432	
		0.060			0.749
915	-0.083		1310	0.166	
		0.065			0.074
920	-0.095		1315	0.145	
		-0.901			-1.283
925	0.102		1320	0.691	
		-0.206			-0.127
930	0.151		1325	0.776	
		0.337			0.031
935	0.074		1330	0.754	
		1.013			-0.450
940	-0.151		1335	1.077	
		-0.561			0.381
945	-0.034		1340	0.827	
		0.175			-0.461
950	-0.068		1345	1.161	
		0.179			0.385
955	-0.104		1350	0.883	
		-0.278			-0.266
1000	-0.045		1355	1.035	
		-1.859			1.122
1005	0.926		1400	0.421	
		1.463			-1.862
1010	0.165		1405	1.692	
		-1.023			1.377
1015	0.523		1410	0.700	
		0.531			0.080
1020	0.317		1415	0.663	
		1.808			-0.026
1025	-0.170		1420	0.672	
		-1.004			0.726
1030	0.001		1425	0.418	
		-0.552			0.643
1035	0.197		1430	0.215	
		-0.092			**-1.964** *
1040	0.244		1435	0.792	
		0.266			0.684
1045	0.121		1440	0.593	
		-0.438			-0.936
1050	0.377		1445	1.868	
		0.073			0.473
1055	0.324		1450	1.163	
		0.675			0.614
1100	-0.027		1455	0.719	
		-1.153			0.173
1105	0.242		1500	0.642	
		0.933			-0.588
1110	0.014		1505	0.875	
		0.836			1.047
1115	-0.165		1510	0.477	
		-0.738			-0.503
1120	-0.003		1515	0.639	
		0.478			-1.107
1125	-0.105		1520	1.082	
		-0.090			0.769
1130	-0.088		1525	0.758	
		0.517			-1.137
1135	-0.184		1530	2.125	
		0.124			0.111
1140	-0.209		1535	1.971	
		0.153			0.950
1145	-0.242		1540	1.166	
		-0.387			-0.165
1150	-0.168		1545	1.291	
		0.012			1.115
1155	-0.171		1550	0.549	
		-0.138			-0.985
1200	-0.146		1555	1.300	
		-2.182 *			1.050
1205	0.470		1600	0.522	
		1.077			-0.583
1210	0.129		1605	0.700	
		0.549			0.567
1215	-0.006		1610	0.489	
		-0.055			0.363
1220	0.006		1615	0.369	
		0.955			-0.702
1225	-0.186		1620	0.703	
		-0.668			0.613
1230	-0.063		1625	0.405	
		-0.783			0.654
1235	0.160		1630	0.210	
		0.205			-1.142
1240	0.091		1635	3.972	
		-0.163			0.820
1245	0.149		1640	1.160	
		-0.258			0.329
1250	0.251		1645	0.798	
		0.365			0.579
1255	0.136		1650	0.470	
		-0.154			0.973
1300	0.180		1655	0.227	
		-0.672			0.001
1305	0.432		1700	0.227	

TABLE 3.7.9.D: T-statistic for Industrial News. This table reports the t-values resulting when testing two adjacent means against each other within successive intraday periods of 5 minutes for Industrial News. The t- values consider the period from December 1, 1999 to March 30, 2000). (*) means that results are significant at 5% level of significance, whereas (**) indicates significance at 1% level.

TIME	INDUSTRIAL	VALUE OF DIFF.	
905	-0.389		
		1.462	
910	-0.487		
		1.179	
915	-0.542		
		-6.450	**
920	-0.337		
		4.932	**
925	-0.509		
		0.676	
930	-0.535		
		-3.098	**
935	-0.420		
		3.170	**
940	-0.525		
		0.258	
945	-0.532		
		-1.355	
950	-0.491		
		0.201	
955	-0.498		
		0.323	
1000	-0.509		
		-3.475	**
1005	-0.343		
		2.394	*
1010	-0.476		
		-0.028	
1015	-0.475		
		-3.696	**
1020	-0.165		
		3.887	**
1025	-0.500		
		-0.168	
1030	-0.494		
		-1.673	
1035	-0.422		
		0.998	
1040	-0.472		
		0.917	
1045	-0.508		
		-2.846	**
1050	-0.376		
		2.252	*
1055	-0.497		
		-0.310	
1100	-0.483		
		-3.043	**
1105	-0.077		
		2.058	*
1110	-0.383		
		-0.061	
1115	-0.378		
		-4.105	**
1120	1.270		
		3.801	**
1125	-0.264		
		2.475	*
1130	-0.456		
		-1.546	
1135	-0.337		
		1.065	
1140	-0.414		
		-0.221	
1145	-0.402		
		-3.783	**
1150	0.071		
		3.655	**
1155	-0.373		
		1.876	
1200	-0.460		
		-4.751	**
1205	0.516		
		2.499	*
1210	-0.104		
		0.287	
1215	-0.148		
		-7.402	**
1220	2.566		
		6.555	**
1225	0.140		
		3.496	**
1230	-0.221		
		-3.317	**
1235	0.262		
		2.586	**
1240	-0.151		
		-0.247	
1245	-0.118		
		-4.542	**
1250	1.036		
		4.120	**
1255	-0.032		
		-0.732	
1300	0.097		
		-4.248	**
1305	1.651		

TIME	INDUSTRIAL	VALUE OF DIFF.	
1305	1.651		
		2.103	*
1310	0.726		
		-0.243	
1315	0.821		
		-5.404	**
1320	4.198		
		1.834	
1325	2.581		
		1.850	
1330	1.147		
		-0.647	
1335	1.413		
		3.100	**
1340	0.574		
		0.593	
1345	0.422		
		-5.366	**
1350	2.522		
		4.294	**
1355	0.815		
		0.479	
1400	0.721		
		-4.774	**
1405	2.695		
		1.654	
1410	1.809		
		0.687	
1415	1.541		
		-7.968	**
1420	5.485		
		3.705	**
1425	3.336		
		5.294	**
1430	1.324		
		-1.457	
1435	1.692		
		3.414	**
1440	0.961		
		2.894	**
1445	0.645		
		-5.008	**
1450	2.269		
		4.507	**
1455	0.773		
		-0.434	
1500	0.826		
		-3.183	**
1505	2.138		
		1.468	
1510	1.450		
		1.839	
1515	0.968		
		-4.014	**
1520	3.424		
		2.703	**
1525	1.539		
		2.136	*
1530	0.777		
		-1.985	*
1535	1.012		
		3.342	**
1540	0.654		
		0.640	
1545	0.608		
		-3.783	**
1550	1.096		
		4.281	**
1555	0.575		
		0.028	
1600	0.574		
		-3.508	**
1605	1.107		
		2.105	*
1610	0.742		
		1.132	
1615	0.616		
		-7.413	**
1620	1.958		
		7.096	**
1625	0.691		
		2.617	**
1630	0.522		
		-3.366	**
1635	0.710		
		2.772	**
1640	0.562		
		-0.456	
1645	0.585		
		-3.255	**
1650	0.846		
		3.733	**
1655	0.511		
		-0.836	
1700	0.568		

TABLE 3.7.9.E: T-statistic for General News. This table reports the t-values resulting when testing two adjacent means against each other within successive intraday periods of 5 minutes for General News. The t- values consider the period from December 1, 1999 to March 30, 2000). (*) means that results are significant at 5% level of significance, whereas (**) indicates significance at 1% level.

TIME	GENERAL	VALUE OF DIFF.		TIME	GENERAL	VALUE OF DIFF.	
905	0.127	**2.186**	*	1305	0.552	1.082	
910	0.028	0.917		1310	0.353	1.141	
915	-0.022	**-3.095**	**	1315	0.247	**-4.333**	**
920	0.782	1.316		1320	0.833	1.826	
925	0.363	1.423		1325	0.522	1.590	
930	0.083	0.476		1330	0.280	-1.729	
935	0.053	1.166		1335	0.504	**2.632**	**
940	-0.002	-0.418		1340	0.209	1.354	
945	0.016	1.459		1345	0.101	**-6.053**	**
950	-0.058	-1.027		1350	0.637	**5.313**	**
955	0.002	0.764		1355	0.214	-0.430	
1000	-0.046	-1.432		1400	0.243	**-2.734**	**
1005	0.038	1.199		1405	1.056	0.997	
1010	-0.021	0.201		1410	0.696	0.832	
1015	-0.030	-1.842		1415	0.491	**-5.266**	**
1020	0.089	1.852		1420	1.316	**4.690**	**
1025	-0.034	-0.985		1425	0.766	**3.389**	**
1030	0.023	-0.581		1430	0.457	-1.716	
1035	0.060	1.114		1435	0.787	**2.167**	*
1040	-0.010	0.667		1440	0.369	0.433	
1045	-0.043	0.648		1445	0.334	**-3.957**	**
1050	-0.075	-0.727		1450	0.722	**4.620**	**
1055	-0.035	0.468		1455	0.299	-1.359	
1100	-0.061	**-8.081**	**	1500	0.375	**-2.892**	**
1105	0.439	**6.234**	**	1505	1.179	1.838	
1110	0.014	0.717		1510	0.601	1.089	
1115	-0.033	**-3.349**	**	1515	0.417	**-4.278**	**
1120	0.377	**2.786**	**	1520	0.972	**2.913**	**
1125	0.035	0.132		1525	0.607	**2.372**	*
1130	0.027	0.173		1530	0.404	-1.304	
1135	0.018	-0.597		1535	0.546	**2.024**	*
1140	0.053	0.542		1540	0.343	-0.305	
1145	0.022	**-2.062**	*	1545	0.358	-1.958	
1150	0.184	1.748		1550	0.487	1.027	
1155	0.038	0.687		1555	0.408	1.912	
1200	-0.004	**-6.959**	**	1600	0.276	**-2.883**	**
1205	0.731	**5.236**	**	1605	0.689	1.548	
1210	0.173	0.547		1610	0.455	0.596	
1215	0.137	**-4.418**	**	1615	0.410	**-4.770**	**
1220	0.632	**4.331**	**	1620	0.737	**5.598**	**
1225	0.115	-0.129		1625	0.356	-1.689	
1230	0.125	**-2.370**	**	1630	0.467	0.658	
1235	0.273	**3.799**	**	1635	0.408	-0.058	
1240	0.017	-0.649		1640	0.413	0.372	
1245	0.054	**-3.055**	**	1645	0.389	-0.881	
1250	0.234	**3.398**	**	1650	0.447	0.931	
1255	0.036	-0.591		1655	0.389	0.834	
1300	0.069	**-2.707**	**	1700	0.323		
1305	0.552						

TABLE 3.7.9.F: T-statistic for Economic News. This table reports the t-values resulting when testing two adjacent means against each other within successive intraday periods of 5 minutes for Economic News. The t- values consider the period from December 1, 1999 to March 30, 2000). (*) means that results are significant at 5% level of significance, whereas (**) indicates significance at 1% level.

TIME	ECONOMIC	VALUE OF DIFF.		TIME	ECONOMIC	VALUE OF DIFF.	
905	0.683			1305	0.783		
910	0.068	**9.026**	**	1310	0.477	**3.899**	**
915	0.044	0.354		1315	0.430	0.499	
920	0.142	-1.493		1320	1.487	**-3.729**	**
925	0.021	1.482		1325	0.934	1.481	
930	0.016	0.054		1330	0.526	1.340	
935	0.418	**-5.102**	**	1335	0.811	-1.438	
940	0.281	1.836		1340	0.470	**2.366**	*
945	0.162	1.765		1345	0.456	0.103	
950	0.103	1.080		1350	1.186	**-3.494**	**
955	0.062	0.553		1355	0.546	**3.371**	**
1000	0.075	-0.177		1400	0.393	**2.246**	*
1005	0.592	**-4.998**	**	1405	0.980	**-6.295**	**
1010	0.183	**3.834**	**	1410	0.616	**2.812**	**
1015	0.127	0.828		1415	0.673	-0.441	
1020	0.226	-1.371		1420	1.685	**-4.691**	**
1025	0.039	**2.675**	**	1425	0.982	**2.963**	**
1030	0.043	-0.060		1430	0.520	**3.647**	**
1035	0.264	**-3.245**	**	1435	1.064	**-6.045**	**
1040	0.070	**2.757**	**	1440	0.656	**3.758**	**
1045	0.031	0.602		1445	0.583	0.892	
1050	0.011	0.349		1450	1.125	**-4.416**	**
1055	-0.012	0.579		1455	0.612	**4.063**	**
1100	0.025	-0.701		1500	0.663	-0.497	
1105	0.824	**-9.946**	**	1505	1.174	**-4.321**	**
1110	0.188	**7.243**	**	1510	0.707	**4.931**	**
1115	0.142	0.648		1515	0.722	-0.200	
1120	0.872	**-4.663**	**	1520	1.391	**-4.784**	**
1125	0.128	**4.767**	**	1525	0.792	**4.048**	**
1130	0.034	**2.128**	*	1530	0.702	1.098	
1135	0.128	**-2.650**	**	1535	0.796	-1.681	
1140	0.072	1.534		1540	0.590	**4.221**	**
1145	-0.001	**2.030**	*	1545	0.577	0.285	
1150	0.039	-0.719		1550	0.739	**-2.505**	**
1155	-0.045	1.538		1555	0.536	**3.205**	**
1200	-0.002	-1.269		1600	0.671	**-2.528**	*
1205	0.818	**-11.735**	**	1605	0.940	**-2.690**	**
1210	0.143	**8.900**	**	1610	0.574	**3.564**	**
1215	0.155	-0.239		1615	0.600	-0.378	
1220	0.838	**-4.294**	**	1620	1.035	**-4.455**	**
1225	0.121	**4.431**	**	1625	0.556	**5.272**	**
1230	0.090	0.542		1630	0.567	-0.210	
1235	0.244	**-2.106**	*	1635	0.719	**-2.784**	**
1240	0.145	1.239		1640	0.535	**3.370**	**
1245	0.208	-0.750		1645	0.538	-0.070	
1250	0.615	**-2.446**	*	1650	0.632	-1.931	
1255	0.271	**1.971**	*	1655	0.502	**2.560**	*
1300	0.267	0.041		1700	0.409	1.271	
1305	0.783	**-6.416**	**				

TABLE 3.7.9.G: T-statistic for Corporate News. This table reports the t-values resulting when testing two adjacent means against each other within successive intraday periods of 5 minutes for Economic News. The t- values consider the period from December 1, 1999 to March 30, 2000). (*) means that results are significant at 5% level of significance, whereas (**) indicates significance at 1% level.

TIME	CORPORATE	VALUE OF DIFF.		TIME	CORPORATE	VALUE OF DIFF.	
905	0.068						
910	-0.096	**2.037**	*	1305	0.745		
915	-0.120	0.373		1310	0.404	1.924	
920	0.084	**-3.054**	**	1315	0.344	0.393	
925	-0.108	**3.080**	**	1320	1.627	**-5.556**	**
930	-0.077	-0.478		1325	0.956	**2.095**	*
935	0.175	**-2.720**	**	1330	0.502	1.606	
940	-0.088	**3.071**	**	1335	0.927	**-2.191**	*
945	-0.101	0.208		1340	0.420	**3.263**	**
950	-0.056	-0.691		1345	0.350	0.575	
955	-0.055	-0.023		1350	1.494	**-5.395**	**
1000	-0.085	0.431		1355	0.467	**4.538**	**
1005	0.180	**-3.558**	**	1400	0.367	0.711	
1010	-0.030	**2.671**	**	1405	0.964	**-4.229**	**
1015	-0.053	0.313		1410	0.857	0.677	
1020	0.076	-1.482		1415	0.766	0.702	
1025	-0.133	**2.498**	*	1420	2.162	**-6.387**	**
1030	-0.105	-0.480		1425	1.266	**3.672**	**
1035	0.042	**-2.553**	*	1430	0.714	**3.426**	**
1040	-0.095	**2.278**	*	1435	1.047	**-2.518**	*
1045	-0.070	-0.378		1440	0.729	**2.154**	*
1050	-0.051	-0.303		1445	0.614	0.713	
1055	-0.059	0.129		1450	1.428	**-3.514**	**
1100	-0.011	-0.703		1455	0.673	**3.477**	**
1105	0.278	**-3.308**	**	1500	0.623	0.413	
1110	0.053	**2.512**	*	1505	1.044	**-2.939**	**
1115	-0.010	0.883		1510	0.764	**1.968**	*
1120	0.707	**-4.354**	**	1515	0.756	0.075	
1125	0.024	**4.054**	**	1520	1.644	**-4.013**	**
1130	-0.032	0.727		1525	0.926	**2.893**	**
1135	0.056	-1.084		1530	0.706	1.530	
1140	-0.057	1.566		1535	0.887	-1.955	
1145	-0.106	0.928		1540	0.670	**2.016**	*
1150	0.082	**-2.182**	*	1545	0.600	0.594	
1155	-0.032	1.318		1550	0.805	-1.933	
1200	-0.065	0.605		1555	0.539	**2.597**	**
1205	0.649	**-4.652**	**	1600	0.602	-0.654	
1210	0.202	**2.444**	*	1605	0.815	**-2.302**	*
1215	0.136	0.560		1610	0.656	1.275	
1220	1.163	**-5.656**	**	1615	0.640	0.131	
1225	0.140	**5.522**	**	1620	1.083	**-3.775**	**
1230	-0.000	**1.977**	*	1625	0.641	**3.209**	**
1235	0.297	**-2.713**	**	1630	0.529	0.881	
1240	0.054	1.902		1635	0.673	-1.443	
1245	-0.019	0.856		1640	0.588	0.969	
1250	0.562	**-4.703**	**	1645	0.629	-0.474	
1255	-0.062	**4.847**	**	1650	0.630	-0.011	
1300	0.017	-1.018		1655	0.642	-0.112	
1305	0.745	**-5.289**	**	1700	0.483	1.702	

TABLE 3.7.10.A: Mean equality test among months of the year and days of the week for All Alerts News: This test is based on a single-factor, between-subjects, analysis of variance (ANOVA). The basic idea is that if the subgroups have the same mean, then the variability between the sample means (between group) should be the same as the variability within any subgroup (within group).This test covers a one year period (December 1, 1999 – November 30, 2000) by month of the year and by day of the week within successive intraday periods of five minutes for All Alerts news related and non- to France.

All Alerts news

Method	df	Value	Probability
Anova F-statistic	(8, 2583)	4.837	0.000

Analysis of Variance

Source of Variation	df	Sum of Sq.	Mean Sq.
Between	8	3329.235	416.154
Within	2583	222227.000	86.034
Total	2591	225556.200	87.054

Category Statistics

Variable	Count	Mean	Std. Dev.	Std. Err. of Mean
DECEMBER	288	11.792	7.610	0.448
JANUARY	288	13.108	8.953	0.528
FEBRUARY	288	15.118	10.104	0.595
MARCH	288	15.161	10.167	0.599
APRIL	288	13.306	9.105	0.537
MAY	288	15.250	9.916	0.584
SEPTEMBER	288	13.257	8.935	0.526
OCTOBER	288	14.600	9.767	0.576
NOVEMBER	288	14.578	8.622	0.508
All	2592	14.019	9.330	0.183

Method	df	Value	Probability
Anova F-statistic	(4, 1435)	5.511	0.000

Analysis of Variance

Source of Variation	df	Sum of Sq.	Mean Sq.
Between	4	2316.198	579.050
Within	1435	150773.900	105.069
Total	1439	153090.100	106.386

Category Statistics

Variable	Count	Mean	Std. Dev.	Std. Err. of Mean
MONDAY	288	15.533	11.246	0.663
TUESDAY	288	17.008	11.323	0.667
WEDNESDAY	288	16.955	10.823	0.638
THURSDAY	288	16.368	10.152	0.598
FRIDAY	288	13.588	7.104	0.419
All	1440	15.890	10.314	0.272

All Alerts news France

Method	df	Value	Probability
Anova F-statistic	(8, 2583)	5.485	0.000

Analysis of Variance

Source of Variation	df	Sum of Sq.	Mean Sq.
Between	8.000	4.146	0.518
Within	2583.000	244.088	0.094
Total	2591.000	248.235	0.096

Category Statistics

Variable	Count	Mean	Std. Dev.	Std. Err. of Mean
DECEMBER	288.000	0.340	0.269	0.016
JANUARY	288.000	0.396	0.303	0.018
FEBRUARY	288.000	0.457	0.353	0.021
MARCH	288.000	0.469	0.347	0.020
APRIL	288.000	0.351	0.270	0.016
MAY	288.000	0.419	0.322	0.019
SEPTEMBER	288.000	0.418	0.292	0.017
OCTOBER	288.000	0.412	0.307	0.018
NOVEMBER	288.000	0.404	0.291	0.017
All	2592.000	0.407	0.310	0.006

Method	df	Value	Probability
Anova F-statistic	(4, 1435)	4.747	0.001

Analysis of Variance

Source of Variation	df	Sum of Sq.	Mean Sq.
Between	4.000	2.636	0.659
Within	1435.000	199.218	0.139
Total	1439.000	201.854	0.140

Category Statistics

Variable	Count	Mean	Std. Dev.	Std. Err. of Mean
MONDAY	288.000	0.439	0.339	0.020
TUESDAY	288.000	0.514	0.379	0.022
WEDNESDAY	288.000	0.534	0.381	0.022
THURSDAY	288.000	0.555	0.418	0.025
FRIDAY	288.000	0.467	0.339	0.020
All	1440.000	0.502	0.375	0.010

TABLE 3.7.10.B: Median equality tests among months of the year and days of the week for All Alerts News: This table reports various rank-based nonparametric tests of the hypothesis that the subgroups have the same median, against the alternative that at least one subgroup has a different median. ***Kruskal-Wallis one-way ANOVA by ranks test***. This is a generalization of the Mann-Whitney test to more than two subgroups. The test is based on a one-way analysis of variance using only ranks of the data. The Table reports the chi-square approximation to the Kruskal-Wallis test statistic (with tie correction). Under the null hypothesis, this statistic is approximately distributed as a χ^2 with the number of subgroups-1 degrees of freedom (see Sheskin, 1997). ***Van der Waerden (normal scores) test***. This test is analogous to the Kruskal-Wallis test, except that the ranks are smoothed by converting them into normal quantiles (Conover, 1980). This table reports a statistic which is approximately distributed as a χ^2 with the number of subgroups -1 degrees of freedom under the null hypothesis. ***Chi-square test for the median***. This is a rank-based ANOVA test based on the comparison of the number of observations above and below the overall median in each subgroup. This test is also known as the median test (Conover, 1980). These tests cover a one year period (December 1, 1999 – November 30, 2000) by month of the year and by day of the week within successive intraday periods of five minutes for All Alerts news related and non- to France.

All Alerts news

Method	df	Value	Probability
Med. Chi-square	8.000	66.429	0.000
Adj. Med. Chi-square	8.000	64.000	0.000
Kruskal-Wallis	8.000	52.251	0.000
van der Waerden	8.000	60.732	0.000

Category Statistics					
			> Overall		
Variable	Count	Median	Median	Mean Rank	Mean Score
DECEMBER	288	10.629	102.000	1098.851	-0.281
JANUARY	288	11.226	120.000	1198.913	-0.138
FEBRUARY	288	12.793	162.000	1380.302	0.128
MARCH	288	13.403	174.000	1403.668	0.155
APRIL	288	11.567	128.000	1220.017	-0.125
MAY	288	13.387	173.000	1421.280	0.174
SEPTEMBER	288	11.900	137.000	1233.267	-0.075
OCTOBER	288	12.371	147.000	1324.507	0.025
NOVEMBER	288	12.483	152.000	1387.694	0.137
All	2592	12.233	1295.000	1296.500	0.000

Method	df	Value	Probability
Med. Chi-square	4.000	22.789	0.000
Adj. Med. Chi-square	4.000	21.595	0.000
Kruskal-Wallis	4.000	18.001	0.001
van der Waerden	4.000	24.470	0.000

Category Statistics				
			> Overall	
Variable	Count	Median	Median	Mean Rank
MONDAY	288.000	13.221	126.000	672.764
TUESDAY	288.000	14.519	155.000	754.946
WEDNESDAY	288.000	15.009	162.000	768.476
THURSDAY	288.000	14.726	158.000	750.271
FRIDAY	288.000	12.731	118.000	656.043
All	1440.000	14.077	719.000	720.500

All Alerts news France

Method	df	Value	Probability
Med. Chi-square	8.000	14.773	0.064
Adj. Med. Chi-square	8.000	13.767	0.088
Kruskal-Wallis	8.000	34.681	0.000
van der Waerden	8.000	44.221	0.000

Category Statistics					
			> Overall		
Variable	Count	Median	Median	Mean Rank	Mean Score
DECEMBER	288.000	0.290	120.000	1138.231	-0.211
JANUARY	288.000	0.355	143.000	1271.148	-0.028
FEBRUARY	288.000	0.431	157.000	1396.321	0.167
MARCH	288.000	0.419	154.000	1415.227	0.193
APRIL	288.000	0.333	130.000	1178.075	-0.175
MAY	288.000	0.387	147.000	1311.753	0.025
SEPTEMBER	288.000	0.400	145.000	1354.134	0.084
OCTOBER	288.000	0.419	148.000	1298.095	-0.010
NOVEMBER	288.000	0.367	141.000	1305.516	-0.003
All	2592.000	0.367	1285.000	1296.500	0.005

Method	df	Value	Probability
Med. Chi-square	4.000	2.961	0.564
Adj. Med. Chi-square	4.000	2.540	0.638
Kruskal-Wallis	4.000	16.373	0.003
van der Waerden	4.000	25.220	0.000

Category Statistics				
			> Overall	
Variable	Count	Median	Median	Mean Rank
MONDAY	288.000	0.413	134.000	646.420
TUESDAY	288.000	0.500	149.000	734.240
WEDNESDAY	288.000	0.528	149.000	755.339
THURSDAY	288.000	0.509	148.000	769.399
FRIDAY	288.000	0.404	137.000	697.102
All	1440.000	0.462	717.000	720.500

TABLE 3.7.10.C: Variance equality tests among months of the year and days of the week for All Alerts news: Tests the null hypothesis that the variances in all subgroups are equal against the alternative that at least one subgroup has a different variance. See Conover, et al. (1981) for a general discussion of variance testing. ***Bartlett test***. This test compares the logarithm of the weighted average variance with the weighted sum of the logarithms of the variances. Under the joint null hypothesis that the subgroup variances are equal and that the sample is normally distributed, the test statistic is approximately distributed as a χ^2 with the number of subgroups-1 degrees of freedom. Note, however, that the joint hypothesis implies that this test is sensitive to departures from normality. ***Levene test***. This test is based on an analysis of variance (ANOVA) of the absolute difference from the mean. The F-statistic for the Levene test has an approximate F-distribution with the number of subgroups -1 numerator degrees of freedom and N- the number of subgroups denominator degrees of freedom under the null hypothesis of equal variances in each subgroup (Levene, 1960). ***Brown-Forsythe (modified Levene) test.*** This is a modification of the Levene test in which the absolute mean difference is replaced with the absolute median difference and appears to be a superior test in terms of robustness and power (Conover, et al. (1981), Brown and Forsythe (1974), Neter, et al. (1996)).These test cover a one year period (December 1, 1999 – November 30, 2000) by month of the year and by day of the week within successive intraday periods of five minutes for All Alerts News related and non- to France.

All Alerts news

Method	df	Value	Probability
Bartlett	8.000	38.205	0.000
Levene	(8, 2583)	3.505	0.001
Brown-Forsythe	(8, 2583)	2.573	0.009

Category Statistics				
			Mean Abs.	Mean Abs.
Variable	Count	Std. Dev.	Mean Diff.	Median Diff.
DECEMBER	288.000	7.610	5.547	5.385
JANUARY	288.000	8.953	6.740	6.465
FEBRUARY	288.000	10.104	7.606	7.251
MARCH	288.000	10.167	7.221	6.932
APRIL	288.000	9.105	6.811	6.595
MAY	288.000	9.916	7.163	6.938
SEPTEMBER	288.000	8.935	6.541	6.374
OCTOBER	288.000	9.767	7.709	7.361
NOVEMBER	288.000	8.622	6.203	5.893
All	2592.000	9.330	6.838	6.577

Bartlett weighted standard deviation: 9.275476

Method	df	Value	Probability
Bartlett	4.000	74.363	0.000
Levene	(4, 1435)	9.731	0.000
Brown-Forsythe	(4, 1435)	6.871	0.000

Category Statistics				
			Mean Abs.	Mean Abs.
Variable	Count	Std. Dev.	Mean Diff.	Median Diff.
MONDAY	288.000	11.246	8.388	8.075
TUESDAY	288.000	11.323	8.618	8.281
WEDNESDAY	288.000	10.823	8.206	7.960
THURSDAY	288.000	10.152	7.719	7.520
FRIDAY	288.000	7.104	5.599	5.554
All	1440.000	10.314	7.706	7.478

Bartlett weighted standard deviation: 10.25031

All Alerts news France

Method	df	Value	Probability
Bartlett	8.000	44.292	0.000
Levene	(8, 2583)	9.748	0.000
Brown-Forsythe	(8, 2583)	9.074	0.000

Category Statistics				
			Mean Abs.	Mean Abs.
Variable	Count	Std. Dev.	Mean Diff.	Median Diff.
DECEMBER	288.000	0.269	0.230	0.228
JANUARY	288.000	0.303	0.265	0.265
FEBRUARY	288.000	0.353	0.309	0.308
MARCH	288.000	0.347	0.304	0.302
APRIL	288.000	0.270	0.235	0.234
MAY	288.000	0.322	0.282	0.282
SEPTEMBER	288.000	0.292	0.256	0.256
OCTOBER	288.000	0.307	0.264	0.264
NOVEMBER	288.000	0.291	0.250	0.249
All	2592.000	0.310	0.266	0.265

Bartlett weighted standard deviation: 0.307405

Method	df	Value	Probability
Bartlett	4.000	18.399	0.001
Levene	(4, 1435)	8.989	0.000
Brown-Forsythe	(4, 1435)	8.387	0.000

Category Statistics				
			Mean Abs.	Mean Abs.
Variable	Count	Std. Dev.	Mean Diff.	Median Diff.
MONDAY	288.000	0.339	0.304	0.303
TUESDAY	288.000	0.379	0.341	0.341
WEDNESDAY	288.000	0.381	0.338	0.338
THURSDAY	288.000	0.418	0.375	0.373
FRIDAY	288.000	0.339	0.307	0.305
All	1440.000	0.375	0.333	0.332

Bartlett weighted standard deviation: 0.372596

TABLE 3.7.11.A: Mean equality test among months of the year and days of the week for Political news: This test is based on a single-factor, between-subjects, analysis of variance (ANOVA). The basic idea is that if the subgroups have the same mean, then the variability between the sample means (between group) should be the same as the variability within any subgroup (within group).This test covers a one year period (December 1, 1999 – November 30, 2000) by month of the year and by day of the week within successive intraday periods of five minutes for Political news related and non- to France. Due to technical problems with the Reuters Terminal some periods are left out from the analysis.

Political news

Method	df	Value	Probability
Anova F-statistic	(8, 2583)	15.375	0.000

Analysis of Variance

Source of Variation	df	Sum of Sq.	Mean Sq.
Between	8.000	2803.674	350.459
Within	2583.000	58878.370	22.795
Total	2591.000	61682.050	23.806

Category Statistics

Variable	Count	Mean	Std. Dev.	Std. Err. of Mean
DECEMBER	288.000	4.438	3.701	0.218
JANUARY	288.000	4.614	4.016	0.237
FEBRUARY	288.000	8.157	7.289	0.429
MARCH	288.000	5.822	4.759	0.280
APRIL	288.000	5.701	4.810	0.283
MAY	288.000	5.517	4.655	0.274
SEPTEMBER	288.000	4.996	4.213	0.248
OCTOBER	288.000	4.896	3.819	0.225
NOVEMBER	288.000	5.520	4.735	0.279
All	2592.000	5.518	4.879	0.096

Method	df	Value	Probability
Anova F-statistic	(4, 1435)	3.084	0.015

Analysis of Variance

Source of Variation	df	Sum of Sq.	Mean Sq.
Between	4.000	330.869	82.717
Within	1435.000	38494.800	26.826
Total	1439.000	38825.670	26.981

Category Statistics

Variable	Count	Mean	Std. Dev.	Std. Err. of Mean
MONDAY	288.000	5.752	4.751	0.280
TUESDAY	288.000	6.771	5.451	0.321
THURSDAY	288.000	6.773	5.352	0.315
WEDNESDAY	288.000	6.829	5.533	0.326
FRIDAY	288.000	5.882	4.753	0.280
All	1440.000	6.401	5.194	0.137

Political news France

Method	df	Value	Probability
Anova F-statistic	(8, 2583)	2.210	0.024

Analysis of Variance

Source of Variation	df	Sum of Sq.	Mean Sq.
Between	8.000	1.466	0.183
Within	2583.000	214.146	0.083
Total	2591.000	215.611	0.083

Category Statistics

Variable	Count	Mean	Std. Dev.	Std. Err. of Mean
DECEMBER	288.000	0.276	0.255	0.015
JANUARY	288.000	0.303	0.279	0.016
FEBRUARY	288.000	0.344	0.309	0.018
MARCH	288.000	0.350	0.331	0.019
APRIL	288.000	0.286	0.254	0.015
MAY	288.000	0.323	0.287	0.017
SEPTEMBER	288.000	0.335	0.288	0.017
OCTOBER	288.000	0.326	0.300	0.018
NOVEMBER	288.000	0.314	0.281	0.017
All	2592.000	0.317	0.288	0.006

Method	df	Value	Probability
Anova F-statistic	(4, 1435)	3.606	0.006

Analysis of Variance

Source of Variation	df	Sum of Sq.	Mean Sq.
Between	4.000	1.744	0.436
Within	1435.000	173.572	0.121
Total	1439.000	175.317	0.122

Category Statistics

Variable	Count	Mean	Std. Dev.	Std. Err. of Mean
MONDAY	288.000	0.343	0.297	0.017
TUESDAY	288.000	0.408	0.360	0.021
WEDNESDAY	288.000	0.423	0.363	0.021
THURSDAY	288.000	0.440	0.390	0.023
FRIDAY	288.000	0.373	0.322	0.019
All	1440.000	0.397	0.349	0.009

TABLE 3.7.11.B: Median equality tests among months of the year and days of the week for Political news: This table reports various rank-based nonparametric tests of the hypothesis that the subgroups have the same median, against the alternative that at least one subgroup has a different median. ***Kruskal-Wallis one-way ANOVA by ranks test***. This is a generalization of the Mann-Whitney test to more than two subgroups. The test is based on a one-way analysis of variance using only ranks of the data. The Table reports the chi-square approximation to the Kruskal-Wallis test statistic (with tie correction). Under the null hypothesis, this statistic is approximately distributed as a χ^2 with the number of subgroups-1 degrees of freedom (see Sheskin, 1997). ***Van der Waerden (normal scores) test***. This test is analogous to the Kruskal-Wallis test, except that the ranks are smoothed by converting them into normal quantiles (Conover, 1980). This table reports a statistic which is approximately distributed as a χ^2 with the number of subgroups -1 degrees of freedom under the null hypothesis. ***Chi-square test for the median***. This is a rank-based ANOVA test based on the comparison of the number of observations above and below the overall median in each subgroup. This test is also known as the median test (Conover, 1980). These tests cover a one year period (December 1, 1999 – November 30, 2000) by month of the year and by day of the week within successive intraday periods of five minutes for Political news related and non- to France. Due to technical problems with the Reuters Terminal some periods are left out from the analysis.

Political news

Method	df	Value	Probability
Med. Chi-square	8.000	2.583	0.958
Adj. Med. Chi-square	8.000	2.198	0.974
Kruskal-Wallis	8.000	92.598	0.000
van der Waerden	8.000	150.948	0.000

Category Statistics					
			> Overall		
Variable	Count	Median	Median	Mean Rank	Mean Score
DECEMBER	288.000	2.548	141.000	1102.510	-0.284
JANUARY	288.000	2.855	140.000	1121.201	-0.302
FEBRUARY	288.000	4.724	155.000	1598.674	0.556
MARCH	288.000	4.129	145.000	1381.161	0.105
APRIL	288.000	4.083	146.000	1357.071	0.074
MAY	288.000	3.952	145.000	1323.361	0.022
SEPTEMBER	288.000	3.133	139.000	1228.134	-0.107
OCTOBER	288.000	3.645	141.000	1236.328	-0.102
NOVEMBER	288.000	3.850	144.000	1320.059	0.039
All	2592.000	3.814	1296.000	1296.500	0.000

Method	df	Value	Probability
Med. Chi-square	4.000	0.628	0.960
Adj. Med. Chi-square	4.000	0.445	0.979
Kruskal-Wallis	4.000	20.551	0.000
van der Waerden	4.000	39.386	0.000

Category Statistics				
			> Overall	
Variable	Count	Median	Median	Mean Rank
MONDAY	288.000	4.673	140.000	643.658
TUESDAY	288.000	5.587	146.000	752.988
THURSDAY	288.000	5.208	145.000	762.639
WEDNESDAY	288.000	5.670	147.000	764.038
FRIDAY	288.000	4.558	140.000	679.177
All	1440.000	5.000	718.000	720.500

Political news France

Method	df	Value	Probability
Med. Chi-square	8.000	4.334	0.826
Adj. Med. Chi-square	8.000	3.829	0.872
Kruskal-Wallis	8.000	16.794	0.032
van der Waerden	8.000	21.064	0.007

Category Statistics					
			> Overall		
Variable	Count	Median	Median	Mean Rank	Mean Score
DECEMBER	288.000	0.210	129.000	1186.623	-0.138
JANUARY	288.000	0.258	140.000	1238.663	-0.064
FEBRUARY	288.000	0.276	145.000	1371.679	0.118
MARCH	288.000	0.258	141.000	1339.286	0.097
APRIL	288.000	0.233	142.000	1240.759	-0.076
MAY	288.000	0.258	140.000	1310.913	0.032
SEPTEMBER	288.000	0.267	151.000	1375.816	0.117
OCTOBER	288.000	0.258	139.000	1301.330	0.018
NOVEMBER	288.000	0.267	148.000	1303.431	0.021
All	2592.000	0.258	1275.000	1296.500	0.014

Method	df	Value	Probability
Med. Chi-square	4.000	1.067	0.900
Adj. Med. Chi-square	4.000	0.823	0.935
Kruskal-Wallis	4.000	11.580	0.021
van der Waerden	4.000	15.650	0.004

Category Statistics				
			> Overall	
Variable	Count	Median	Median	Mean Rank
MONDAY	288.000	0.308	138.000	654.403
TUESDAY	288.000	0.365	147.000	732.950
WEDNESDAY	288.000	0.368	145.000	749.432
THURSDAY	288.000	0.368	147.000	758.181
FRIDAY	288.000	0.260	139.000	707.535
All	1440.000	0.327	716.000	720.500

TABLE 3.7.11.C: Variance equality tests among months of the year and days of the week for Political news: Tests the null hypothesis that the variances in all subgroups are equal against the alternative that at least one subgroup has a different variance. See Conover, et al. (1981) for a general discussion of variance testing. ***Bartlett test*.** This test compares the logarithm of the weighted average variance with the weighted sum of the logarithms of the variances. Under the joint null hypothesis that the subgroup variances are equal and that the sample is normally distributed, the test statistic is approximately distributed as a χ^2 with the number of subgroups-1 degrees of freedom. Note, however, that the joint hypothesis implies that this test is sensitive to departures from normality. ***Levene test*.** This test is based on an analysis of variance (ANOVA) of the absolute difference from the mean. The F-statistic for the Levene test has an approximate F-distribution with the number of subgroups -1 numerator degrees of freedom and N- the number of subgroups denominator degrees of freedom under the null hypothesis of equal variances in each subgroup (Levene, 1960). ***Brown-Forsythe (modified Levene) test.*** This is a modification of the Levene test in which the absolute mean difference is replaced with the absolute median difference and appears to be a superior test in terms of robustness and power (Conover, et al. (1981), Brown and Forsythe (1974), Neter, et al. (1996)).These test cover a one year period (December 1, 1999 – November 30, 2000) by month of the year and by day of the week within successive intraday periods of five minutes for Political News related and non- to France. Due to technical problems with the Reuters Terminal some periods are left out from the analysis.

Political news

Method	df	Value	Probability
Bartlett	8.000	219.277	0.000
Levene	(8, 2583)	38.894	0.000
Brown-Forsythe	(8, 2583)	22.471	0.000

Variable	Count	Std. Dev.	Mean Abs. Mean Diff.	Mean Abs. Median Diff.
DECEMBER	288.000	3.701	3.201	3.164
JANUARY	288.000	4.016	3.482	3.437
FEBRUARY	288.000	7.289	6.254	6.160
MARCH	288.000	4.759	4.137	4.112
APRIL	288.000	4.810	4.033	3.989
MAY	288.000	4.655	3.903	3.860
SEPTEMBER	288.000	4.213	3.538	3.485
OCTOBER	288.000	3.819	3.309	3.247
NOVEMBER	288.000	4.735	3.895	3.848
All	2592.000	4.879	3.972	3.922

Category Statistics

Bartlett weighted standard deviation: 4.774366

Method	df	Value	Probability
Bartlett	4.000	12.833	0.012
Levene	(4, 1435)	6.002	0.000
Brown-Forsythe	(4, 1435)	4.422	0.002

Variable	Count	Std. Dev.	Mean Abs. Mean Diff.	Mean Abs. Median Diff.
MONDAY	288.000	4.751	4.243	4.207
TUESDAY	288.000	5.451	4.907	4.856
THURSDAY	288.000	5.352	4.785	4.753
WEDNESDAY	288.000	5.533	4.850	4.827
FRIDAY	288.000	4.753	4.229	4.191
All	1440.000	5.194	4.603	4.567

Category Statistics

Bartlett weighted standard deviation: 5.179348

Political news France

Method	df	Value	Probability
Bartlett	8.000	33.094	0.000
Levene	(8, 2583)	5.738	0.000
Brown-Forsythe	(8, 2583)	4.375	0.000

Variable	Count	Std. Dev.	Mean Abs. Mean Diff.	Mean Abs. Median Diff.
DECEMBER	288.000	0.255	0.217	0.213
JANUARY	288.000	0.279	0.242	0.240
FEBRUARY	288.000	0.309	0.273	0.271
MARCH	288.000	0.331	0.282	0.277
APRIL	288.000	0.254	0.224	0.223
MAY	288.000	0.287	0.248	0.246
SEPTEMBER	288.000	0.288	0.243	0.241
OCTOBER	288.000	0.300	0.247	0.244
NOVEMBER	288.000	0.281	0.236	0.235
All	2592.000	0.288	0.246	0.243

Category Statistics

Method	df	Value	Probability
Bartlett	4.000	25.853	0.000
Levene	(4, 1435)	11.113	0.000
Brown-Forsythe	(4, 1435)	9.000	0.000

Variable	Count	Std. Dev.	Mean Abs. Mean Diff.	Mean Abs. Median Diff.
MONDAY	288.000	0.297	0.261	0.260
TUESDAY	288.000	0.360	0.315	0.314
WEDNESDAY	288.000	0.363	0.323	0.321
THURSDAY	288.000	0.390	0.343	0.341
FRIDAY	288.000	0.322	0.288	0.285
All	1440.000	0.349	0.306	0.304

Category Statistics

Bartlett weighted standard deviation: 0.347788

TABLE 3.7.12.A: Mean equality test among months of the year and days of the week for Market news: This test is based on a single-factor, between-subjects, analysis of variance (ANOVA). The basic idea is that if the subgroups have the same mean, then the variability between the sample means (between group) should be the same as the variability within any subgroup (within group).This test covers a one year period (December 1, 1999 – November 30, 2000) by month of the year and by day of the week within successive intraday periods of five minutes for Market news related and non- to France. Due to technical problems with the Reuters Terminal some periods are left out from the analysis.

Market news

Method	df	Value	Probability
Anova F-statistic	(7, 2296)	23.079	0.000

Analysis of Variance

Source of Variation	df	Sum of Sq.	Mean Sq.
Between	7.000	1781.642	254.520
Within	2296.000	25321.280	11.028
Total	2303.000	27102.920	11.769

Category Statistics

Variable	Count	Mean	Std. Dev.	Std. Err. of Mean
DECEMBER	288.000	6.211	3.094	0.182
JANUARY	288.000	6.762	3.640	0.214
FEBRUARY	288.000	7.525	3.716	0.219
MARCH	288.000	6.592	3.285	0.194
APRIL	288.000	4.817	2.512	0.148
SEPTEMBER	288.000	6.469	3.233	0.190
OCTOBER	288.000	7.211	3.606	0.212
NOVEMBER	288.000	7.881	3.323	0.196
All	2304.000	6.683	3.431	0.071

Method	df	Value	Probability
Anova F-statistic	(4, 1435)	4.467	0.001

Analysis of Variance

Source of Variation	df	Sum of Sq.	Mean Sq.
Between	4.000	148.163	37.041
Within	1435.000	11898.260	8.291
Total	1439.000	12046.420	8.371

Category Statistics

Variable	Count	Mean	Std. Dev.	Std. Err. of Mean
MONDAY	288.000	5.584	2.754	0.162
TUESDAY	288.000	6.212	2.899	0.171
WEDNESDAY	288.000	6.347	2.934	0.173
THURSDAY	288.000	6.366	3.212	0.189
FRIDAY	288.000	5.763	2.558	0.151
All	1440.000	6.054	2.893	0.076

Market news France

Method	df	Value	Probability
Anova F-statistic	(8, 2583)	97.984	0.000

Analysis of Variance

Source of Variation	df	Sum of Sq.	Mean Sq.
Between	8.000	99.420	12.427
Within	2583.000	327.605	0.127
Total	2591.000	427.024	0.165

Category Statistics

Variable	Count	Mean	Std. Dev.	Std. Err. of Mean
DECEMBER	288.000	0.269	0.234	0.014
JANUARY	288.000	0.305	0.255	0.015
FEBRUARY	288.000	0.467	0.332	0.020
MARCH	288.000	0.874	0.548	0.032
APRIL	288.000	0.731	0.491	0.029
MAY	288.000	0.483	0.362	0.021
SEPTEMBER	288.000	0.372	0.305	0.018
OCTOBER	288.000	0.352	0.283	0.017
NOVEMBER	288.000	0.319	0.255	0.015
All	2592.000	0.464	0.406	0.008

Method	df	Value	Probability
Anova F-statistic	(4, 1435)	5.156	0.000

Analysis of Variance

Source of Variation	df	Sum of Sq.	Mean Sq.
Between	4.000	3.462	0.866
Within	1435.000	240.903	0.168
Total	1439.000	244.365	0.170

Category Statistics

Variable	Count	Mean	Std. Dev.	Std. Err. of Mean
MONDAY	288.000	0.505	0.377	0.022
TUESDAY	288.000	0.588	0.425	0.025
WEDNESDAY	288.000	0.610	0.426	0.025
THURSDAY	288.000	0.623	0.448	0.026
FRIDAY	288.000	0.515	0.367	0.022
All	1440.000	0.568	0.412	0.011

TABLE 3.7.12.B: Median equality tests among months of the year and days of the week for Market news: This table reports various rank-based nonparametric tests of the hypothesis that the subgroups have the same median, against the alternative that at least one subgroup has a different median. ***Kruskal-Wallis one-way ANOVA by ranks test***. This is a generalization of the Mann-Whitney test to more than two subgroups. The test is based on a one-way analysis of variance using only ranks of the data. The Table reports the chi-square approximation to the Kruskal-Wallis test statistic (with tie correction). Under the null hypothesis, this statistic is approximately distributed as a χ^2 with the number of subgroups-1 degrees of freedom (see Sheskin, 1997). ***Van der Waerden (normal scores) test***. This test is analogous to the Kruskal-Wallis test, except that the ranks are smoothed by converting them into normal quantiles (Conover, 1980). This table reports a statistic which is approximately distributed as a χ^2 with the number of subgroups -1 degrees of freedom under the null hypothesis. ***Chi-square test for the median***. This is a rank-based ANOVA test based on the comparison of the number of observations above and below the overall median in each subgroup. This test is also known as the median test (Conover, 1980). These tests cover a one year period (December 1, 1999 – November 30, 2000) by month of the year and by day of the week within successive intraday periods of five minutes for Market news related and non- to France. Due to technical problems with the Reuters Terminal some periods are left out from the analysis.

Market News

Method	df	Value	Probability
Med. Chi-square	7.000	112.827	0.000
Adj. Med. Chi-square	7.000	110.375	0.000
Kruskal-Wallis	7.000	163.195	0.000
van der Waerden	7.000	206.759	0.000

Category Statistics					
Variable	Count	Median	> Overall Median	Mean Rank	Mean Score
DECEMBER	288.000	5.919	128.000	1067.424	-0.110
JANUARY	288.000	6.516	148.000	1155.349	0.030
FEBRUARY	288.000	7.138	170.000	1307.665	0.269
MARCH	288.000	6.323	143.000	1139.318	0.006
APRIL	288.000	4.750	71.000	770.700	-0.673
SEPTEMBER	288.000	6.450	145.000	1123.222	-0.059
OCTOBER	288.000	6.855	162.000	1254.215	0.155
NOVEMBER	288.000	7.500	183.000	1402.108	0.384
All	2304.000	6.323	1150.000	1152.500	0.000

Method	df	Value	Probability
Med. Chi-square	4.000	14.722	0.005
Adj. Med. Chi-square	4.000	13.795	0.008
Kruskal-Wallis	4.000	14.261	0.007
van der Waerden	4.000	23.495	0.000

Category Statistics				
Variable	Count	Median	> Overall Median	Mean Rank
MONDAY	288.000	5.683	123.000	651.865
TUESDAY	288.000	6.288	157.000	744.276
WEDNESDAY	288.000	6.330	160.000	763.516
THURSDAY	288.000	6.179	149.000	748.200
FRIDAY	288.000	5.519	131.000	694.644
All	1440.000	6.048	720.000	720.500

Market news France

Method	df	Value	Probability
Med. Chi-square	8.000	183.140	0.000
Adj. Med. Chi-square	8.000	179.329	0.000
Kruskal-Wallis	8.000	462.374	0.000
van der Waerden	8.000	542.123	0.000

Category Statistics					
Variable	Count	Median	> Overall Median	Mean Rank	Mean Score
DECEMBER	288.000	0.226	92.000	916.443	-0.503
JANUARY	288.000	0.258	110.000	1002.054	-0.400
FEBRUARY	288.000	0.414	148.000	1386.590	0.108
MARCH	288.000	0.839	211.000	1898.684	0.898
APRIL	288.000	0.733	205.000	1733.800	0.619
MAY	288.000	0.419	149.000	1373.477	0.083
SEPTEMBER	288.000	0.300	132.000	1171.384	-0.186
OCTOBER	288.000	0.290	128.000	1118.394	-0.267
NOVEMBER	288.000	0.300	118.000	1067.674	-0.303
All	2592.000	0.387	1293.000	1296.500	0.006

Method	df	Value	Probability
Med. Chi-square	4.000	2.622	0.623
Adj. Med. Chi-square	4.000	2.240	0.692
Kruskal-Wallis	4.000	18.038	0.001
van der Waerden	4.000	27.519	0.000

Category Statistics				
Variable	Count	Median	> Overall Median	Mean Rank
MONDAY	288.000	0.462	134.000	653.642
TUESDAY	288.000	0.538	148.000	741.722
WEDNESDAY	288.000	0.566	150.000	763.078
THURSDAY	288.000	0.538	146.000	767.255
FRIDAY	288.000	0.462	138.000	676.802
All	1440.000	0.509	716.000	720.500

TABLE 3.7.12.C: Variance equality tests among months of the year and days of the week for Market news: Tests the null hypothesis that the variances in all subgroups are equal against the alternative that at least one subgroup has a different variance. See Conover, et al. (1981) for a general discussion of variance testing. ***Bartlett test***. This test compares the logarithm of the weighted average variance with the weighted sum of the logarithms of the variances. Under the joint null hypothesis that the subgroup variances are equal and that the sample is normally distributed, the test statistic is approximately distributed as a χ^2 with the number of subgroups-1 degrees of freedom. Note, however, that the joint hypothesis implies that this test is sensitive to departures from normality. ***Levene test***. This test is based on an analysis of variance (ANOVA) of the absolute difference from the mean. The F-statistic for the Levene test has an approximate F-distribution with the number of subgroups -1 numerator degrees of freedom and N- the number of subgroups denominator degrees of freedom under the null hypothesis of equal variances in each subgroup (Levene, 1960). ***Brown-Forsythe (modified Levene) test.*** This is a modification of the Levene test in which the absolute mean difference is replaced with the absolute median difference and appears to be a superior test in terms of robustness and power (Conover, et al. (1981), Brown and Forsythe (1974), Neter, et al. (1996)).These test cover a one year period (December 1, 1999 – November 30, 2000) by month of the year and by day of the week within successive intraday periods of five minutes for Market News related and non- to France. Due to technical problems with the Reuters Terminal some periods are left out from the analysis.

Market news

Method	df	Value	Probability
Bartlett	7.000	57.643	0.000
Levene	(7, 2296)	6.780	0.000
Brown-Forsythe	(7, 2296)	6.357	0.000

Category Statistics				
Variable	Count	Std. Dev.	Mean Abs. Mean Diff.	Mean Abs. Median Diff.
DECEMBER	288.000	3.094	2.461	2.452
JANUARY	288.000	3.640	2.789	2.778
FEBRUARY	288.000	3.716	2.946	2.927
MARCH	288.000	3.285	2.583	2.570
APRIL	288.000	2.512	2.022	2.021
SEPTEMBER	288.000	3.233	2.703	2.703
OCTOBER	288.000	3.606	2.968	2.953
NOVEMBER	288.000	3.323	2.690	2.671
All	2304.000	3.431	2.645	2.634

Bartlett weighted standard deviation: 3.320908

Method	df	Value	Probability
Bartlett	4.000	16.181	0.003
Levene	(4, 1435)	1.738	0.139
Brown-Forsythe	(4, 1435)	1.697	0.148

Category Statistics				
Variable	Count	Std. Dev.	Mean Abs. Mean Diff.	Mean Abs. Median Diff.
MONDAY	288.000	2.754	2.227	2.226
TUESDAY	288.000	2.899	2.290	2.289
WEDNESDAY	288.000	2.934	2.323	2.323
THURSDAY	288.000	3.212	2.523	2.516
FRIDAY	288.000	2.558	2.176	2.169
All	1440.000	2.893	2.308	2.305

Bartlett weighted standard deviation: 2.879491

Market news France

Method	df	Value	Probability
Bartlett	8.000	441.756	0.000
Levene	(8, 2583)	57.491	0.000
Brown-Forsythe	(8, 2583)	52.886	0.000

Category Statistics				
Variable	Count	Std. Dev.	Mean Abs. Mean Diff.	Mean Abs. Median Diff.
DECEMBER	288.000	0.234	0.203	0.202
JANUARY	288.000	0.255	0.228	0.227
FEBRUARY	288.000	0.332	0.287	0.285
MARCH	288.000	0.548	0.444	0.443
APRIL	288.000	0.491	0.406	0.406
MAY	288.000	0.362	0.318	0.316
SEPTEMBER	288.000	0.305	0.270	0.267
OCTOBER	288.000	0.283	0.254	0.252
NOVEMBER	288.000	0.255	0.224	0.223
All	2592.000	0.406	0.293	0.291

Bartlett weighted standard deviation: 0.356133

Method	df	Value	Probability
Bartlett	4.000	16.563	0.002
Levene	(4, 1435)	7.553	0.000
Brown-Forsythe	(4, 1435)	6.492	0.000

Category Statistics				
Variable	Count	Std. Dev.	Mean Abs. Mean Diff.	Mean Abs. Median Diff.
MONDAY	288.000	0.377	0.327	0.326
TUESDAY	288.000	0.425	0.375	0.374
WEDNESDAY	288.000	0.426	0.379	0.376
THURSDAY	288.000	0.448	0.397	0.394
FRIDAY	288.000	0.367	0.332	0.331
All	1440.000	0.412	0.362	0.360

Bartlett weighted standard deviation: 0.409728

TABLE 3.7.13.A: Mean equality test among months of the year and days of the week for Industrial news: This test is based on a single-factor, between-subjects, analysis of variance (ANOVA). The basic idea is that if the subgroups have the same mean, then the variability between the sample means (between group) should be the same as the variability within any subgroup (within group).This test covers a one year period (December 1, 1999 – November 30, 2000) by month of the year and by day of the week within successive intraday periods of five minutes for Industrial news related and non- to France. Due to technical problems with the Reuters Terminal some periods are left out from the analysis.

Industrial news

Method	df	Value	Probability
Anova F-statistic	(8, 2583)	8.806	0.000

Analysis of Variance			
Source of Variation	df	Sum of Sq.	Mean Sq.
Between	8.000	1613.660	201.708
Within	2583.000	59167.090	22.906
Total	2591.000	60780.750	23.458

Category Statistics				
Variable	Count	Mean	Std. Dev.	Std. Err. of Mean
DECEMBER	288.000	4.199	4.093	0.241
JANUARY	288.000	3.175	3.703	0.218
FEBRUARY	288.000	5.786	5.430	0.320
MARCH	288.000	5.441	5.233	0.308
APRIL	288.000	5.024	4.803	0.283
MAY	288.000	5.689	5.342	0.315
SEPTEMBER	288.000	4.943	4.941	0.291
OCTOBER	288.000	5.457	4.844	0.285
NOVEMBER	288.000	5.364	4.397	0.259
All	2592.000	5.009	4.843	0.095

Method	df	Value	Probability
Anova F-statistic	(4, 1435)	8.055	0.000

Analysis of Variance			
Source of Variation	df	Sum of Sq.	Mean Sq.
Between	4.000	1029.453	257.363
Within	1435.000	45846.640	31.949
Total	1439.000	46876.090	32.575

Category Statistics				
Variable	Count	Mean	Std. Dev.	Std. Err. of Mean
MONDAY	288.000	6.512	6.675	0.393
TUESDAY	288.000	7.049	6.536	0.385
WEDNESDAY	288.000	6.682	6.019	0.355
THURSDAY	288.000	6.217	5.201	0.306
FRIDAY	288.000	4.611	3.032	0.179
All	1440.000	6.214	5.707	0.150

Industrial news France

Method	df	Value	Probability
Anova F-statistic	(8, 2583)	34.748	0.000

Analysis of Variance			
Source of Variation	df	Sum of Sq.	Mean Sq.
Between	8.000	10.681	1.335
Within	2583.000	99.250	0.038
Total	2591.000	109.931	0.042

Category Statistics				
Variable	Count	Mean	Std. Dev.	Std. Err. of Mean
DECEMBER	288.000	0.117	0.114	0.007
JANUARY	288.000	0.142	0.129	0.008
FEBRUARY	288.000	0.215	0.184	0.011
MARCH	288.000	0.334	0.269	0.016
APRIL	288.000	0.272	0.226	0.013
MAY	288.000	0.273	0.222	0.013
SEPTEMBER	288.000	0.257	0.202	0.012
OCTOBER	288.000	0.207	0.166	0.010
NOVEMBER	288.000	0.257	0.202	0.012
All	2592.000	0.231	0.206	0.004

Method	df	Value	Probability
Anova F-statistic	(4, 1435)	5.255	0.000

Analysis of Variance			
Source of Variation	df	Sum of Sq.	Mean Sq.
Between	4.000	1.112	0.278
Within	1435.000	75.930	0.053
Total	1439.000	77.043	0.054

Category Statistics				
Variable	Count	Mean	Std. Dev.	Std. Err. of Mean
MONDAY	288.000	0.267	0.216	0.013
TUESDAY	288.000	0.309	0.238	0.014
WEDNESDAY	288.000	0.313	0.233	0.014
THURSDAY	288.000	0.334	0.258	0.015
FRIDAY	288.000	0.262	0.201	0.012
All	1440.000	0.297	0.231	0.006

TABLE 3.7.13.B: Median equality tests among months of the year and days of the week for Industrial news: This table reports various rank-based nonparametric tests of the hypothesis that the subgroups have the same median, against the alternative that at least one subgroup has a different median. ***Kruskal-Wallis one-way ANOVA by ranks test***. This is a generalization of the Mann-Whitney test to more than two subgroups. The test is based on a one-way analysis of variance using only ranks of the data. The Table reports the chi-square approximation to the Kruskal-Wallis test statistic (with tie correction). Under the null hypothesis, this statistic is approximately distributed as a χ^2 with the number of subgroups-1 degrees of freedom (see Sheskin, 1997). ***Van der Waerden (normal scores) test***. This test is analogous to the Kruskal-Wallis test, except that the ranks are smoothed by converting them into normal quantiles (Conover, 1980). This table reports a statistic which is approximately distributed as a χ^2 with the number of subgroups -1 degrees of freedom under the null hypothesis. ***Chi-square test for the median***. This is a rank-based ANOVA test based on the comparison of the number of observations above and below the overall median in each subgroup. This test is also known as the median test (Conover, 1980). These tests cover a one year period (December 1, 1999 – November 30, 2000) by month of the year and by day of the week within successive intraday periods of five minutes for Industrial news related and non- to France. Due to technical problems with the Reuters Terminal some periods are left out from the analysis.

Industrial news

Method	df	Value	Probability
Med. Chi-square	8.000	66.346	0.000
Adj. Med. Chi-square	8.000	64.278	0.000
Kruskal-Wallis	8.000	148.972	0.000
van der Waerden	8.000	176.717	0.000

Category Statistics					
Variable	Count	Median	> Overall Median	Mean Rank	Mean Score
DECEMBER	288.000	2.903	127.000	1159.089	-0.176
JANUARY	288.000	1.935	88.000	863.083	-0.645
FEBRUARY	288.000	4.155	154.000	1425.715	0.194
MARCH	288.000	4.048	159.000	1384.009	0.131
APRIL	288.000	3.600	143.000	1294.144	0.005
MAY	288.000	4.581	169.000	1453.505	0.215
SEPTEMBER	288.000	3.433	142.000	1258.028	-0.053
OCTOBER	288.000	3.774	150.000	1369.726	0.109
NOVEMBER	288.000	4.317	163.000	1461.201	0.220
All	2592.000	3.600	1295.000	1296.500	0.000

Method	df	Value	Probability
Med. Chi-square	4.000	6.028	0.197
Adj. Med. Chi-square	4.000	5.545	0.236
Kruskal-Wallis	4.000	19.021	0.001
van der Waerden	4.000	23.131	0.000

Category Statistics				
Variable	Count	Median	> Overall Median	Mean Rank
MONDAY	288.000	4.865	151.000	698.436
TUESDAY	288.000	4.904	150.000	768.205
WEDNESDAY	288.000	4.811	149.000	757.802
THURSDAY	288.000	4.491	144.000	740.438
FRIDAY	288.000	3.981	126.000	637.620
All	1440.000	4.476	720.000	720.500

Industrial news France

Method	df	Value	Probability
Med. Chi-square	8.000	165.757	0.000
Adj. Med. Chi-square	8.000	162.042	0.000
Kruskal-Wallis	8.000	246.396	0.000
van der Waerden	8.000	266.934	0.000

Category Statistics					
Variable	Count	Median	> Overall Median	Mean Rank	Mean Score
DECEMBER	288.000	0.097	61.000	845.262	-0.575
JANUARY	288.000	0.097	84.000	960.662	-0.441
FEBRUARY	288.000	0.172	136.000	1292.076	-0.014
MARCH	288.000	0.258	168.000	1573.345	0.432
APRIL	288.000	0.200	156.000	1453.576	0.234
MAY	288.000	0.226	151.000	1437.089	0.202
SEPTEMBER	288.000	0.217	166.000	1433.509	0.170
OCTOBER	288.000	0.161	125.000	1239.472	-0.080
NOVEMBER	288.000	0.217	166.000	1433.509	0.170
All	2592.000	0.194	1213.000	1296.500	0.011

Method	df	Value	Probability
Med. Chi-square	4.000	8.375	0.079
Adj. Med. Chi-square	4.000	7.743	0.102
Kruskal-Wallis	4.000	11.938	0.018
van der Waerden	4.000	14.975	0.005

Category Statistics				
Variable	Count	Median	> Overall Median	Mean Rank
MONDAY	288.000	0.231	136.000	672.646
TUESDAY	288.000	0.279	150.000	743.504
WEDNESDAY	288.000	0.245	143.000	744.646
THURSDAY	288.000	0.283	154.000	764.229
FRIDAY	288.000	0.192	123.000	677.476
All	1440.000	0.250	706.000	720.500

TABLE 3.7.13.C: Variance equality tests among months of the year and days of the week for Industrial news: Tests the null hypothesis that the variances in all subgroups are equal against the alternative that at least one subgroup has a different variance. See Conover, et al. (1981) for a general discussion of variance testing. ***Bartlett test***. This test compares the logarithm of the weighted average variance with the weighted sum of the logarithms of the variances. Under the joint null hypothesis that the subgroup variances are equal and that the sample is normally distributed, the test statistic is approximately distributed as a χ^2 with the number of subgroups-1 degrees of freedom. Note, however, that the joint hypothesis implies that this test is sensitive to departures from normality. ***Levene test***. This test is based on an analysis of variance (ANOVA) of the absolute difference from the mean. The F-statistic for the Levene test has an approximate F-distribution with the number of subgroups -1 numerator degrees of freedom and N- the number of subgroups denominator degrees of freedom under the null hypothesis of equal variances in each subgroup (Levene, 1960). ***Brown-Forsythe (modified Levene) test.*** This is a modification of the Levene test in which the absolute mean difference is replaced with the absolute median difference and appears to be a superior test in terms of robustness and power (Conover, et al. (1981), Brown and Forsythe (1974), Neter, et al. (1996)).These test cover a one year period (December 1, 1999 – November 30, 2000) by month of the year and by day of the week within successive intraday periods of five minutes for Industrial News related and non- to France. Due to technical problems with the Reuters Terminal some periods are left out from the analysis.

Industrial news

Method	df	Value	Probability
Bartlett	8.000	71.568	0.000
Levene	(8, 2583)	4.634	0.000
Brown-Forsythe	(8, 2583)	3.595	0.000

Category Statistics				
			Mean Abs.	Mean Abs.
Variable	Count	Std. Dev.	Mean Diff.	Median Diff.
DECEMBER	288.000	4.093	2.692	2.537
JANUARY	288.000	3.703	2.348	2.188
FEBRUARY	288.000	5.430	3.716	3.506
MARCH	288.000	5.233	3.416	3.219
APRIL	288.000	4.803	3.285	3.128
MAY	288.000	5.342	3.309	3.171
SEPTEMBER	288.000	4.941	3.358	3.200
OCTOBER	288.000	4.844	3.590	3.448
NOVEMBER	288.000	4.397	2.825	2.699
All	2592.000	4.843	3.171	3.011

Bartlett weighted standard deviation: 4.786057

Method	df	Value	Probability
Bartlett	4.000	190.061	0.000
Levene	(4, 1435)	18.800	0.000
Brown-Forsythe	(4, 1435)	13.212	0.000

Category Statistics				
			Mean Abs.	Mean Abs.
Variable	Count	Std. Dev.	Mean Diff.	Median Diff.
MONDAY	288.000	6.675	4.594	4.405
TUESDAY	288.000	6.536	4.646	4.421
WEDNESDAY	288.000	6.019	4.239	4.086
THURSDAY	288.000	5.201	3.736	3.640
FRIDAY	288.000	3.032	2.165	2.113
All	1440.000	5.707	3.876	3.733

Bartlett weighted standard deviation: 5.652334

Industrial news France

Method	df	Value	Probability
Bartlett	8.000	311.369	0.000
Levene	(8, 2583)	38.632	0.000
Brown-Forsythe	(8, 2583)	28.336	0.000

Category Statistics				
			Mean Abs.	Mean Abs.
Variable	Count	Std. Dev.	Mean Diff.	Median Diff.
DECEMBER	288.000	0.114	0.093	0.089
JANUARY	288.000	0.129	0.109	0.107
FEBRUARY	288.000	0.184	0.156	0.153
MARCH	288.000	0.269	0.225	0.219
APRIL	288.000	0.226	0.188	0.183
MAY	288.000	0.222	0.178	0.174
SEPTEMBER	288.000	0.202	0.166	0.163
OCTOBER	288.000	0.166	0.138	0.135
NOVEMBER	288.000	0.202	0.166	0.163
All	2592.000	0.206	0.158	0.154

Bartlett weighted standard deviation: 0.196021

Method	df	Value	Probability
Bartlett	4.000	20.638	0.000
Levene	(4, 1435)	5.827	0.000
Brown-Forsythe	(4, 1435)	4.791	0.001

Category Statistics				
			Mean Abs.	Mean Abs.
Variable	Count	Std. Dev.	Mean Diff.	Median Diff.
MONDAY	288.000	0.216	0.178	0.177
TUESDAY	288.000	0.238	0.196	0.194
WEDNESDAY	288.000	0.233	0.195	0.191
THURSDAY	288.000	0.258	0.218	0.215
FRIDAY	288.000	0.201	0.173	0.169
All	1440.000	0.231	0.192	0.189

Bartlett weighted standard deviation: 0.230029

TABLE 3.7.14.A: Mean equality test among months of the year and days of the week for General news: This test is based on a single-factor, between-subjects, analysis of variance (ANOVA). The basic idea is that if the subgroups have the same mean, then the variability between the sample means (between group) should be the same as the variability within any subgroup (within group).This test covers a one year period (December 1, 1999 – November 30, 2000) by month of the year and by day of the week within successive intraday periods of five minutes for General news related and non- to France. Due to technical problems with the Reuters Terminal some periods are left out from the analysis.

General news

Method	df	Value	Probability
Anova F-statistic	(8, 2583)	23.855	0.000

Analysis of Variance

Source of Variation	df	Sum of Sq.	Mean Sq.
Between	8.000	416.705	52.088
Within	2583.000	5640.044	2.184
Total	2591.000	6056.750	2.338

Category Statistics

Variable	Count	Mean	Std. Dev.	Std. Err. of Mean
DECEMBER	288.000	2.251	1.016	0.060
JANUARY	288.000	2.436	1.119	0.066
FEBRUARY	288.000	2.697	1.273	0.075
MARCH	288.000	2.866	1.266	0.075
APRIL	288.000	2.759	1.272	0.075
MAY	288.000	3.120	1.468	0.087
SEPTEMBER	288.000	3.202	1.282	0.076
OCTOBER	288.000	3.146	1.457	0.086
NOVEMBER	288.000	3.640	2.570	0.151
All	2592.000	2.902	1.529	0.030

Method	df	Value	Probability
Anova F-statistic	(4, 1435)	8.286	0.000

Analysis of Variance

Source of Variation	df	Sum of Sq.	Mean Sq.
Between	4.000	80.119	20.030
Within	1435.000	3468.723	2.417
Total	1439.000	3548.842	2.466

Category Statistics

Variable	Count	Mean	Std. Dev.	Std. Err. of Mean
MONDAY	288.000	3.248	1.638	0.097
TUESDAY	288.000	3.533	1.642	0.097
WEDNESDAY	288.000	3.680	1.663	0.098
THURSDAY	288.000	3.589	1.596	0.094
FRIDAY	288.000	3.046	1.181	0.070
All	1440.000	3.419	1.570	0.041

General news France

Method	df	Value	Probability
Anova F-statistic	(8, 2583)	4.819	0.000

Analysis of Variance

Source of Variation	df	Sum of Sq.	Mean Sq.
Between	8.000	3.683	0.460
Within	2583.000	246.768	0.096
Total	2591.000	250.450	0.097

Category Statistics

Variable	Count	Mean	Std. Dev.	Std. Err. of Mean
DECEMBER	288.000	0.340	0.269	0.016
JANUARY	288.000	0.396	0.303	0.018
FEBRUARY	288.000	0.457	0.353	0.021
MARCH	288.000	0.469	0.347	0.020
APRIL	288.000	0.369	0.283	0.017
MAY	288.000	0.418	0.321	0.019
SEPTEMBER	288.000	0.424	0.295	0.017
OCTOBER	288.000	0.417	0.308	0.018
NOVEMBER	288.000	0.403	0.292	0.017
All	2592.000	0.410	0.311	0.006

Method	df	Value	Probability
Anova F-statistic	(4, 1435)	4.262	0.002

Analysis of Variance

Source of Variation	df	Sum of Sq.	Mean Sq.
Between	4.000	2.390	0.597
Within	1435.000	201.154	0.140
Total	1439.000	203.544	0.141

Category Statistics

Variable	Count	Mean	Std. Dev.	Std. Err. of Mean
MONDAY	288.000	0.440	0.340	0.020
TUESDAY	288.000	0.514	0.380	0.022
WEDNESDAY	288.000	0.535	0.382	0.023
THURSDAY	288.000	0.554	0.418	0.025
FRIDAY	288.000	0.479	0.348	0.020
All	1440.000	0.504	0.376	0.010

TABLE 3.7.14.B: Median equality tests among months of the year and days of the week for General news: This table reports various rank-based nonparametric tests of the hypothesis that the subgroups have the same median, against the alternative that at least one subgroup has a different median. ***Kruskal-Wallis one-way ANOVA by ranks test***. This is a generalization of the Mann-Whitney test to more than two subgroups. The test is based on a one-way analysis of variance using only ranks of the data. The Table reports the chi-square approximation to the Kruskal-Wallis test statistic (with tie correction). Under the null hypothesis, this statistic is approximately distributed as a χ^2 with the number of subgroups-1 degrees of freedom (see Sheskin, 1997). ***Van der Waerden (normal scores) test***. This test is analogous to the Kruskal-Wallis test, except that the ranks are smoothed by converting them into normal quantiles (Conover, 1980). This table reports a statistic which is approximately distributed as a χ^2 with the number of subgroups -1 degrees of freedom under the null hypothesis. ***Chi-square test for the median***. This is a rank-based ANOVA test based on the comparison of the number of observations above and below the overall median in each subgroup. This test is also known as the median test (Conover, 1980). These tests cover a one year period (December 1, 1999 – November 30, 2000) by month of the year and by day of the week within successive intraday periods of five minutes for General news related and non- to France. Due to technical problems with the Reuters Terminal some periods are left out from the analysis.

General news

Method	df	Value	Probability
Med. Chi-square	8.000	186.219	0.000
Adj. Med. Chi-square	8.000	182.256	0.000
Kruskal-Wallis	8.000	176.225	0.000
van der Waerden	8.000	172.317	0.000

Category Statistics					
			> Overall		
Variable	Count	Median	Median	Mean Rank	Mean Score
DECEMBER	288.000	2.258	70.000	932.201	-0.462
JANUARY	288.000	2.403	87.000	1044.870	-0.314
FEBRUARY	288.000	2.707	131.000	1206.764	-0.137
MARCH	288.000	2.839	149.000	1310.319	0.013
APRIL	288.000	2.767	138.000	1257.082	-0.085
MAY	288.000	3.129	176.000	1442.030	0.177
SEPTEMBER	288.000	3.283	187.000	1516.983	0.278
OCTOBER	288.000	3.226	176.000	1465.280	0.198
NOVEMBER	288.000	3.100	168.000	1492.972	0.332
All	2592.000	2.806	1282.000	1296.500	0.000

Method	df	Value	Probability
Med. Chi-square	4.000	30.628	0.000
Adj. Med. Chi-square	4.000	29.362	0.000
Kruskal-Wallis	4.000	35.459	0.000
van der Waerden	4.000	37.512	0.000

Category Statistics				
			> Overall	
Variable	Count	Median	Median	Mean Rank
MONDAY	288.000	3.298	131.000	666.356
TUESDAY	288.000	3.538	148.000	749.917
WEDNESDAY	288.000	3.764	168.000	792.712
THURSDAY	288.000	3.689	161.000	771.427
FRIDAY	288.000	3.154	110.000	622.089
All	1440.000	3.472	718.000	720.500

General news France

Method	df	Value	Probability
Med. Chi-square	8.000	14.028	0.081
Adj. Med. Chi-square	8.000	13.050	0.110
Kruskal-Wallis	8.000	31.217	0.000
van der Waerden	8.000	39.659	0.000

Category Statistics					
			> Overall		
Variable	Count	Median	Median	Mean Rank	Mean Score
DECEMBER	288.000	0.290	120.000	1131.771	-0.219
JANUARY	288.000	0.355	143.000	1264.674	-0.037
FEBRUARY	288.000	0.431	157.000	1390.146	0.158
MARCH	288.000	0.419	154.000	1408.519	0.183
APRIL	288.000	0.333	133.000	1212.024	-0.129
MAY	288.000	0.387	147.000	1303.693	0.014
SEPTEMBER	288.000	0.400	146.000	1359.839	0.094
OCTOBER	288.000	0.403	149.000	1300.424	-0.008
NOVEMBER	288.000	0.367	141.000	1297.411	-0.013
All	2592.000	0.367	1290.000	1296.500	0.005

Method	df	Value	Probability
Med. Chi-square	4.000	2.794	0.593
Adj. Med. Chi-square	4.000	2.390	0.665
Kruskal-Wallis	4.000	15.316	0.004
van der Waerden	4.000	23.818	0.000

Category Statistics				
			> Overall	
Variable	Count	Median	Median	Mean Rank
MONDAY	288.000	0.423	134.000	644.837
TUESDAY	288.000	0.500	149.000	732.009
WEDNESDAY	288.000	0.528	149.000	752.672
THURSDAY	288.000	0.509	148.000	766.412
FRIDAY	288.000	0.423	138.000	706.571
All	1440.000	0.462	718.000	720.500

TABLE 3.7.14.C: Variance equality tests among months of the year and days of the week for General news: Tests the null hypothesis that the variances in all subgroups are equal against the alternative that at least one subgroup has a different variance. See Conover, et al. (1981) for a general discussion of variance testing. ***Bartlett test***. This test compares the logarithm of the weighted average variance with the weighted sum of the logarithms of the variances. Under the joint null hypothesis that the subgroup variances are equal and that the sample is normally distributed, the test statistic is approximately distributed as a χ^2 with the number of subgroups-1 degrees of freedom. Note, however, that the joint hypothesis implies that this test is sensitive to departures from normality. ***Levene test***. This test is based on an analysis of variance (ANOVA) of the absolute difference from the mean. The F-statistic for the Levene test has an approximate F-distribution with the number of subgroups -1 numerator degrees of freedom and N- the number of subgroups denominator degrees of freedom under the null hypothesis of equal variances in each subgroup (Levene, 1960). ***Brown-Forsythe (modified Levene) test.*** This is a modification of the Levene test in which the absolute mean difference is replaced with the absolute median difference and appears to be a superior test in terms of robustness and power (Conover, et al. (1981), Brown and Forsythe (1974), Neter, et al. (1996)).These test cover a one year period (December 1, 1999 – November 30, 2000) by month of the year and by day of the week within successive intraday periods of five minutes for General News related and non- to France. Due to technical problems with the Reuters Terminal some periods are left out from the analysis.

General news

Method	df	Value	Probability
Bartlett	8.000	410.114	0.000
Levene	(8, 2583)	27.247	0.000
Brown-Forsythe	(8, 2583)	22.966	0.000

Category Statistics				
			Mean Abs.	Mean Abs.
Variable	Count	Std. Dev.	Mean Diff.	Median Diff.
DECEMBER	288.000	1.016	0.753	0.753
JANUARY	288.000	1.119	0.842	0.842
FEBRUARY	288.000	1.273	0.994	0.994
MARCH	288.000	1.266	0.973	0.973
APRIL	288.000	1.272	1.016	1.016
MAY	288.000	1.468	1.163	1.163
SEPTEMBER	288.000	1.282	0.989	0.986
OCTOBER	288.000	1.457	1.185	1.181
NOVEMBER	288.000	2.570	1.786	1.731
All	2592.000	1.529	1.078	1.071

Bartlett weighted standard deviation: 1.477675

Method	df	Value	Probability
Bartlett	4.000	42.966	0.000
Levene	(4, 1435)	7.339	0.000
Brown-Forsythe	(4, 1435)	7.428	0.000

Category Statistics				
			Mean Abs.	Mean Abs.
Variable	Count	Std. Dev.	Mean Diff.	Median Diff.
MONDAY	288.000	1.638	1.275	1.274
TUESDAY	288.000	1.642	1.302	1.302
WEDNESDAY	288.000	1.663	1.316	1.313
THURSDAY	288.000	1.596	1.268	1.265
FRIDAY	288.000	1.181	0.955	0.949
All	1440.000	1.570	1.223	1.221

Bartlett weighted standard deviation: 1.554744

General news France

Method	df	Value	Probability
Bartlett	8.000	38.329	0.000
Levene	(8, 2583)	8.558	0.000
Brown-Forsythe	(8, 2583)	7.918	0.000

Category Statistics				
			Mean Abs.	Mean Abs.
Variable	Count	Std. Dev.	Mean Diff.	Median Diff.
DECEMBER	288.000	0.269	0.230	0.229
JANUARY	288.000	0.303	0.265	0.265
FEBRUARY	288.000	0.353	0.309	0.308
MARCH	288.000	0.347	0.304	0.302
APRIL	288.000	0.283	0.247	0.246
MAY	288.000	0.321	0.282	0.281
SEPTEMBER	288.000	0.295	0.258	0.257
OCTOBER	288.000	0.308	0.265	0.265
NOVEMBER	288.000	0.292	0.250	0.249
All	2592.000	0.311	0.268	0.267

Bartlett weighted standard deviation: 0.309088

Method	df	Value	Probability
Bartlett	4.000	15.781	0.003
Levene	(4, 1435)	7.896	0.000
Brown-Forsythe	(4, 1435)	7.380	0.000

Category Statistics				
			Mean Abs.	Mean Abs.
Variable	Count	Std. Dev.	Mean Diff.	Median Diff.
MONDAY	288.000	0.340	0.304	0.304
TUESDAY	288.000	0.380	0.341	0.341
WEDNESDAY	288.000	0.382	0.339	0.339
THURSDAY	288.000	0.418	0.375	0.373
FRIDAY	288.000	0.348	0.315	0.313
All	1440.000	0.376	0.335	0.334

Bartlett weighted standard deviation: 0.374402

TABLE 3.7.15.A: Mean equality test among months of the year and days of the week for Economic news: This test is based on a single-factor, between-subjects, analysis of variance (ANOVA). The basic idea is that if the subgroups have the same mean, then the variability between the sample means (between group) should be the same as the variability within any subgroup (within group).This test covers a one year period (December 1, 1999 – November 30, 2000) by month of the year and by day of the week within successive intraday periods of five minutes for Economic news related and non- to France. Due to technical problems with the Reuters Terminal some periods are left out from the analysis.

Economic news

Method	df	Value	Probability
Anova F-statistic	(8, 2583)	3.060	0.002

Analysis of Variance			
Source of Variation	df	Sum of Sq.	Mean Sq.
Between	8.000	53.384	6.673
Within	2583.000	5632.539	2.181
Total	2591.000	5685.923	2.194

Category Statistics				
Variable	Count	Mean	Std. Dev.	Std. Err. of Mean
DECEMBER	288.000	2.755	1.336	0.079
JANUARY	288.000	2.926	1.526	0.090
FEBRUARY	288.000	3.124	1.613	0.095
MARCH	288.000	3.099	1.538	0.091
APRIL	288.000	2.650	1.431	0.084
MAY	288.000	2.962	1.522	0.090
SEPTEMBER	288.000	2.839	1.454	0.086
OCTOBER	288.000	2.967	1.505	0.089
NOVEMBER	288.000	2.958	1.341	0.079
All	2592.000	2.920	1.481	0.029

Method	df	Value	Probability
Anova F-statistic	(4, 1435)	5.233	0.000

Analysis of Variance			
Source of Variation	df	Sum of Sq.	Mean Sq.
Between	4.000	80.802	20.200
Within	1435.000	5539.043	3.860
Total	1439.000	5619.844	3.905

Category Statistics				
Variable	Count	Mean	Std. Dev.	Std. Err. of Mean
MONDAY	288.000	3.635	2.081	0.123
TUESDAY	288.000	4.013	2.043	0.120
WEDNESDAY	288.000	4.119	2.095	0.123
THURSDAY	288.000	4.007	1.972	0.116
FRIDAY	288.000	3.516	1.587	0.094
All	1440.000	3.858	1.976	0.052

Economic news France

Method	df	Value	Probability
Anova F-statistic	(7, 2296)	1.654	0.116

Analysis of Variance			
Source of Variation	df	Sum of Sq.	Mean Sq.
Between	7.000	0.126	0.018
Within	2296.000	24.947	0.011
Total	2303.000	25.073	0.011

Category Statistics				
Variable	Count	Mean	Std. Dev.	Std. Err. of Mean
DECEMBER	288.000	0.104	0.102	0.006
JANUARY	288.000	0.111	0.103	0.006
FEBRUARY	288.000	0.108	0.106	0.006
MARCH	288.000	0.116	0.109	0.006
APRIL	288.000	0.099	0.094	0.006
SEPTEMBER	288.000	0.125	0.111	0.007
OCTOBER	288.000	0.107	0.101	0.006
NOVEMBER	288.000	0.111	0.107	0.006
All	2304.000	0.110	0.104	0.002

Method	df	Value	Probability
Anova F-statistic	(4, 1435)	1.353	0.248

Analysis of Variance			
Source of Variation	df	Sum of Sq.	Mean Sq.
Between	4.000	0.077	0.019
Within	1435.000	20.457	0.014
Total	1439.000	20.534	0.014

Category Statistics				
Variable	Count	Mean	Std. Dev.	Std. Err. of Mean
MONDAY	288.000	0.125	0.113	0.007
TUESDAY	288.000	0.139	0.122	0.007
WEDNESDAY	288.000	0.141	0.119	0.007
THURSDAY	288.000	0.147	0.121	0.007
FRIDAY	288.000	0.142	0.123	0.007
All	1440.000	0.139	0.119	0.003

TABLE 3.7.15.B: Median equality tests among months of the year and days of the week for Economic news: This table reports various rank-based nonparametric tests of the hypothesis that the subgroups have the same median, against the alternative that at least one subgroup has a different median. ***Kruskal-Wallis one-way ANOVA by ranks test***. This is a generalization of the Mann-Whitney test to more than two subgroups. The test is based on a one-way analysis of variance using only ranks of the data. The Table reports the chi-square approximation to the Kruskal-Wallis test statistic (with tie correction). Under the null hypothesis, this statistic is approximately distributed as a χ^2 with the number of subgroups-1 degrees of freedom (see Sheskin, 1997). ***Van der Waerden (normal scores) test***. This test is analogous to the Kruskal-Wallis test, except that the ranks are smoothed by converting them into normal quantiles (Conover, 1980). This table reports a statistic which is approximately distributed as a χ^2 with the number of subgroups -1 degrees of freedom under the null hypothesis. ***Chi-square test for the median***. This is a rank-based ANOVA test based on the comparison of the number of observations above and below the overall median in each subgroup. This test is also known as the median test (Conover, 1980). These tests cover a one year period (December 1, 1999 – November 30, 2000) by month of the year and by day of the week within successive intraday periods of five minutes for Economic news related and non- to France. Due to technical problems with the Reuters Terminal some periods are left out from the analysis.

Economic news

Method	df	Value	Probability
Med. Chi-square	8.000	22.448	0.004
Adj. Med. Chi-square	8.000	21.072	0.007
Kruskal-Wallis	8.000	25.532	0.001
van der Waerden	8.000	30.400	0.000

Category Statistics					
			> Overall		
Variable	Count	Median	Median	Mean Rank	Mean Score
DECEMBER	288.000	2.694	130.000	1225.878	-0.099
JANUARY	288.000	2.839	149.000	1292.127	-0.016
FEBRUARY	288.000	3.034	155.000	1385.396	0.135
MARCH	288.000	2.968	158.000	1384.944	0.140
APRIL	288.000	2.583	114.000	1141.210	-0.218
MAY	288.000	2.935	152.000	1319.729	0.031
SEPTEMBER	288.000	2.733	136.000	1256.542	-0.062
OCTOBER	288.000	2.855	148.000	1320.307	0.022
NOVEMBER	288.000	2.933	150.000	1342.366	0.066
All	2592.000	2.833	1292.000	1296.500	0.000

Method	df	Value	Probability
Med. Chi-square	4.000	26.028	0.000
Adj. Med. Chi-square	4.000	24.740	0.000
Kruskal-Wallis	4.000	20.523	0.000
van der Waerden	4.000	27.587	0.000

Category Statistics				
			> Overall	
Variable	Count	Median	Median	Mean Rank
MONDAY	288.000	3.500	118.000	655.049
TUESDAY	288.000	4.029	161.000	751.245
WEDNESDAY	288.000	4.123	162.000	773.828
THURSDAY	288.000	3.953	156.000	756.332
FRIDAY	288.000	3.452	123.000	666.047
All	1440.000	3.790	720.000	720.500

Economic news France

Method	df	Value	Probability
Med. Chi-square	7.000	6.722	0.458
Adj. Med. Chi-square	7.000	6.014	0.538
Kruskal-Wallis	7.000	13.729	0.056
van der Waerden	7.000	15.448	0.031

Category Statistics					
			> Overall		
Variable	Count	Median	Median	Mean Rank	Mean Score
DECEMBER	288.000	0.065	138.000	1084.161	-0.067
JANUARY	288.000	0.065	141.000	1132.852	0.003
FEBRUARY	288.000	0.069	137.000	1173.524	0.041
MARCH	288.000	0.097	151.000	1153.125	0.044
APRIL	288.000	0.067	134.000	1126.644	-0.028
SEPTEMBER	288.000	0.100	159.000	1263.667	0.185
OCTOBER	288.000	0.065	141.000	1110.319	-0.029
NOVEMBER	288.000	0.100	147.000	1175.707	0.055
All	2304.000	0.069	1148.000	1152.500	0.026

Method	df	Value	Probability
Med. Chi-square	4.000	2.623	0.623
Adj. Med. Chi-square	4.000	2.318	0.678
Kruskal-Wallis	4.000	3.839	0.428
van der Waerden	4.000	4.946	0.293

Category Statistics				
			> Overall	
Variable	Count	Median	Median	Mean Rank
MONDAY	288.000	0.115	132.000	685.418
TUESDAY	288.000	0.115	141.000	728.913
WEDNESDAY	288.000	0.113	143.000	708.262
THURSDAY	288.000	0.132	151.000	733.200
FRIDAY	288.000	0.115	139.000	746.707
All	1440.000	0.115	706.000	720.500

TABLE 3.7.15.C: Variance equality tests among months of the year and days of the week for Economic news: Tests the null hypothesis that the variances in all subgroups are equal against the alternative that at least one subgroup has a different variance. See Conover, et al. (1981) for a general discussion of variance testing. ***Bartlett test***. This test compares the logarithm of the weighted average variance with the weighted sum of the logarithms of the variances. Under the joint null hypothesis that the subgroup variances are equal and that the sample is normally distributed, the test statistic is approximately distributed as a χ^2 with the number of subgroups-1 degrees of freedom. Note, however, that the joint hypothesis implies that this test is sensitive to departures from normality. ***Levene test***. This test is based on an analysis of variance (ANOVA) of the absolute difference from the mean. The F-statistic for the Levene test has an approximate F-distribution with the number of subgroups -1 numerator degrees of freedom and N- the number of subgroups denominator degrees of freedom under the null hypothesis of equal variances in each subgroup (Levene, 1960). ***Brown-Forsythe (modified Levene) test.*** This is a modification of the Levene test in which the absolute mean difference is replaced with the absolute median difference and appears to be a superior test in terms of robustness and power (Conover, et al. (1981), Brown and Forsythe (1974), Neter, et al. (1996)).These test cover a one year period (December 1, 1999 – November 30, 2000) by month of the year and by day of the week within successive intraday periods of five minutes for Economic News related and non- to France. Due to technical problems with the Reuters Terminal some periods are left out from the analysis.

Economic news

Method	df	Value	Probability
Bartlett	8.000	18.196	0.020
Levene	(8, 2583)	2.196	0.025
Brown-Forsythe	(8, 2583)	2.133	0.030

Category Statistics				
Variable	Count	Std. Dev.	Mean Abs. Mean Diff.	Mean Abs. Median Diff.
DECEMBER	288.000	1.336	1.088	1.087
JANUARY	288.000	1.526	1.223	1.220
FEBRUARY	288.000	1.613	1.298	1.295
MARCH	288.000	1.538	1.204	1.198
APRIL	288.000	1.431	1.110	1.107
MAY	288.000	1.522	1.252	1.252
SEPTEMBER	288.000	1.454	1.186	1.183
OCTOBER	288.000	1.505	1.220	1.218
NOVEMBER	288.000	1.341	1.078	1.078
All	2592.000	1.481	1.184	1.182

Bartlett weighted standard deviation: 1.476692

Method	df	Value	Probability
Bartlett	4.000	28.106	0.000
Levene	(4, 1435)	4.056	0.003
Brown-Forsythe	(4, 1435)	4.018	0.003

Category Statistics				
Variable	Count	Std. Dev.	Mean Abs. Mean Diff.	Mean Abs. Median Diff.
MONDAY	288.000	2.081	1.625	1.619
TUESDAY	288.000	2.043	1.633	1.633
WEDNESDAY	288.000	2.095	1.651	1.651
THURSDAY	288.000	1.972	1.598	1.597
FRIDAY	288.000	1.587	1.317	1.316
All	1440.000	1.976	1.565	1.563

Bartlett weighted standard deviation: 1.964678

Economic news France

Method	df	Value	Probability
Bartlett	7.000	10.740	0.150
Levene	(7, 2296)	1.950	0.058
Brown-Forsythe	(7, 2296)	1.532	0.152

Category Statistics				
Variable	Count	Std. Dev.	Mean Abs. Mean Diff.	Mean Abs. Median Diff.
DECEMBER	288.000	0.102	0.082	0.079
JANUARY	288.000	0.103	0.086	0.084
FEBRUARY	288.000	0.106	0.090	0.088
MARCH	288.000	0.109	0.088	0.086
APRIL	288.000	0.094	0.078	0.076
SEPTEMBER	288.000	0.111	0.092	0.091
OCTOBER	288.000	0.101	0.082	0.079
NOVEMBER	288.000	0.107	0.089	0.087
All	2304.000	0.104	0.086	0.084

Bartlett weighted standard deviation: 0.104238

Method	df	Value	Probability
Bartlett	4.000	2.759	0.599
Levene	(4, 1435)	2.755	0.027
Brown-Forsythe	(4, 1435)	2.262	0.060

Category Statistics				
Variable	Count	Std. Dev.	Mean Abs. Mean Diff.	Mean Abs. Median Diff.
MONDAY	288.000	0.113	0.091	0.090
TUESDAY	288.000	0.122	0.105	0.104
WEDNESDAY	288.000	0.119	0.103	0.102
THURSDAY	288.000	0.121	0.104	0.103
FRIDAY	288.000	0.123	0.106	0.105
All	1440.000	0.119	0.102	0.101

Bartlett weighted standard deviation: 0.119397

TABLE 3.7.16.A: Mean equality test among months of the year and days of the week for Corporate news: This test is based on a single-factor, between-subjects, analysis of variance (ANOVA). The basic idea is that if the subgroups have the same mean, then the variability between the sample means (between group) should be the same as the variability within any subgroup (within group).This test covers a one year period (December 1, 1999 – November 30, 2000) by month of the year and by day of the week within successive intraday periods of five minutes for Corporate news related and non- to France. Due to technical problems with the Reuters Terminal some periods are left out from the analysis.

Corporate news

Method	df	Value	Probability
Anova F-statistic	(8, 2583)	16.789	0.000

Source of Variation	df	Sum of Sq.	Mean Sq.
Analysis of Variance			
Between	8.000	882.454	110.307
Within	2583.000	16970.570	6.570
Total	2591.000	17853.030	6.890

Variable	Count	Mean	Std. Dev.	Std. Err. of Mean
Category Statistics				
DECEMBER	288.000	3.366	1.980	0.117
JANUARY	288.000	4.084	2.704	0.159
FEBRUARY	288.000	4.832	2.918	0.172
MARCH	288.000	4.203	2.497	0.147
APRIL	288.000	3.935	2.552	0.150
MAY	288.000	3.887	2.527	0.149
SEPTEMBER	288.000	3.093	2.243	0.132
OCTOBER	288.000	3.994	2.660	0.157
NOVEMBER	288.000	5.050	2.853	0.168
All	2592.000	4.049	2.625	0.052

Method	df	Value	Probability
Anova F-statistic	(4, 1435)	7.433	0.000

Source of Variation	df	Sum of Sq.	Mean Sq.
Analysis of Variance			
Between	4.000	235.408	58.852
Within	1435.000	11362.100	7.918
Total	1439.000	11597.500	8.059

Variable	Count	Mean	Std. Dev.	Std. Err. of Mean
Category Statistics				
MONDAY	288.000	4.549	2.758	0.163
TUESDAY	288.000	5.315	3.014	0.178
WEDNESDAY	288.000	5.349	3.022	0.178
THURSDAY	288.000	5.313	2.980	0.176
FRIDAY	288.000	4.457	2.210	0.130
All	1440.000	4.997	2.839	0.075

Corporate news France

Method	df	Value	Probability
Anova F-statistic	(8, 2583)	46.590	0.000

Source of Variation	df	Sum of Sq.	Mean Sq.
Analysis of Variance			
Between	8.000	13.132	1.641
Within	2583.000	91.005	0.035
Total	2591.000	104.136	0.040

Variable	Count	Mean	Std. Dev.	Std. Err. of Mean
Category Statistics				
DECEMBER	288.000	0.117	0.114	0.007
JANUARY	288.000	0.142	0.129	0.008
FEBRUARY	288.000	0.215	0.184	0.011
MARCH	288.000	0.334	0.269	0.016
APRIL	288.000	0.272	0.226	0.013
MAY	288.000	0.273	0.222	0.013
SEPTEMBER	288.000	0.257	0.202	0.012
OCTOBER	288.000	0.207	0.166	0.010
NOVEMBER	288.000	0.125	0.111	0.007
All	2592.000	0.216	0.200	0.004

Method	df	Value	Probability
Anova F-statistic	(4, 1435)	5.255	0.000

Source of Variation	df	Sum of Sq.	Mean Sq.
Analysis of Variance			
Between	4.000	1.112	0.278
Within	1435.000	75.930	0.053
Total	1439.000	77.043	0.054

Variable	Count	Mean	Std. Dev.	Std. Err. of Mean
Category Statistics				
MONDAY	288.000	0.267	0.216	0.013
TUESDAY	288.000	0.309	0.238	0.014
WEDNESDAY	288.000	0.313	0.233	0.014
THURSDAY	288.000	0.334	0.258	0.015
FRIDAY	288.000	0.262	0.201	0.012
All	1440.000	0.297	0.231	0.006

TABLE 3.7.16.B: Median equality tests among months of the year and days of the week for Corporate news: This table reports various rank-based nonparametric tests of the hypothesis that the subgroups have the same median, against the alternative that at least one subgroup has a different median. ***Kruskal-Wallis one-way ANOVA by ranks test***. This is a generalization of the Mann-Whitney test to more than two subgroups. The test is based on a one-way analysis of variance using only ranks of the data. The Table reports the chi-square approximation to the Kruskal-Wallis test statistic (with tie correction). Under the null hypothesis, this statistic is approximately distributed as a χ^2 with the number of subgroups-1 degrees of freedom (see Sheskin, 1997). ***Van der Waerden (normal scores) test***. This test is analogous to the Kruskal-Wallis test, except that the ranks are smoothed by converting them into normal quantiles (Conover, 1980). This table reports a statistic which is approximately distributed as a χ^2 with the number of subgroups -1 degrees of freedom under the null hypothesis. ***Chi-square test for the median***. This is a rank-based ANOVA test based on the comparison of the number of observations above and below the overall median in each subgroup. This test is also known as the median test (Conover, 1980). These tests cover a one year period (December 1, 1999 – November 30, 2000) by month of the year and by day of the week within successive intraday periods of five minutes for Corporate news related and non- to France. Due to technical problems with the Reuters Terminal some periods are left out from the analysis.

Corporate news

Method	df	Value	Probability
Med. Chi-square	8.000	115.556	0.000
Adj. Med. Chi-square	8.000	112.448	0.000
Kruskal-Wallis	8.000	143.034	0.000
van der Waerden	8.000	167.574	0.000

Category Statistics					
Variable	Count	Median	> Overall Median	Mean Rank	Mean Score
DECEMBER	288.000	3.032	109.000	1114.457	-0.236
JANUARY	288.000	3.403	139.000	1293.583	0.011
FEBRUARY	288.000	4.276	188.000	1524.139	0.323
MARCH	288.000	3.871	171.000	1379.384	0.110
APRIL	288.000	3.367	137.000	1264.394	-0.040
MAY	288.000	3.629	147.000	1265.141	-0.038
SEPTEMBER	288.000	2.650	93.000	982.201	-0.483
OCTOBER	288.000	3.306	129.000	1258.703	-0.056
NOVEMBER	288.000	4.250	183.000	1586.498	0.409
All	2592.000	3.541	1296.000	1296.500	0.000

Method	df	Value	Probability
Med. Chi-square	4.000	18.428	0.001
Adj. Med. Chi-square	4.000	17.351	0.002
Kruskal-Wallis	4.000	23.224	0.000
van der Waerden	4.000	33.441	0.000

Category Statistics				
Variable	Count	Median	> Overall Median	Mean Rank
MONDAY	288.000	4.317	125.000	652.967
TUESDAY	288.000	4.837	152.000	759.479
WEDNESDAY	288.000	4.953	159.000	766.865
THURSDAY	288.000	4.925	158.000	764.300
FRIDAY	288.000	3.981	122.000	658.889
All	1440.000	4.654	716.000	720.500

Corporate news France

Method	df	Value	Probability
Med. Chi-square	8.000	169.634	0.000
Adj. Med. Chi-square	8.000	165.643	0.000
Kruskal-Wallis	8.000	285.894	0.000
van der Waerden	8.000	313.180	0.000

Category Statistics					
Variable	Count	Median	> Overall Median	Mean Rank	Mean Score
DECEMBER	288.000	0.097	81.000	895.342	-0.513
JANUARY	288.000	0.097	107.000	1013.457	-0.376
FEBRUARY	288.000	0.172	147.000	1349.795	0.059
MARCH	288.000	0.258	183.000	1620.891	0.498
APRIL	288.000	0.200	179.000	1506.939	0.303
MAY	288.000	0.226	164.000	1492.061	0.273
SEPTEMBER	288.000	0.217	184.000	1490.002	0.243
OCTOBER	288.000	0.161	139.000	1296.264	-0.010
NOVEMBER	288.000	0.100	98.000	1003.750	-0.369
All	2592.000	0.161	1282.000	1296.500	0.012

Method	df	Value	Probability
Med. Chi-square	4.000	8.375	0.079
Adj. Med. Chi-square	4.000	7.743	0.102
Kruskal-Wallis	4.000	11.938	0.018
van der Waerden	4.000	14.975	0.005

Category Statistics				
Variable	Count	Median	> Overall Median	Mean Rank
MONDAY	288.000	0.231	136.000	672.646
TUESDAY	288.000	0.279	150.000	743.504
WEDNESDAY	288.000	0.245	143.000	744.646
THURSDAY	288.000	0.283	154.000	764.229
FRIDAY	288.000	0.192	123.000	677.476
All	1440.000	0.250	706.000	720.500

TABLE 3.7.16.C: Variance equality tests among months of the year and days of the week for Corporate news: Tests the null hypothesis that the variances in all subgroups are equal against the alternative that at least one subgroup has a different variance. See Conover, et al. (1981) for a general discussion of variance testing. ***Bartlett test***. This test compares the logarithm of the weighted average variance with the weighted sum of the logarithms of the variances. Under the joint null hypothesis that the subgroup variances are equal and that the sample is normally distributed, the test statistic is approximately distributed as a χ^2 with the number of subgroups-1 degrees of freedom. Note, however, that the joint hypothesis implies that this test is sensitive to departures from normality. ***Levene test***. This test is based on an analysis of variance (ANOVA) of the absolute difference from the mean. The F-statistic for the Levene test has an approximate F-distribution with the number of subgroups -1 numerator degrees of freedom and N- the number of subgroups denominator degrees of freedom under the null hypothesis of equal variances in each subgroup (Levene, 1960). ***Brown-Forsythe (modified Levene) test.*** This is a modification of the Levene test in which the absolute mean difference is replaced with the absolute median difference and appears to be a superior test in terms of robustness and power (Conover, et al. (1981), Brown and Forsythe (1974), Neter, et al. (1996)).These test cover a one year period (December 1, 1999 – November 30, 2000) by month of the year and by day of the week within successive intraday periods of five minutes for Corporate News related and non- to France. Due to technical problems with the Reuters Terminal some periods are left out from the analysis.

Corporate news

Method	df	Value	Probability
Bartlett	8.000	62.357	0.000
Levene	(8, 2583)	6.792	0.000
Brown-Forsythe	(8, 2583)	4.659	0.000

Category Statistics				
			Mean Abs.	Mean Abs.
Variable	Count	Std. Dev.	Mean Diff.	Median Diff.
DECEMBER	288.000	1.980	1.529	1.493
JANUARY	288.000	2.704	2.127	2.045
FEBRUARY	288.000	2.918	2.218	2.146
MARCH	288.000	2.497	1.851	1.832
APRIL	288.000	2.552	2.030	1.976
MAY	288.000	2.527	1.808	1.794
SEPTEMBER	288.000	2.243	1.713	1.674
OCTOBER	288.000	2.660	2.204	2.104
NOVEMBER	288.000	2.853	2.200	2.121
All	2592.000	2.625	1.964	1.909

Bartlett weighted standard deviation: 2.563221

Method	df	Value	Probability
Bartlett	4.000	36.756	0.000
Levene	(4, 1435)	6.296	0.000
Brown-Forsythe	(4, 1435)	5.571	0.000

Category Statistics				
			Mean Abs.	Mean Abs.
Variable	Count	Std. Dev.	Mean Diff.	Median Diff.
MONDAY	288.000	2.758	2.177	2.165
TUESDAY	288.000	3.014	2.406	2.368
WEDNESDAY	288.000	3.022	2.387	2.363
THURSDAY	288.000	2.980	2.361	2.334
FRIDAY	288.000	2.210	1.809	1.787
All	1440.000	2.839	2.228	2.203

Bartlett weighted standard deviation: 2.813865

Corporate news France

Method	df	Value	Probability
Bartlett	8.000	433.349	0.000
Levene	(8, 2583)	54.720	0.000
Brown-Forsythe	(8, 2583)	39.925	0.000

Category Statistics				
			Mean Abs.	Mean Abs.
Variable	Count	Std. Dev.	Mean Diff.	Median Diff.
DECEMBER	288.000	0.114	0.093	0.089
JANUARY	288.000	0.129	0.109	0.107
FEBRUARY	288.000	0.184	0.156	0.153
MARCH	288.000	0.269	0.225	0.219
APRIL	288.000	0.226	0.188	0.183
MAY	288.000	0.222	0.178	0.174
SEPTEMBER	288.000	0.202	0.166	0.163
OCTOBER	288.000	0.166	0.138	0.135
NOVEMBER	288.000	0.111	0.091	0.087
All	2592.000	0.200	0.149	0.145

Bartlett weighted standard deviation: 0.187702

Method	df	Value	Probability
Bartlett	4.000	20.638	0.000
Levene	(4, 1435)	5.827	0.000
Brown-Forsythe	(4, 1435)	4.791	0.001

Category Statistics				
			Mean Abs.	Mean Abs.
Variable	Count	Std. Dev.	Mean Diff.	Median Diff.
MONDAY	288.000	0.216	0.178	0.177
TUESDAY	288.000	0.238	0.196	0.194
WEDNESDAY	288.000	0.233	0.195	0.191
THURSDAY	288.000	0.258	0.218	0.215
FRIDAY	288.000	0.201	0.173	0.169
All	1440.000	0.231	0.192	0.189

Bartlett weighted standard deviation: 0.230029

TABLE 3.7.17: The Pearsons correlation between 15 news categories during a one year period. This Table shows the correlations among the 15 news categories defined in Chapter 3 during a one year period (December 1, 1999 – November 30, 2000). All correlations are significant at the 0.01 level (two-tailed). The meaning of each acronym is indicated in the list of abbreviations.

	AA	AA_FR	POL	POL_FR	MARKET	MARKET_FR	INDU	INDU_FR	GENERAL	GENERAL_FR	ECO	ECO_FR	CORP	CORP_FR	CAC40
AA	1	0.175	0.695	0.167	0.698	0.212	0.580	0.190	0.413	0.175	0.493	0.102	0.642	0.190	0.121
AA_FR	0.175	1	0.184	0.848	0.191	0.709	0.109	0.517	0.407	1.000	0.105	0.450	0.149	0.517	0.471
POL	0.695	0.184	1	0.201	0.499	0.215	0.379	0.201	0.309	0.184	0.354	0.112	0.518	0.201	0.139
POL_FR	0.167	0.848	0.201	1	0.194	0.649	0.109	0.471	0.377	0.848	0.116	0.517	0.158	0.471	0.517
MARKET	0.698	0.191	0.499	0.194	1	0.184	0.339	0.144	0.239	0.191	0.537	0.123	0.498	0.144	0.156
MARKET_FR	0.212	0.709	0.215	0.649	0.184	1	0.170	0.507	0.338	0.709	0.119	0.363	0.157	0.507	0.368
INDU	0.580	0.109	0.379	0.109	0.339	0.170	1	0.236	0.248	0.109	0.231	0.046	0.369	0.236	0.080
INDU_FR	0.190	0.517	0.201	0.471	0.144	0.507	0.236	1	0.276	0.516	0.060	0.153	0.145	1.000	0.321
GENERAL	0.413	0.407	0.309	0.377	0.239	0.338	0.248	0.276	1	0.407	0.188	0.227	0.211	0.276	0.232
GENERAL_FR	0.175	1.000	0.184	0.848	0.191	0.709	0.109	0.516	0.407	1	0.105	0.451	0.149	0.516	0.472
ECO	0.493	0.105	0.354	0.116	0.537	0.119	0.231	0.060	0.188	0.105	1	0.200	0.441	0.060	0.059
ECO_FR	0.102	0.450	0.112	0.517	0.123	0.363	0.046	0.153	0.227	0.451	0.200	1	0.105	0.153	0.178
CORP	0.642	0.149	0.518	0.158	0.498	0.157	0.369	0.145	0.211	0.149	0.441	0.105	1	0.145	0.129
CORP_FR	0.190	0.517	0.201	0.471	0.144	0.507	0.236	1.000	0.276	0.516	0.060	0.153	0.145	1	0.321
CAC40	0.121	0.471	0.139	0.517	0.156	0.368	0.080	0.321	0.232	0.472	0.059	0.178	0.129	0.321	1

CHAPTER 4

PUBLIC INFORMATION IMPACT ON THE PARIS BOURSE

4.1 Abstract

This chapter studies and analyses the intraday information flow impact on the stocks that compose the CAC 40 index during a one year period. Two approaches are used: first, the classical regression model based on a broad range of public information released by the Reuters 2000 alert system (as independent variables) and intraday market liquidity indicators (as dependent variables). Second, the price impact indicator developed by Bessembinder and Kaufman (1997), which allows to measure the average information content of trades. The results show, in most cases, a strong and positive relation between information flow and transaction volume as well as with market volatility, although less strong, and quoted half spread from order data. Instead, quoted half spread from the WAS file, is, in most cases, negatively related. In some cases, the return seems to anticipate the arrival of public information. The majority of the results rarely show a contemporaneous relation between news arrival and liquidity proxies. Corporate news and All Alerts news seem to be the categories which have the greatest impact on stock liquidity indicators.

The price impact indicates that private information might be present before the news is released. However, no clear price impact pattern has been found, although the informational role of trading is stronger during the opening, the closing and during the trading hours corresponding to the pre-opening and opening of the US markets.

4.2. Introduction and literature review

Public information has always been a major topic in the financial literature, above all concerning its relation to market activity. In the semi-strong form of efficient market hypothesis, Fama (1970) explains that a market is efficient if it fully reflects all publicly available information[42]. In the same paper, Fama (1970) developed the strong-form, which includes the private information concept. A distinction between public and private information has often been made and studied in the literature (French and Roll, 1986). Damodaran (1985), Admati and Pfleiderer (1988) and Ross (1989) are examples of theories of the impact of private and public information arrival on securities returns. These authors conclude that return volatility increases as a result of trades related to the arrival of private information. The latter has been used as a basic concept in order to explain seasonality in trading activity (Admati and Pfleiderer, 1988), whereas public information has played a lesser role in explaining such an intraday phenomenon, even if some attempts have been reported (Atkins and Basu, 1995). In the last two decades, the relation between market activity and specific news events, such as corporate earnings, share issue, dividends and so on has dominated financial economics. A variety of event studies[43] has been reported in the financial literature in order to explain the behaviour of securities around this publicly available information.

Based on the above-mentioned literature, the straightforward question will be asked in this chapter whether the publicly available information affects trading activity (transaction volume), price movement in securities markets, spread and volatility. The primary contribution of my research to this important issue is that I employ a distinctive proxy for information, namely the number of intraday announcements released during a one year period by the Reuters 2000 News Alert System. First, each news item is put into one of eight categories according to its nature. Second, a broad range of stocks is considered, namely the 43 stocks belonging to the CAC 40 index. Third, the analysis is also performed considering each individual stock instead of only the overall index, as usually reported in the literature. Fourth, new light is shed by looking contemporaneously at five market activity indicators. Fifth, the price impact measure is applied and calculated, which had previously been proposed by Bessembinder and Kaufmann (1997). Based on second-by-second data, I used this indicator in an order-driven market, instead of the price-driven market described by them. This procedure allows to measure the average information content of a trade. Finally, it is the first time that such a broad range of data, especially for news activity, is used in the analysis of the Paris Bourse.

Usually, information is received and processed by the agent, and the market reacts to it. In particular, the adjustment of an asset to new information changes investors' expectations. The trader interprets the news, revises his assumptions, and trades in order to arrive at new optimal positions. The outcome of this series of events is the generation of a new transaction volume and a new equilibrium price. In particular, if market participants disagree about the effects of

[42] This strong version is true in the case that information and trading costs, i.e. the costs of getting prices which reflect information, are always zero (Grossman and Stiglitz, 1980). A weaker version hypothesizes that prices which reflect information (the profits to be made) do not exceed the marginal costs (Jensen, 1978).
[43] The semi-strong form of the efficient market hypothesis has been renamed "event study" by Fama (1991).

surprises in announcements, there ought be increased trading activity in the market soon after the announcements. In contrast, if they are in consensus about the effects of new information, trading may not be abnormal even if prices change. Thus, examining trading activity, one can obtain useful information about the actions taken by the market participants based on incoming news, which one cannot get from stock returns alone. It is taking into consideration this reasoning that Jennings, Starks and Fellinghan (1981) developed their model.

According to the efficient market hypothesis, however, only unexpected announcements immediately affect market reactions, as was partially demonstrated by Pearce and Roley (1985). They found, in fact, like Cornell (1983) and Hardouvelis (1987), that only unexpected stock announcements significantly affect stock prices. On the other hand, unexpected inflation and real economy data news do not cause any significant reaction (Pearcey and Roley (1985). As predicted by the theory, anticipated macroeconomic news do not affect market reactions. Furthermore, Pearce and Roley (1985) did not find any link between surprises in CPI announcements and stock market reaction, whereas Schwert (1981) reported a negative relationship.

A similar study, but based on hourly data, concerning the NYSE, was performed by Jain (1988). He tried to establish a relationship between unexpected macroeconomic news and trading volume, as well as between unexpected macroeconomic news and returns. According to his findings, hourly returns react to announcements concerning supply and consumer price index (response completed within one hour), but not to the producer price index, not even to the unemployment rate. Trading volume is not affected by any of the five economic variable announcements, indicating that market participants do not differ substantially in their interpretation of the effects of announcements.

Macroeconomic news is one of the two categories mostly considered in the financial literature (the second one being firm-specific news). In the following two sections I shall survey both of them in order to highlight the major empirical findings in this research field.

A. Macroeconomic news

Many researchers have reported a more or less pronounced relation between stock prices and macroeconomic announcements. Among them is Roll (1988) who found that news stories in the financial press have little effect on the returns of 96 large stocks. Mitchell and Mulherin (1994), however, using the Dow Jones News Stories, saw a significant relationship between macroeconomic and firm-specific news and trading volume. In a similar investigation, Schwert (1981) found only a weak relation between stock prices and macroeconomic announcements. More general analyses by Cutler, Poterba and Summers (1981) and Haugen, Talmor and Torous (1991) failed to find a linkage between major news stories and large movements in market prices. Nofsinger (2001) investigated the trading behaviour of institutional and individual investors around macroeconomic announcements. Both of them buy large firms after good economic news and sell large firms after bad economic news. The trading of small firms does not appear to be motivated by macroeconomic news.

McQueen and Roley (1993) showed that, by allowing for different stages in the business cycle, a stronger relationship between stock prices and news is evident. They found that when the economy is strong the stock market responds negatively to news about higher real economic activity. This negative relation is caused by the longer increase in discount rates relative to expected cash flows.

Becker, Finnerty and Friedman (1995) provide a different approach. The authors wanted to find out how long it takes for UK equities to adjust to U.S. macroeconomic news, considering index future contracts traded in both countries. They found that UK markets immediately react to US news, while US markets ignore UK news. More precisely, they saw that FTSE returns from 1:30 to 2:00 p.m. (i.e. the macroeconomic news release in the USA) are highly correlated to US overnight returns.

Empirical investigations have been made not only concerning the stock market, but also the foreign exchange market. Andersen and Bollerslev (1997), described, for example, the market reaction of the DEM-USD foreign exchange market to macroeconomic announcements. Using 5 minutes returns and all the news headlines that appeared on Reuters Money News Alert screens (October 1992-October 1993), they found that the largest returns are linked to the release of public information.

The exchange market was also considered by Chang and Taylor (1996). In a methodology similar to mine, which consists in separating news stories of the Reuters News Service into different categories, the authors tried to establish a link between information flow and volatility. The total headlines have a significant impact on exchange rate volatility, as shown with ARCH models for periods of 15, 10 and 5 minutes. The authors provide evidence that US macroeconomic news have a significant impact on DEM / USD volatility at high frequencies, but they are unable to show that German macroeconomic news have an impact on DEM / USD volatility, suggesting the presence of an asymmetric component.

De Gennaro and Shrieves (1997) used three categories of news extracted from the Reuters Terminal in order to estimate their impact on the volatility of returns in the exchange market for Japanese YEN and US dollars: first, the scheduled macroeconomic news items; second, unscheduled policy news; and finally unscheduled rate reports. The results document that news effects are important determinants of exchange rate volatility.

The relation between macroeconomic announcements and volatility is central to Li and Engle (1998). They analyse the reaction of conditional volatility, implied by ARCH models, to scheduled announcements. They hypothesize that first, after macroeconomic announcements there is a lower persistence in volatility and volume, and second, there are different reactions to good and bad news. Their results support the Kim-Verrecchia model (1991), which claims that, though not significantly, the post-release days have a lower than average volatility. As far as conditional variance is concerned, the market absorbs scheduled news more quickly than non-scheduled ones. Their results also show that first, information asymmetry, estimated by the volume absolute return ratio (Kim and Verrecchia 1991), decreases after news disclosure, and second, that bad news has a stronger asymmetric effect than good news.

There is also some literature on the question how the futures market processes information around macroeconomic announcements on an intraday basis, such as Ederington and Lee (1993, 1995), Crain and Lee (1995), Leng (1996) and Becker et al. 1996. These authors examined the volatility and returns in various futures markets. Leng (1996) found that the impact of major announcements lasts for at least an hour, whereas that of minor announcements is relatively short-lived. Crain and Lee (1995) also found that most of the price adjustments occur within the first hour, with some evidence that volatility remains higher than normal for several hours. Bollerslev, Cai and Song (2000), Ederington and Lee (1993), Fleming and Remolora (1997) and Balduzzi et al. (1999) examine, instead, the impact of macroeconomic announcements on the US

Treasury bond (future) market. They found that economic announcements are an important source of volatility. Furthermore, Ederington and Lee (1993) show that the return volatility is much higher between 08:30 and 08:35 EST than during any other 5 minutes trading period. Fleming and Remolora (1997, 1998) also found a significant effect on BAS and trading activity of the 5 year US treasury note. Ederington and Lee (1995) performed another study focusing on the information contained in the scheduled macroeconomic news release. More precisely, they examined the adjustment of prices in interest rate and foreign exchange futures to the new information. Using 10 second returns, they found that prices adjust in a series of numerous small, but rapid price changes starting within 10 seconds from the news release, and are basically completed within 40 seconds after the release. This is a considerably more rapid adjustment than that observed by Patell and Wolfson (1984) in equity markets.

The financial literature reports also evidence of macroeconomic announcement impact on the BAS. In particular, Green (2001), using the MRR (1997) model, studied the impact of government bond trading on transaction prices surrounding the release of economic news. He found a significant increase in the adverse selection component of the BAS following economic announcements with greater price impact, which suggests a rise in the level of information asymmetry and an increase in the informational role of trading. Quoted spreads narrow after the announcement release, but the adverse selection component increases, suggesting that the level of information asymmetry rises following economic announcements. This result is analogous to Krinsky and Lee's (1996) finding that the adverse selection component of equity spreads increases after earnings announcements, and is consistent with the presence of a superior information processor as modelled by Kim and Verrecchia (1994).

Frino and Hill (2001) examine, instead, the intraday behaviour of the Sydney Futures Exchange around major scheduled macroeconomic announcements. The analysis of price volatility, trading volume and quoted BAS indicates that the majority of adjustments to new information occurs rapidly, namely, within 240 seconds after the scheduled time for major announcements, with some evidence of abnormal activity prior to the announcements. Analysis of quoted BAS suggests that it significantly widens in the 20 seconds prior to announcements, and remains significantly wider for 30 seconds following announcements. The increase in quoted spread is related to both expected and unexpected volatility, implying that market participants increase quoted spreads around information announcements with the consequence of adverse selection costs.

B. Firm-specific news

Instead of "semi-strong form tests" of price adjustment to public announcements, Fama (1991) uses the expression, "event studies". Event studies are an important part of finance, especially corporate finance. Using simple tools, such research works document interesting regularities in the response of stock prices to particular firm-specific news.

Patell and Wolfson (1984) measure the price reaction to earnings and dividend announcements. The effects can be felt very quickly and are evident in the first few price changes, even if they disappear within five to ten minutes. The results also reveal some activity 1 or 2 hours before the news release. Finally, the variance and serial correlation tests show that the disturbances persist for several hours after public disclosure and extend well into the following day.

Earnings are also central in Kim and Verrecchia's (1991) paper. They suggest that earnings announcements may lead to more information asymmetry by increasing the BAS and reducing market liquidity. The empirical evidence concerning this issue is not unequivocal. For example, Morse and Ushman (1983) and Skinner (1991), using samples of OTC securities, found no clear evidence that the BAS changes around earnings announcements. Skinner (1991), however, does note that spreads increase immediately after announcements conveying relatively large earnings surprises. Examining a sample of NYSE firms, Venkatesh and Chiang (1986) document an increase in spreads for scheduled announcements of earnings and dividend, but not otherwise. Patell (1991) offers evidence that spreads increase after earnings announcements, implying an increase in information asymmetry after these disclosures. Lee et al. (1993), using NYSE specialist quotes, found a significant increase in spreads surrounding earnings announcements. They also show that the announcement effect on the BAS rapidly dissipates.

The widening of the spread is also characteristic for McQueen and Roley's (1993) paper. They examined the market reaction to earnings announcements concerning both intraday BAS and volumes and found that the spread widens before earnings announcements (30 minutes) and after (during 1 day).

Juergens (1999) proposed another way of investigation. She explores the impact of analyst recommendations on intraday stock returns and volatility when those recommendations coincide with the release of public news. She found that there is a significant intraday price reaction, both in terms of returns and volatility. Furthermore, analysts' recommendations have an immediate impact on the market when they are released both with and without public news release.

Ahmed, Schreible and Stevens (2001) analyse, instead, two distinct periods: first, 1996-1999, as a period with a significant amount of online trading, and second, 1992-1995, as a period without online trading. Their procedure allows to show how, based on noisy rational expectation models, the online trading investors react to quarterly earnings announcements, and the corresponding effects. They found that the three day stock price reaction to earnings announcements is significantly larger in the online trading period as compared to the pre-online trading period, after having checked for contemporaneous market returns.

Ranaldo (2002) investigated the transaction cost components around the firm-specific news arrivals. His main results show that: first, spread is tight and LOB is thick in response to news arrival. Second, the Glosten and Harris (1988), the Lin, Sanger and Booth (1995) and the AR model show that the order processing costs appear to be the largest component. On the other hand, the autocorrelation and the adverse selection, which decreases with market liquidity and with the rate of public information arrival, are smaller components of transaction costs. Finally, another interesting result shows that adverse selection is slightly higher before, rather than after, the news arrivals.

C. *Global public information flow*

Berry and Howe (1994) describe intraday relationships between news arrival estimated by the Reuters News Arrival, trading volume, and returns calculated on the S&P 500 index. They show, first, that intraday return does not react to contemporaneous and lagged news arrival (insignificant relationship with price volatility); second, the impact on trading volume is low (moderate relationship between public information and trading volume), and finally, overnight news and opening volume (09:30 – 10 a.m) are significantly related.

Exchange rate volatility is central to Melvin and Yin's (1995) approach. They use the Reuters Money-Market Headlines News in order to measure the impact of public information arrival, impact on the DEM / USD and the YEN / USD. Their results suggest that higher than normal public information brings more than normal quoting activity and volatility.

Gay and Mohorovic (1999) study the impact of daily public news arrival, distinguishing news according to its macroeconomic or firm-specific content. The former news show no strong results, having a significant impact only on trading volume. The latter, however, shows a positive relationship with trading market activity.

All these investigations prove that financial markets react in some cases rapidly and significantly to a specific kind of public news item. Furthermore, these studies focus on aggregate market activity rather than individual stock behaviour. The distinction between corporate, macroeconomic news and other types of news is rarely made, and if so, it is restricted to few categories only. In contrast, my purpose is to study the impact of information flow on individual stocks quoted on the CAC 40 and on the relative index. Furthermore, the information flow is not restricted to one category only, but it is extended to eight groups contemporaneously. This dissociation allows to complement the definition of information flow used in the literature. The main objective of this chapter is to analyse whether the volume of publicly reported information affects the behaviour of trading activity.

In section 4.3, the data and the methodology used in this study will be described. Section 4.4 reports the empirical results, and conclusions are given in Section 4.5. Tables and Figures are depicted in sections 4.6 and 4.7 respectively.

4.3. Data and methodology

The impact of information flow on trading activity is calculated and analysed using two data providers: the *Société de Bourse Française* and the *Reuters 2000 News Alert System*, which will be explained below in more detail.

4.3.1. Transactions and order data

The Société de Bourse Française provides the tick-by-tick data for a one year period (December 1, 1999 – November 30, 2000). Among all the available data, trades and orders are recorded in two different files, called BDM1D2 and BDM2D2 respectively. The trade file provides the time stamp, precise to the second, and the price and quantity traded, whereas the order file gives access to the time stamp, cumulated order size and price quotes of the prevailing bid and ask quotes. Matching these files allows to reconstruct the LOB before, after and within the quotes. Using the Lee and Ready (1991) methodology I identified the buyer- and seller-initiated trades for all the 43 stock analysed. The stocks were chosen selectively, namely shares that belonged to the CAC 40 index during the one year period. The CAC 40 index is the principal index of the Paris Bourse where the heavily traded stocks are quoted.

The French Stock Exchange is an order-driven market, i.e. without designated market makers. Its main characteristic is that it is based on a centralized limit order book which is publicly visible and where traders voluntarily offer liquidity by filling the order book with limit orders during the whole trading day, which lasts continuously from 09:00 a.m. to 05:00 p.m. (until March 31, 2000) and until 05:30 p.m. (from April 1, 2000 onwards). Before the opening and after the closing, two call auctions are performed in order to determine the opening and closing prices respectively. This data has been deleted, like in other research works, from my sample. Analogously, "applications"[44] were omitted. This procedure left me with 23'525'550 transactions, as already shown in the descriptive statistics of Table 2.10.1.A of chapter 2, where also a more precise description of the Paris Bourse has been given.

4.3.2 Public information releases

Reuters is one of the major sources of information used by professionals and can be considered as a public information proxy, as previously reported by Berry and Howe (1994), Goodhart and Demos (1990), Goodhart and O'Hara (1997) and De Gennaro and Shrieves (1997). Since it is the purpose of this chapter to examine the impact of public information on volume, volatility and spread, the question arises how we might measure news arrival. The information content of news is difficult to quantify, and likewise it is difficult to identify whether a news item is positive or negative. In fact, investors sometimes diverge in their interpretation of a news item. It is for this reason that I consider the overall news flow instead. But since the Reuters 2000 News Alert System pages are very diverse and include not only macroeconomic news, but any sort of news worldwide, my first task was the identification of all those news

[44] See Chapter 2.

categories expected to have, potentially, an influence on market trading activity. Using various keyword combinations, I scanned the mass of different news items, which then were classified into one of the following eight categories: All Alerts News, Political News, Market News, Industrial News, General News, Economic News, Corporate News and Firm-specific News. A description of these categories and of the subgroups included in them was given in Chapter 3. The Reuters 2000 News Alert System provides intraday news with time stamps. After having saved all the news in which I was interested, I proceeded to the elimination of news which had showed exactly the same time, date and headline. Thus, I arrived at the basic dataset (the detailed description of the public information dataset is given in Tables 3.7.1 to 3.7.6 of Chapter 3). I then divided it into two distinct periods: one between December 1, 1999 and March 31, 2000, and the other between April 1, 2000 and November 30, 2000. This operation was necessary because the trading time had changed after April 1, 2000.

4.3.3 Methodology

A. Regression analysis

As a first step, in order to organize the data, a time series of spread (measured as quoted half spread from the order data and quoted half spread from the weighted average spread file), trading volume, return and volatility (measured as log range) had to be defined over a time interval of a fixed length. Following Ederington and Lee's (1993) procedure I decomposed the trading day into 96 periods of 5 minutes each, for the first part (December 1, 1999 – March 31, 2000), and into 102 periods in the second part (April 1, 2000 – November 30, 2000). The former period give me 8'352 observations and, the latter, which is not presented, 17'238. I took into consideration twelve time-series: spread (QHS and QHS_WAS), volume (SUMVOL), return (RET), volatility (VOLA) and the eight news categories (All Alerts, Political, Market, Industrial, General, Economic, Corporate and Firm-specific news). The news category are fifteen if we consider also the news related to France. As shown in Chapter 2 and Chapter 3, these time-series show seasonal patterns which might induce bias in the ARCH family models. In order to avoid possible problems associated with seasonality, I deseasonalized each time-series, using Ranaldo's (2000) method which consists in not using the current level of market liquidity, but rather the logarithmic ratio between the current level and its normal value at the current moment. All the mathematical expressions used in this chapter are provided and explained in Appendix 2.11.2 and 2.11.3. In the light of the similarities and differences in intraday patterns, it will be interesting to relate my measure of public information flow to market activity, in order to test whether French stocks react to public information (French related and non-) reaching the market. An appropriate model, which had also been used in Berry and Howe's (1994) research, consists in applying a regression analysis. In this chapter, the following five general ARMA regression analysis, one for each liquidity indicators, were studied:

$$RQHS_i = C + \sum_{v=1}^{p}\gamma_v RQHS_{i-v} + \sum_{w=-12}^{12}\beta_w RNEWS_{i-w} + \sum_{m=0}^{z}\theta_m \varepsilon_{i-m} \quad (1)$$

$$RQHS\_WAS_i = C + \sum_{v=1}^{p}\gamma_v RQHS\_WAS_{i-v} + \sum_{w=-12}^{12}\beta_w RNEWS_{i-w} + \sum_{m=0}^{z}\theta_m \varepsilon_{i-m} \quad (2)$$

$$RSUMVOL_i = C + \sum_{v=1}^{p} \gamma_v RSUMVOL_{i-v} + \sum_{w=-12}^{12} \beta_w RNEWS_{i-w} + \sum_{k=0}^{q} \delta_k RABSRET_{i-k} + \sum_{m=0}^{z} \theta_m \varepsilon_{i-m} \quad (3)$$

$$RABSRET_i = C + \sum_{v=1}^{p} \gamma_v RABSRET_{i-v} + \sum_{w=-12}^{12} \beta_w RNEWS_{i-w} + \sum_{k=0}^{q} \delta_k RSUMVOL_{i-k} + \sum_{m=0}^{z} \theta_m \varepsilon_{i-m} \quad (4)$$

$$RVOLA_i = C + \sum_{v=1}^{p} \gamma_v RVOLA_{i-v} + \sum_{w=-12}^{12} \beta_w RNEWS_{i-w} + \sum_{m=0}^{z} \theta_m \varepsilon_{i-m} \quad (5)$$

The intraday period of 5 minutes is labelled by *i*. $RNEWS_i$ denotes the ratio of number of news announcements within a five minutes period. $RNEWS_i$ is an acronym that can take the value of one of the fifteen news categories (French related and non-). In the results it will be specified to which category of news, $RNEWS_i$, belongs. Differently from other daily studies, I considered only one independent variable (Equation 1, 2 and 5) due to the problems of multicollinearity and sensitivity analysis (lead and lagged independent variable) which might otherwise emerge. If two or more independent variables, at different lagged intervals, are chosen, no precise conclusion can be drawn about which news items influence liquidity indicators. The general model presented above considers lagged and leading independent variable, i.e. $RNEWS_i$. I established the lead and lag period to be at most one hour. Considering previous studies and statistical problems, after that period it will be much more difficult to draw a conclusion. The regression analysis will be conducted twice: the first one taking into account lagged independent variables and, secondly, leading independent variables. After that, I checked for autocorrelation (using correlograms and correcting with the appropriate ARMA model) and heteroskedasticity (White heteroskedasticity test and ARCH LM test). After running the ARMA models, the Fisher test, the Akaike information criterion and the Schwartz criterion, I found which model have the biggest explanatory power. The ARCH LM test allows to find the most plausible ARCH model. Using the likelihood ratio rest and residual tests, I finally singled out the most powerful solution. Among all the significant regressions, I randomly choose which one to represent in the results and only the significant coefficients will be reported. Other tests and conditional variance equation are presented in detail in Appendix 2.11.1.

B. Price impact

The simplest measure of trade execution costs is the quoted bid-ask spread, i.e. the difference between the quoted ask price and the quoted bid price. Peterson and Fialkowski (1994) and Lee (1993) document that trades may occur at prices within the posted bid and ask quotes, implying that the quoted spread provides biased estimates of actual execution costs. In order to reflect trades within the spread, the effective half spread measure was developed, which gives a better estimation of trade execution costs. In fact, the effective half-spread represents the percentage execution cost actually paid by the trader, and the gross revenue to the supplier of immediacy. As reported, among others, by Glosten and Milgrom (1985), market makers widen the spread in response to better informed traders. Bessembinder and Kaufmann (1997) suggest to decompose the effective half-spread into two components: the price impact and the realized half spread. Price impact refers to the decrease in asset value following a customer sell or the increase in asset value following a customer buy which reflects the market assessment based on the private information the trades convey. Realized half spread measures the average price reversal after trades and the net revenue of market maker after deduction of their losses to better informed traders. However, the realized half spread is difficult to estimate because of intermediation costs, defined as the difference between transaction price and equilibrium price. For this reason it will not be calculated. As my analysis considers the private / public information controversy, it will be interesting to check for the presence of private information and its relation to public information release. The price impact measure is calculated as follows:

$$\text{Price impact}_{i,j} = \frac{1}{n}\sum_{t=1}^{n} 100\, D_{i,j,t}\left(p_{i,j,t+30} - MID_{i,j,t}\right) / \left(MID_{i,j,t}\right)$$

$P_{i,\ t+30}$ denotes the first trade price observed 30 minutes after the trade for which the price impact is measured. $MID_{i,\ j,\ t}$ is the quote midpoint of the most recently posted bid and ask quotes for a security (interpreted as a proxy for the pre-trade value of the asset). $D_{i,\ j,\ t}$ is a binary variable that equals one for customer buy orders and minus one for customer sell orders. To my knowledge, this is the first time that this measure is applied in an order-driven market around public information releases. In order to calculate the price impact measure, I proceeded in the following manner: first, the $P_{i,\ j,\ t+30}$ was calculated by observing the first trade 30 minutes after the news release. Second, the trading day was decomposed into 96 periods of 5 minutes each for the first part and into 102 periods for the second part. Third, I calculated the average price impact within a 5 minutes period. Fourth, the intraday evolution of the average price impact is reported, and finally, the relation with the intraday information flow is checked by using the regression analysis (price impact is the dependent variable). One criticism can be made concerning this procedure. For all the transactions after 16:30, I calculated the price impact using the first trade of the following day. The major problem may be related to the short interval used (5 min.). I'm aware of this problem, but I don't think this will compromise my results.

4.4 Empirical results

Empirical results are presented only for the first period under study, i.e. from December 1, 1999 to March 31, 2000 due to technical problems associated with the use of the Reuters 2000 News Alert System Terminal[45]. Even though there are some categories of news which are complete for the full one-year period, the results of the second period do not change significantly from the first. The results not presented in this section are available from the author upon request. All the statistical procedures and tests follow the method explained in Appendix of Chapter 2 (Appendix 2.11.1).

A. Spread

In the spread analysis, two measures are used: first, ratio of the quoted half spread (RQHS), directly calculated from the order data, and second, the ratio of quoted half spread obtained from the weighted average spread file (RQHS_WAS). The latter represents the price for blocks that exceed normal market size.

The results (Tables 4.7.6.A and 4.7.6.B) are less strong in respect of other liquidity indicators, in the sense that when individual stocks are considered, R^2-adjusted is significant only in 15 cases for the QHS_WAS, whereas for the simple QHS it is situated within the average in 23 cases. The R^2-adjusted, for the QHS_WAS, ranks from a minimum of 0.654 (Accor) to a maximum of 0.933 for the CAC 40 index. For the spread calculated from the order data, R^2-adjusted ranks from a minimum of 0.207 (France Telecom) to a maximum of 0.483 for the CAC 40 index.

The regression analysis shows that the relation between information and QHS (Table 4.7.15) may be negative or positive, and it is therefore difficult to draw any conclusion. Also for the QHS_WAS indicator, the relation may be positive or negative. I found, however, in most cases a negative relation, meaning that higher volume reduces the quoted spread. A contemporaneous relation is rarely noticed, and the best models indicate that information anticipates spread. Such a behaviour can be explained as the aggressiveness of a trader. Depending on the news type and on whether there is an imbalance on one side of the book, investors who want to transact promptly are likely to trade within the quote, therefore reducing the spread.

B. Volume

Trading volume is an important measure of trading activity, and it is regressed, like in other studies, on a specific news category and on the absolute value of returns (Berry and Howe, 1994). The result of Table 4.7.8.A show evidence of a positive and significant relation between the chosen public information proxy (independent variable) and the ratio of transaction volume (dependent variable), expressed as the number of shares traded divided by the total number of shares outstanding. A higher information flow tends to be transformed into a higher transaction volume. However, the opposite may occur in some cases as shown by the Table 4.7.8.B, i.e. more information reduce trading activity. Consistent with Berry and Howe (1994) and the studies mentioned in Karpoff (1987), the coefficients for the ratio of absolute value of return are always significant,

[45] See Chapter 3.

but differently from Berry and Howe (1994), it is at the same time negatively related to the transaction volume. The negative relation between absolute price change and trading volume has also been noticed by Mitchell and Mulherin (1994) in their regression analysis when day of the week dummy variables were included.

The best models (Tables 4.7.8.A to 4.7.8.B) are obtained when the independent variable (public information proxy) is lagged until 5 minutes, as in Table 4.7.6.A and, until 40 minutes as in Table 4.7.6.B. My results are different from those previously obtained by Berry and Howe (1994) who found a positive and significant coefficient of the absolute price change. This difference is due to the following reasons: first, Berry and Howe (1994) regress the corresponding half hour of each day, whereas I regress each consecutive five minutes period of each day. Second, their period under study is different. The period analysed is characterised by the tech bubble, and more precisely by the burst of the latter. The volatility was also higher in respect to other periods (see Figures 4.6.1.A to 4.6.1.C). Berry and Howe (1994) found less important results when considering lagged variables. Table 4.7.16 shows that the R^2-adjusted is significant in the majority of cases, ranking from 0.113 to a maximum of 0.546 when the CAC 40 index is considered.

Karpoff (1987) also tried to shed light on the relation between information and trading volume, giving two possible explanations: first, consistent with conjectures made by empirical researchers, investor disagreement leads to increased trading activity. Second, abnormal trading volume does not necessarily imply disagreement, and volume can increase even if investors interpret the information identically, although their prior expectations may have been different.

As demonstrated by the significant constant term, investors may want to trade even in the absence of new information, be it because of unique liquidity or a speculative desire (1986).

The regression analysis model always shows an autoregressive process and a heteroscedastic behaviour for trading volumes. This means that past values are of considerable importance in explaining the regression, i.e. past trading volumes are followed by high values in subsequent periods.

The heteroscedasticity is a clear signal that volatility shocks persist over time, creating clusters of volatility. This was also reported in other studies on time-series data (Lamoureux and Lastrapes, 1990, Cao and Tsay, 1992, Rabemananjara and Zakoian, 1993, Li and Li, 1996). Their results can be interpreted as a signal that periods of high volatility in trading volume are followed by periods of high volatility also in subsequent periods. Therefore, the best models are ARCH-GARCH models, the latter being much more used (variance past values are more significant in GARCH models). The sum of ARCH and GARCH coefficients is nearly 1, indicating strong shock persistence over time. In some cases I also found, as in Table 4.7.6.A, an asymmetric component in volume volatility (TARCH effects), leading to the conclusion that negative term errors cause a different reaction on volume than positive ones. The coefficient of the asymmetric effect is positive, indicating that volatility shocks tend to be increased unless other news generated heterogeneity. The asymmetry properties lead to a decrease of predictable volatility and speed up market activity, thus increasing liquidity (market depth). Such an interpretation is also given by Lamoureux and Lastrapes (1990) who consider a residual of trading volume as news arrival, implying that negative (positive) shocks slightly decrease (increase) market activity and thus reduce (increase) intraday market depth.

C. Return

The news information flow seems to explain also the absolute price returns (Table 4.7.9.B), but the R^2-adjusted is significant in most of cases, and it ranks from a minimum of 0.070 to a maximum of 0.545 if the CAC 40 index is considered. In my regression, leading and lagged independent variables were included, with the latter giving the stronger results. In some cases, I found that returns anticipate public information (Table 4.7.9.A), and this can interpreted as a signal for the existence of private information. If this happened too often, it would invalidate the strong form of market efficiency. Private information transforms itself progressively into public information. If this hypothesis were true, it would need a deeper investigation by using, for example, the price impact measure as previously adopted by Bessembinder and Kaufmann (1997) or by decomposing the BAS into its component around public information releases as done by Ranaldo (2002) and MRR (1997).

In the majority of cases, however, better regression results give evidence of the leading impact of the information volume proxy on absolute price changes. The coefficients are significant, and negatively related to information flow. The estimate model works better when one considers the autoregressive process, meaning that past values are strictly correlated. I also found, in some cases, even if it is not shown, that the conditional variance equation follows a TARCH model. This can be interpreted in the sense that positive and negative shocks may be positively or negatively related to price change volatility.

D. Volatility

The study of the relation between public information announcements and trading activity is of primary interest when one considers the width of stock price movements, i.e. volatility. The latter is of extreme importance for asset management activities. Also derivatives evaluations are based on volatility behaviour. Theoretically, if there is more information, investors may interpret it in more different ways, thus producing higher volatility. I wanted to test this hypothesis by using the same model as the one defined in equation (1). Volatility is now the dependent variable, and it corresponds to the log range, the statistical characteristics and properties of which are well documented in Alizadeh, Debrandt and Diebold (2002).

The results (see Table 4.7.10) are, like in the case of volume, significant but relatively less strong. The R^2-adjusted ranges from a minimum of 0.127 to a maximum of 0.471 in the case of the CAC 40 index. The most powerful models are obtained when the independent variable is lagged, meaning that a higher information flow anticipates an increase in volatility. Werner and Kleidon (1996) also sustain that a higher level of public information causes higher volatility. When the constant term is significant, it means that there is always a movement of stock prices, independently of public information volume.

The regression shows an autoregressive process and a heteroscedastic behaviour of volatility, meaning that past values are of considerable importance in explaining the regression. I didn't find any asymmetric component.

E. The price impact

The price impact measure gives interesting results (Tables 4.7.11 to 4.7.15), even if the R^2-adjusted is less significant than the other liquidity indicators. The relation is negative for France Telecom and positive for Air Liquide, Axa, Total Fina and Vivendi. More importantly, the results show that the price impact measure anticipates the arrival of public information, meaning that private information is present before the release of publicly available information. This is also evident in the spread decomposition given by Ranaldo (2002), which indicates that the magnitude of the adverse selection is slightly higher before, rather than after, the news release arrivals. This interpretation implies a reduction of information asymmetry from the pre-news to the post-news environment.

Green (2001), in his analysis of the bond market, found a significant increase in the adverse selection component of the BAS following economic announcements with a greater price impact, suggesting a rise in the level of information asymmetry and an increase in the informational role of trading. These results are different from mine because I saw that on the French Stock Exchange the informational role of trading was much more important before the release of information flow (up to 50 minutes as in Tables 4.7.12.A and 4.7.15.B).

Figures 4.6.2 to 4.6.7 show the intraday evolution of the average price impact within a 5 minutes period, whereby significant changes occur in the morning for Air Liquide, Axa, Total Fina, France Telecom and Vivendi). The private information content of trade is significant also in the second part of the day, i.e. after the lunch break (Air Liquide and France Telecom). I saw that trades seem to be more informative around the release of US macroeconomic news and around the US opening hours, even if there are not significant changes for Axa, Total and Vivendi in the afternoon (Tables 4.7.1 to 4.7.5). During these periods, as demonstrated in Chapter 2, the trading activity, measured by the trading volume, is generally higher, supporting the hypothesis that private informed traders tend to disguise their orders. In Figure 4.6.7, also the average price impact measure within a 1 minute period, for France Telecom, is shown. The intraday evolution of price impact is here more sensible and higher changes are visible around 13:00, 14:30, 15:30 and before market close. Another interesting point emerge, however, if we look at the intraday evolution, during a five minutes period, of the five stocks presented, i.e. one peak at the beginning and one at the end of the trading day. Admati and Pfleiderer (1988) suppose that during these periods, the activity of the insider may be highest. Tables 4.7.1 to 4.7.5 show the t-test, when testing two adjacent means against each other, for 5 stocks, namely Air Liquide, Axa, Total, France Telecom and Vivendi.

F. News categories and overnight impact

News impact has been divided into eight different categories, namely All Alerts news, Political news, Market News, Economic News, General News, Industrial News, Corporate News and Firm-specific news, each of which has a different impact on market trading indicators.

The regression analysis conducted on individual stocks shows that the companies of the CAC 40 index are much more sensitive to Corporate news and All Alerts news, and least sensitive to General and Industrial news. Investors seem to be influenced by news that have a great impact on the company's future payoff. Economic news, which include also macroeconomic indicators, play instead a lesser role for the CAC 40 stocks, even if they are significant. This is not surprising if one considers that investors already know when the majority of macroeconomic news is released, since the calendar is fixed by the authorities. Also, such news items are followed by a great number of analysts and economists who give an estimation of macroeconomic indicators. As reported in other studies (Pearce and Roley, 1985), only unexpected announcements cause a stock price reaction. It may be that this unexpected component is much more present in the Corporate news category.

All Alerts news is the second category which has a great influence on stock liquidity indicators. The results of its effect on trading activity are significant. The news items included in this category range from Corporate news to Economic and Industrial news as well as Greenspan's speeches. All Alerts considers only the most important news items, and for this reason it can be used as a proxy of global information. In this category the unexpected announcement component may be higher than in other news category.

General news has not a strong impact on the whole trading activity of individual stocks (see Table 4.7.17), which confirms, considering the news items included in this category, that the procedure of categorisation has been done accurately. It is really difficult to imagine that news such a sports, religion or crime can influence stocks behaviour, even if a casual correlation may be found.

The news which relate to France (for example Industrial France and Corporate France) did not have the same impact, confirming that nowadays companies are much more influenced by the news flow worldwide.

Along the line of procedures previously used by Berry and Howe (1994), also an overnight analysis was conducted in order to consider information released before and after the market trading hours. I calculated the number of news items released after the market closure, i.e. after 05:00 p.m., until March 31, 2000 and after 05:30 p.m. after that date, and before market opening, i.e. before 09:00 a.m.. The total number was added to the first 5 minutes period of the following day. However, the analysis did not change my results significantly.

Finally, using the Granger causality test, I investigate whether trading activity and information are causally related in the Granger sense. The test methodology was applied twice: first, I test whether it is true that a particular liquidity proxy does not cause a particular public information flow and secondly, the opposite was tested. In each cases, the regressions were run with twelve lags. The results, which in most cases support my previous results, are summarized in Tables 4.7.18.A to 4.7.18.E.

G. *Concluding remarks*

The regression model, as the one presented in the methodology section, may lead to some criticism as far as the utilisation of lagged independent variables is concerned. The interpretation of the results requires, in this case, some caution, as evidenced by the to following potential scenarios. First scenario: the significance of the lagged independent variable, when it is reported, may be due to chance or caused by seasonality. In some cases, in fact, the sensitivity analysis shows that not all the lagged independent variables are significant but, for example, the coefficient is statistically different from zero only once at the tenth lag as in table 4.7.6.A. If this occurs two possible explanations can be given: the presence of an extreme value in the time series or a seasonality effect observed for example when Wall Street opens. The former and the latter may cause the independent lagged variable to be significantly different from zero. However, the series used in this study have been adjusted for seasonality reducing therefore the probability that this effect has played a role. Extreme value may be therefore considered as the most plausible effect. Consequently, the conclusion that a relation between two variables exist is not perfectly correct and for this reason is much more difficult to draw a conclusion. Second scenario: the results can be considered stronger if the sensitivity analysis shows that more subsequent lagged independent variables are significant (Table 4.7.7.A). In this case it is possible to consider the results more intriguing. The conclusions are more debatable. The general regression model was applied twice. First, in the analysis of intraday market liquidity determinants in chapter 2 and now in this chapter, i.e. the impact of intraday public information on liquidity proxies. The analysis of intraday market liquidity determinants showed that, even if the ARMA regression model takes up to 12 lags into consideration for each variable, which corresponds to one hour of trading, the results deal, in the majority of cases, only with contemporaneous relations among liquidity proxies. In chapter 2 the question of a possible lead/lag relationship was not raised. In this case, the model seems to work well. It is possible to test only contemporaneous relation leaving out lagged independent variables. The news information impact on intraday market liquidity indicators was, on the contrary, more difficult to interpret. Even if some results show that three subsequent lagged independent variables (15 minutes) are significant, as for example in Table 4.7.7.A, in other cases the unique significant independent variable may only be the consequence of the presence of an extreme value. Another problem may be linked to the choice of the model. If we consider that there are, for example, two independent variables, as in Equation 2 of Section 4.3.3. and that the sensitivity analysis must be conducted for these two variables, it is possible to obtain different combinations of significant independent variables by chance. In order to avoid this problem I tried to limit the sensitivity analysis of the intraday market liquidity indicators by considering much more the news flow variable. This method introduces some subjectivity in the regression analysis and the model seems in some way predetermined. Taking into consideration all these possible criticism of the model, it is important to exert some caution in the interpretation of the results.

Another important aspect concerning the interpretation of the results must be discussed. In fact, the specification of the regression may also lead to some other criticism about the selection of the best model and in the interpretation of the results. The literature identifies some approaches concerning the specification problem. One of them is known as the average economic regression (AER), where practitioners use techniques that adopt specifications on the basis of searches for high R^2 or high t values. This technique is called data mining, fishing, grubbing or number-crunching. Arguments against this mechanism have been reported by Mayer (1975, 1980), Peach and Webb (1983) and Lovell (1983). Mayer (1975, 1980), in particular, focuses on adjusted R^2, showing that it does a weak job of picking out the correct specification, mainly because it capitalizes on chance, choosing a specification because it is able to explain better the peculiarities of that particular data set. Lovell (1983), on the other hand, focuses on the search for significant *t* values, branding it data mining, and concludes that such searches will lead to inappropriate specifications, mainly owing to high probability of type I errors because of the many tests performed. As stated by Lovell (1983), data mining may lead to impressive results in terms of the customer criteria but it may "misleading in terms of what it asserts about the underlying process generating the data under study". However, data mining methodology has positive features. In fact, such testing procedure may discover empirical regularities that point to errors in theoretical specifications. The use of this sequential or "stepwise" procedure, in which a large number of different hypothesis are tested in order to select a model, greatly increase the probability of adopting, by chance, an incorrect model. The terminology "data mining" is often used in the context of pre-test bias. In particular, researchers often run a large number of different regressions on a body of data looking for significant *t* statistics; i.e., the final results chosen are more likely to embody a type I error than the claimed 5%. Lovell (1983) offers a rule of thumb for deflating the exaggerated claims of significance generated by such data mining procedures: when a search has been conducted for the best k out of c candidate explanatory variables, a regression coefficient that appears to be significant at the level α_1 should be regarded as significant only at level $\alpha = (c / k)\ \alpha_1$. Taking into consideration all the aspects mentioned above and pointed out by some authors, my empirical approach, especially the procedure used in the selection of the best model (in particular the lag length) may be similar, in some aspects, to the data mining technique. For this reason the interpretation of the results, i.e. for example if significant variables and the level of significance are considered, require, therefore, some caution. In fact, in the Tables presented, the level of significance does not take into consideration the data mining approach, leading to some incorrect conclusions. Exaggerated claims of significance have not been deflated using the Lovell (1983) approach.

4.5. Conclusions

The objective of this chapter was to find out whether the intraday flow of public information reported second-by-second by the Reuters 2000 News Alert System has an impact on the trading activity of 43 individual stocks and on the CAC 40 index of the Paris Bourse during a one year period (December 1, 1999 – November 30, 2000).

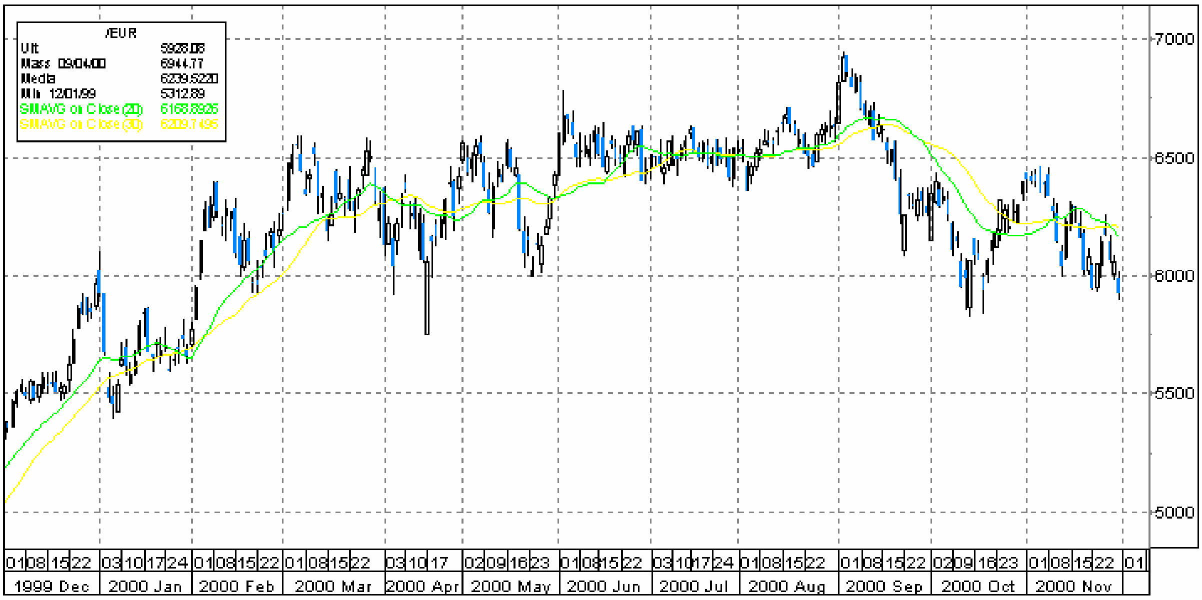
My analysis concerns the impact of the public information flow, grouped into various news categories (All Alerts, Political, Market, Industrial, Economic, Corporate, Firm-specific and General news) on the trading activity of the Paris Bourse. The following results were obtained:

1. The spread measure was divided into two indicators: the ratio of quoted half spread (RQHS), calculated from the order data, and the ratio of quoted half spread calculated from the weighted average spread (RQHS_WAS). The former was in some cases negatively related and in some other positively to information flow, whereas the latter was in the majority of cases negatively related. RQHS_WAS shows very high R^2-adjusted. I interpret this result as aggressiveness on the part of investors' orders.
2. The intraday volume exhibits a strong, positive, and statistically significant relation with the majority of news categories, but to a less extent concerning those related to France only. In particular, one can say that higher news activity leads to higher volume activity, confirming previous theories such as the one reported by Karpoff (1987) that it is either disagreement (the majority of the results reported by empirical investigations) or agreement that causes increased trading activity.
3. When using the absolute price change as dependent variable, the results are somewhat different, with the regression analysis indicating a positive relation. In some cases stock return precedes news flow and this may be a signal of the presence of private information.
4. Volatility, calculated as log range for its statistical properties, shows that it is influenced by the news flow in most of the news categories. The results are relatively less strong than for volume, but significantly and positively related. Depending on the stock chosen, the more robust results are significant up to a one hour lag, indicating that higher news flow leads to higher volatility.
5. The price impact measure shows that trades are much more informative around 14:30, when the US macroeconomic indicators are released, and around 15:30 when the US market opens. Consistent with other empirical investigations, private information precedes the arrival of public information by up to 50 minutes.
6. Finally, among the eight news categories considered, the Corporate news and All Alerts news show a more robust impact on individual stocks and on the CAC 40 index as compared to the other news categories.

Another feature of the results is that the market capitalisation seems to have no influence, i.e. bigger and smaller companies may or may not be influenced by the volume of news. The consideration of other news providers contemporaneously might give a fresh impulse for studying the impact of public information on the trading activity of stock exchanges.

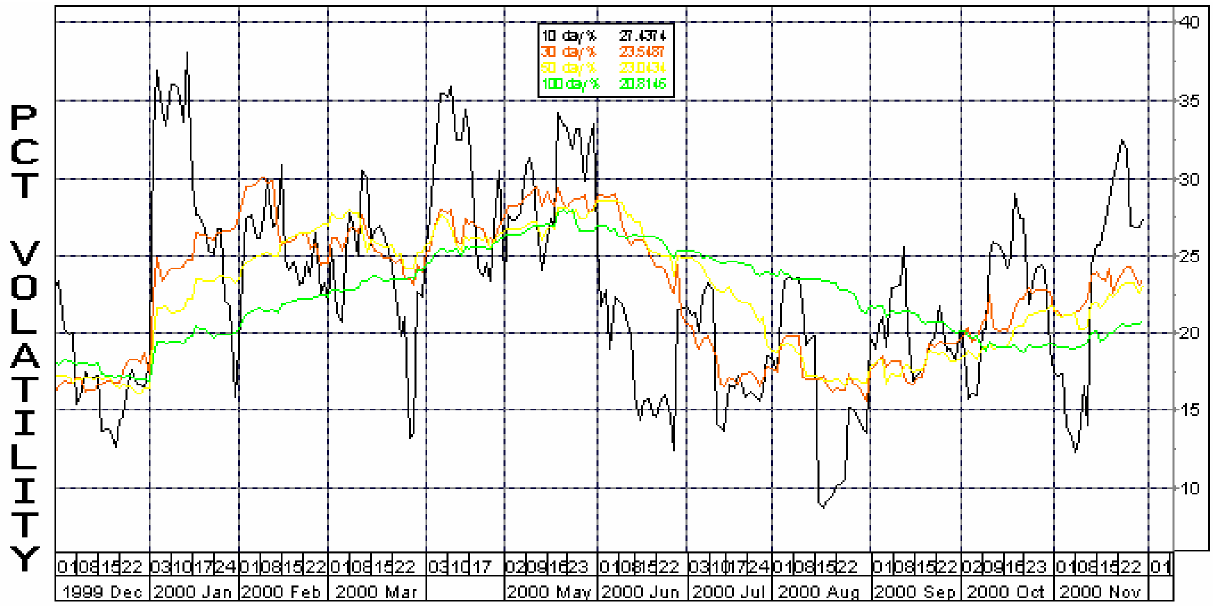
FIGURES

FIGURE 4.6.1.A: Daily evolution of the CAC 40 index (December 1, 1999 – November 30, 2000). This Table shows the daily evolution of the CAC 40 index during a one year period (December 1, 1999 – November 30, 2000). During these period the index ranked from a minimum of 5312.89 points (December 1, 1999) to a maximum of 6944.77 points (September 4, 2000). The last observation is 5928.08 points (November 30, 2000).



Source: Bloomberg

FIGURE 4.6.1.B: Historical volatility of the CAC 40 index (December 1, 1999 – November 30, 2000). This Table shows the historical volatility of the CAC 40 index during a one year period (December 1, 1999 – November 30, 2000). The black line is the volatility at 10 days, the orange line at 30 days, the yellow line at 50 days and the green at 100 days.



Source: Bloomberg

FIGURE 4.6.1.C: Historical volatility of the CAC 40 index between 1999 and 2000. This Table shows the historical volatility of the CAC 40 index during two years period. The black line is the volatility at 10 days, the orange line at 30 days, the yellow line at 50 days and the green at 100 days.

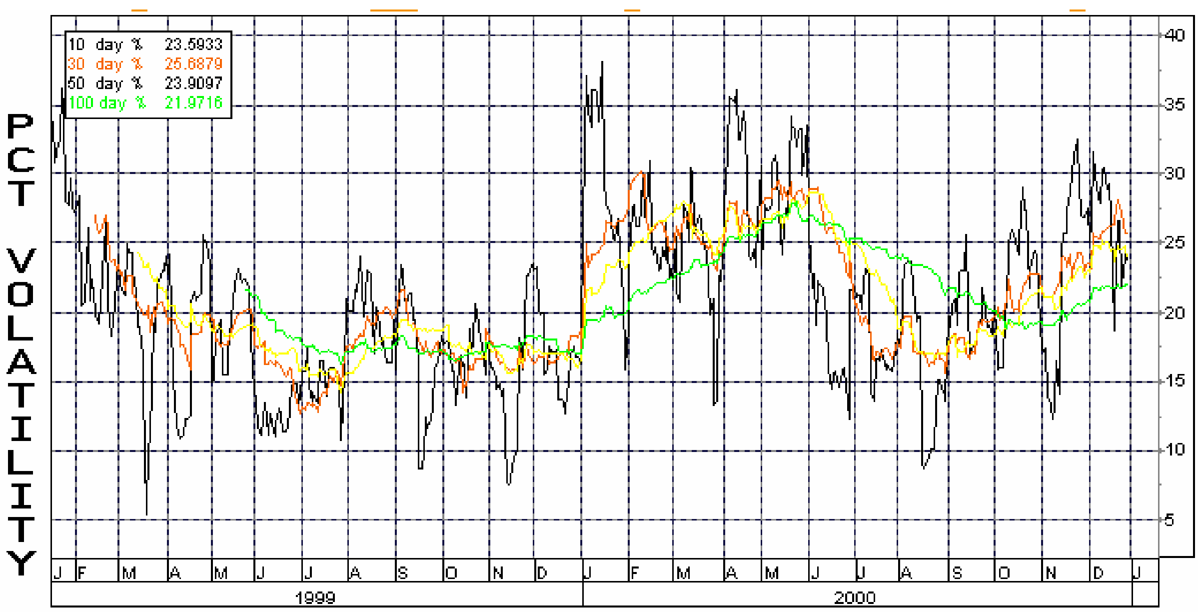


FIGURE 4.6.2: Price impact measure for Air Liquide. This Table shows the intraday evolution for the average price impact measure, which indicates the trade information content, for the Air Liquide stock during the period from December 1, 1999 – March 31, 2000 within successive intraday periods of five minutes.

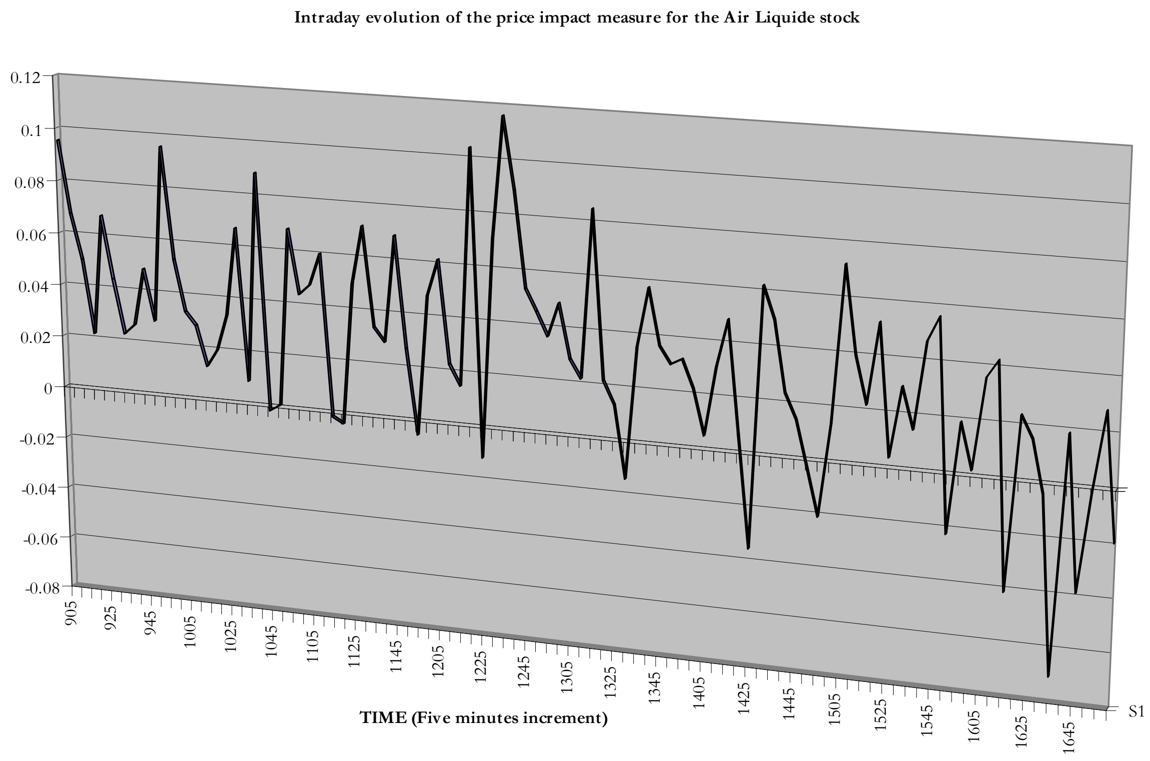


FIGURE 4.6.3: Price impact measure for Axa. This Table shows the intraday evolution for the average price impact measure, which indicates the trade information content, for the Axa stock during the period from December 1, 1999 – March 31, 2000 within successive intraday periods of five minutes.

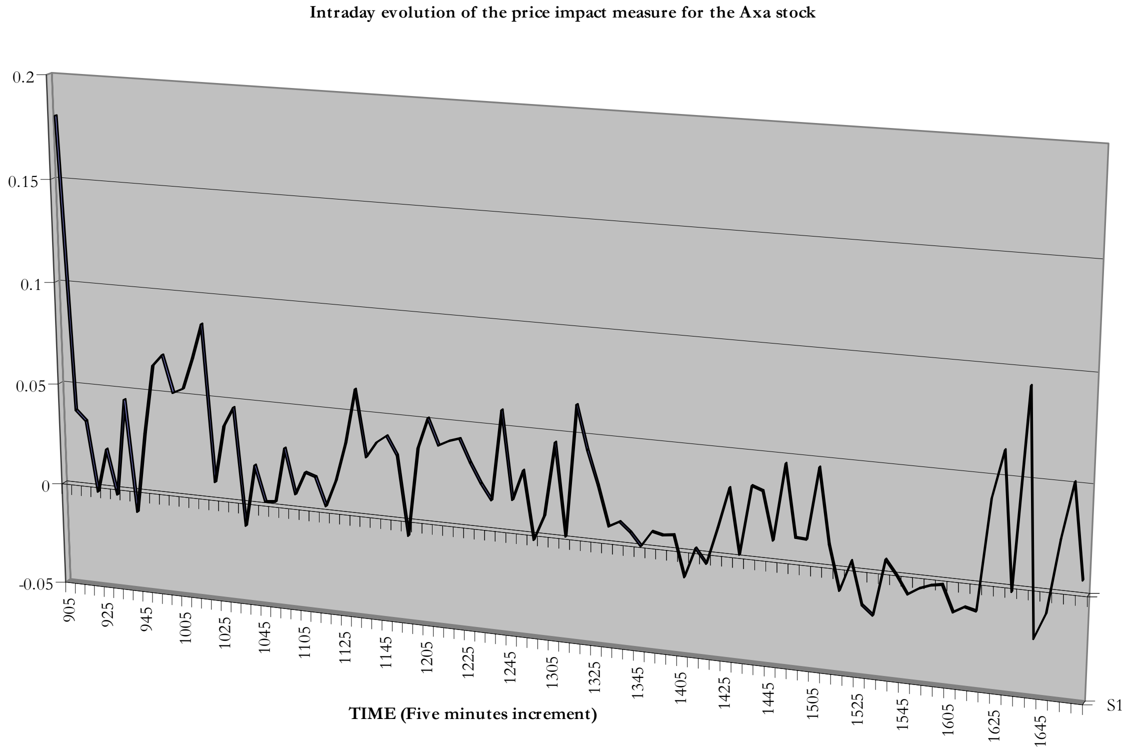


FIGURE 4.6.4: Price impact measure for Total Fina. This Table shows the intraday evolution for the average price impact measure, which indicates the trade information content, for the Total Fina stock during the period from December 1, 1999 – March 31, 2000 within successive intraday periods of five minutes.

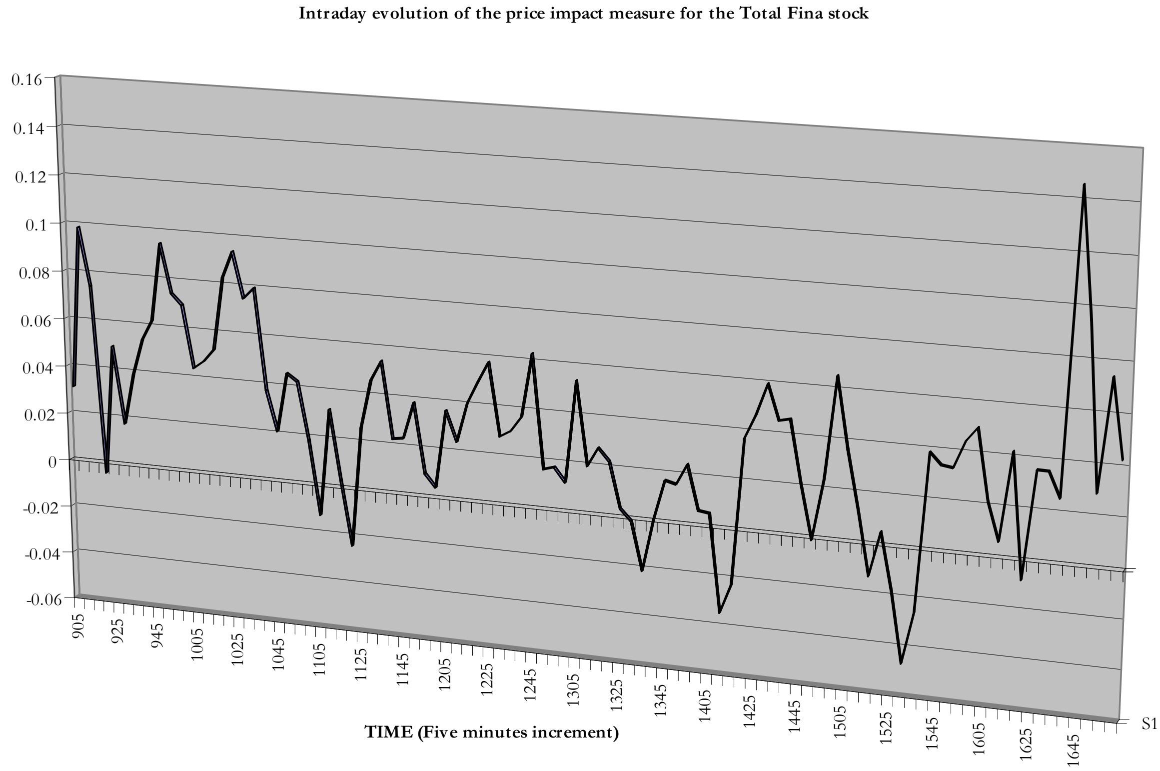


FIGURE 4.6.5: Price impact measure for France Telecom. This Table shows the intraday evolution for the average price impact measure, which indicates the trade information content, for the France Telecom stock during the period from December 1, 1999 – March 31, 2000 within successive intraday periods of five minutes.

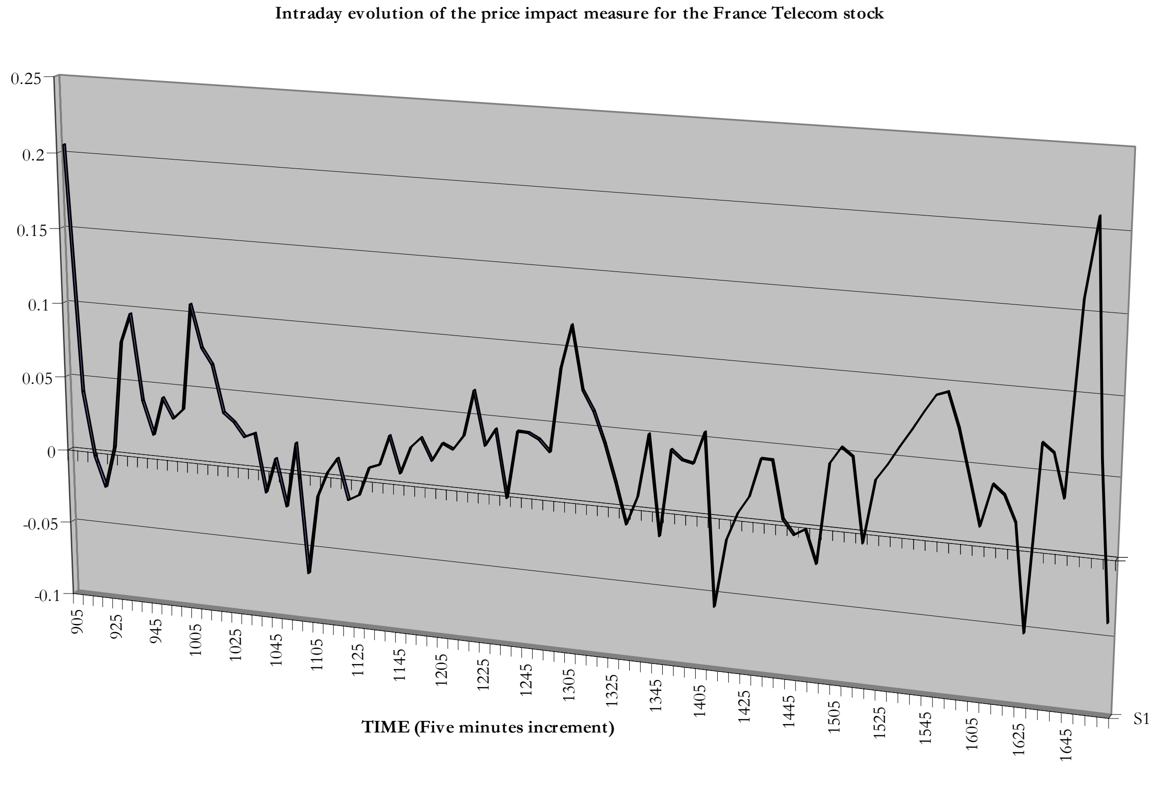


FIGURE 4.6.6: Price impact measure for Vivendi. This Table shows the intraday evolution for the average price impact measure, which indicates the trade information content, for the Vivendi stock during the period from December 1, 1999 – March 31, 2000 within successive intraday periods of five minutes.

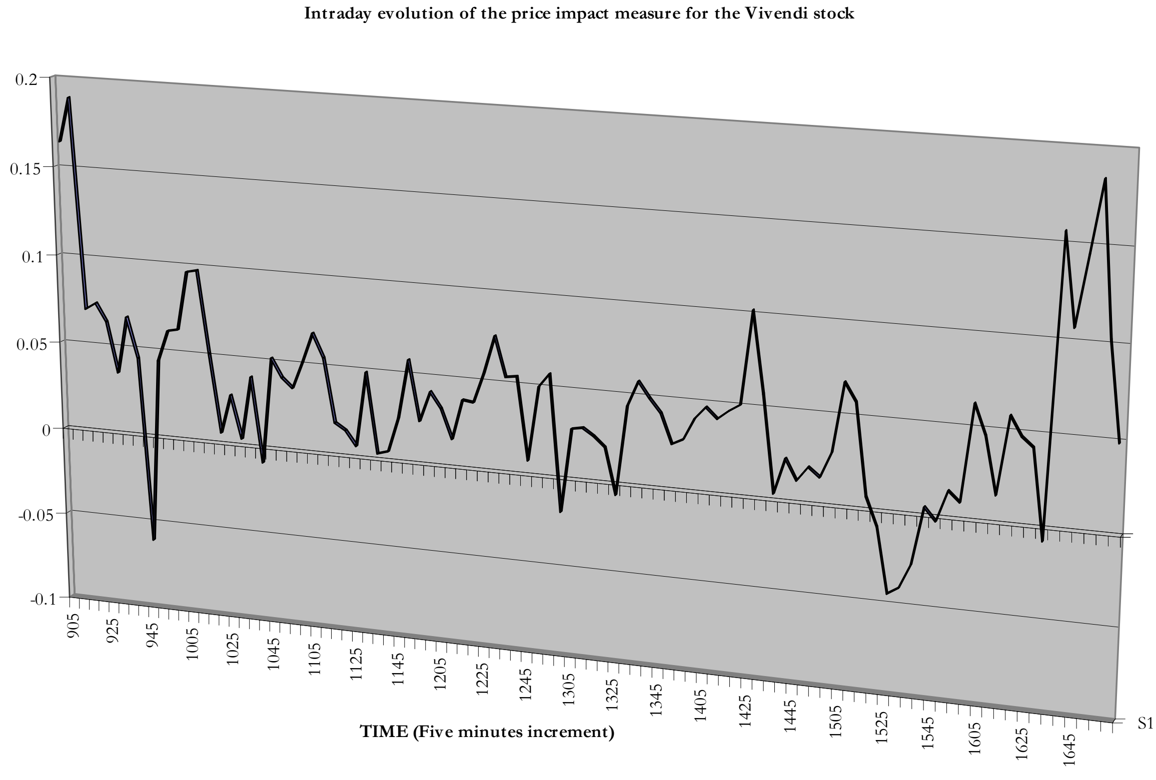
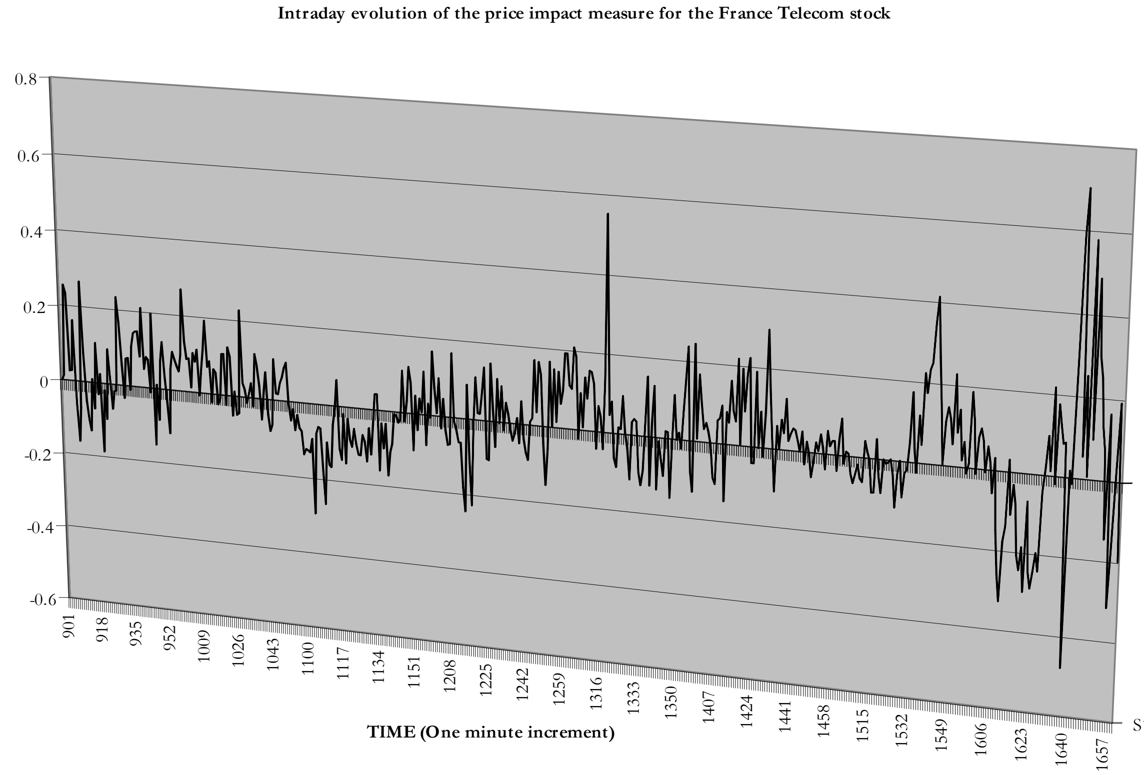


FIGURE 4.6.7: Price impact measure for France Telecom (one minute). This Table shows the intraday evolution for the average price impact measure, which indicates the trade information content, for the Vivendi stock during the period from December 1, 1999 – March 31, 2000 within successive intraday periods of one minute.



TABLES

TABLE 4.7.1: T-test for the Air Liquide stock. This table reports the t-statistic when testing two adjacent means against each other during the period December 1, 1999 – March 31, 2000 for Air Liquide price impact measure.

TIME	AIR LIQUIDE	VALUE OF DIFF	
905	0.302		
		0.799	
910	0.132		
		0.179	
915	0.102		
		0.606	
920	0.015		
		-1.209	
925	0.197		
		1.156	
930	0.016		
		-0.169	
935	0.037		
		0.382	
940	-0.023		
		-0.364	
945	0.040		
		0.159	
950	0.019		
		-1.433	
955	0.203		
		0.834	
1000	0.073		
		0.452	
1005	-0.003		
		0.080	
1010	-0.016		
		0.382	
1015	-0.070		
		-0.204	
1020	-0.043		
		-0.539	
1025	0.030		
		-0.858	
1030	0.164		
		1.325	
1035	-0.024		
		-1.551	
1040	0.198		
		2.150	*
1045	-0.140		
		-0.374	
1050	-0.083		
		-1.163	
1055	0.085		
		-0.129	
1100	0.102		
		0.056	
1105	0.094		
		0.031	
1110	0.089		
		1.538	
1115	-0.085		
		-0.196	
1120	-0.066		
		-1.148	
1125	0.061		
		-0.793	
1130	0.159		
		1.301	
1135	0.013		
		0.538	
1140	-0.042		
		-1.327	
1145	0.123		
		0.492	
1150	0.050		
		0.797	
1155	-0.060		
		-1.159	
1200	0.087		
		0.235	
1205	0.058		
		1.009	
1210	-0.062		
		0.490	
1215	-0.119		
		-1.991	*
1220	0.165		
		2.344	*
1225	-0.174		
		-2.214	*
1230	0.113		
		-0.588	
1235	0.218		
		0.178	
1240	0.185		
		0.888	
1245	0.053		
		-0.520	
1250	0.128		
		0.611	
1255	0.030		
		-0.554	
1300	0.123		
		0.748	
1305	-0.001		

TIME	AIR LIQUIDE	VALUE OF DIFF	
1305	-0.001		
		-0.057	
1310	0.007		
		-1.303	
1315	0.181		
		1.157	
1320	0.005		
		0.092	
1325	-0.009		
		1.097	
1330	-0.169		
		-1.210	
1335	0.014		
		-0.877	
1340	0.130		
		0.492	
1345	0.076		
		0.487	
1350	0.013		
		0.020	
1355	0.011		
		0.644	
1400	-0.065		
		0.136	
1405	-0.086		
		-0.516	
1410	-0.007		
		-0.596	
1415	0.068		
		1.071	
1420	-0.085		
		1.314	
1425	-0.256		
		-2.849	**
1430	0.103		
		-0.039	
1435	0.108		
		0.995	
1440	-0.005		
		0.684	
1445	-0.075		
		0.929	
1450	-0.172		
		0.172	
1455	-0.192		
		-0.620	
1500	-0.114		
		-1.893	
1505	0.113		
		0.819	
1510	0.025		
		0.558	
1515	-0.034		
		-0.763	
1520	0.063		
		1.622	
1525	-0.169		
		-0.699	
1530	-0.062		
		0.104	
1535	-0.077		
		-0.823	
1540	0.034		
		-0.348	
1545	0.097		
		1.665	
1550	-0.210		
		-1.028	
1555	-0.050		
		0.569	
1600	-0.134		
		-0.738	
1605	-0.028		
		-0.475	
1610	0.038		
		2.389	*
1615	-0.269		
		-1.794	
1620	-0.038		
		0.190	
1625	-0.061		
		0.638	
1630	-0.153		
		0.771	
1635	-0.305		
		-1.459	
1640	0.013		
		0.817	
1645	-0.180		
		0.185	
1650	-0.226		
		-0.498	
1655	-0.109		
		0.388	
1700	-0.213		

TABLE 4.7.2: T-test for the Axa stock. This table reports the t-statistic when testing two adjacent means against each other during the period December 1, 1999 – March 31, 2000 for Axa price impact measure.

TIME	AXA	VALUE OF DIFF		TIME	AXA	VALUE OF DIFF
905	0.650	**2.281**	*			
910	0.080	0.123		1305	0.092	1.499
915	0.057	0.731		1310	-0.076	-1.950
920	-0.081	-0.291		1315	0.174	0.724
925	-0.014	0.390		1320	0.053	-0.188
930	-0.096	-1.095		1325	0.085	0.979
935	0.094	1.205		1330	-0.044	-0.118
940	-0.130	-1.077		1335	-0.030	0.311
945	0.058	-0.802		1340	-0.068	0.305
950	0.189	0.253		1345	-0.107	-0.051
955	0.145	0.132		1350	-0.099	-0.303
1000	0.123	0.331		1355	-0.057	-0.119
1005	0.073	-0.768		1400	-0.044	1.354
1010	0.182	-0.320		1405	-0.161	-0.728
1015	0.227	**2.919**	*	1410	-0.070	0.603
1020	-0.103	-0.982		1415	-0.152	-0.827
1025	0.029	-0.538		1420	-0.056	-0.503
1030	0.114	1.570		1425	0.008	1.128
1035	-0.113	-1.035		1430	-0.133	-1.735
1040	0.031	0.362		1435	0.084	-0.109
1045	-0.024	0.266		1440	0.098	1.117
1050	-0.070	-0.606		1445	-0.064	-1.121
1055	0.025	1.122		1450	0.134	1.082
1100	-0.120	-0.943		1455	-0.036	0.003
1105	0.006	0.009		1500	-0.036	-1.954
1110	0.004	0.839		1505	0.108	1.627
1115	-0.147	-0.224		1510	-0.051	0.482
1120	-0.110	-0.751		1515	-0.110	-0.274
1125	0.004	-0.808		1520	-0.073	1.092
1130	0.128	0.561		1525	-0.201	0.222
1135	0.046	-0.127		1530	-0.220	-1.938
1140	0.061	-0.231		1535	-0.060	0.429
1145	0.084	0.165		1540	-0.109	0.216
1150	0.065	1.712		1545	-0.137	-0.011
1155	-0.106	-1.883		1550	-0.136	-0.360
1200	0.080	-0.522		1555	-0.092	0.371
1205	0.143	0.329		1600	-0.136	-0.083
1210	0.102	0.158		1605	-0.126	0.060
1215	0.083	-0.333		1610	-0.134	0.045
1220	0.120	0.923		1615	-0.139	-1.848
1225	0.026	-0.037		1620	0.117	-0.454
1230	0.030	0.547		1625	0.190	1.702
1235	-0.036	-1.692		1630	-0.081	-1.299
1240	0.153	**2.003**		1635	0.196	1.376
1245	-0.070	-0.668		1640	-0.152	-0.421
1250	0.011	0.761		1645	-0.036	-0.297
1255	-0.080	0.292		1650	0.045	-0.547
1300	-0.119	-1.514		1655	0.183	1.403
1305	0.092			1700	-0.146	

TABLE 4.7.3: T-test for the Total Fina stock. This table reports the t-statistic when testing two adjacent means against each other during the period December 1, 1999 – March 31, 2000 for Total Fina price impact measure.

TIME	TOTAL FINA	VALUE OF DIFF		TIME	TOTAL FINA	VALUE OF DIFF	
905	0.067						
		-0.543					
910	0.225			1305	0.070		
		0.252				1.101	
915	0.170			1310	-0.050		
		1.972	*			-0.257	
920	-0.167			1315	-0.023		
		-1.833				0.251	
925	0.106			1320	-0.055		
		1.116				0.365	
930	-0.086			1325	-0.101		
		-0.770				-0.135	
935	0.052			1330	-0.084		
		-0.510				0.786	
940	0.158			1335	-0.184		
		0.261				-0.591	
945	0.100			1340	-0.114		
		-0.757				-0.573	
950	0.252			1345	-0.048		
		0.470				0.409	
955	0.163			1350	-0.092		
		0.014				-0.627	
1000	0.160			1355	-0.027		
		0.621				0.718	
1005	0.056			1400	-0.100		
		-0.169				-0.248	
1010	0.084			1405	-0.073		
		0.361				1.193	
1015	0.032			1410	-0.212		
		-1.322				0.240	
1020	0.173			1415	-0.242		
		-0.326				**-2.126**	*
1025	0.217			1420	0.075		
		0.760				0.173	
1030	0.106			1425	0.049		
		-0.471				-0.386	
1035	0.168			1430	0.100		
		1.244				0.042	
1040	0.019			1435	0.094		
		0.446				0.322	
1045	-0.037			1440	0.052		
		-1.103				0.559	
1050	0.095			1445	-0.010		
		0.361				1.070	
1055	0.046			1450	-0.107		
		0.714				-0.656	
1100	-0.055			1455	-0.039		
		0.707				-1.902	
1105	-0.151			1500	0.151		
		-1.053				1.205	
1110	-0.027			1505	0.028		
		0.666				0.612	
1115	-0.100			1510	-0.049		
		0.960				0.639	
1120	-0.211			1515	-0.143		
		-1.715				-0.532	
1125	-0.022			1520	-0.062		
		-0.655				0.997	
1130	0.065			1525	-0.196		
		-0.322				0.806	
1135	0.114			1530	-0.299		
		0.969				-0.443	
1140	-0.012			1535	-0.231		
		-0.088				-1.746	
1145	-0.002			1540	0.025		
		-0.266				0.028	
1150	0.033			1545	0.021		
		1.074				0.582	
1155	-0.113			1550	-0.088		
		0.121				-0.697	
1200	-0.130			1555	0.024		
		-0.964				-0.298	
1205	0.010			1600	0.056		
		0.283				0.898	
1210	-0.032			1605	-0.068		
		-0.546				0.413	
1215	0.041			1610	-0.129		
		-0.167				-1.539	
1220	0.063			1615	0.064		
		-0.251				**2.099**	*
1225	0.095			1620	-0.190		
		1.138				-1.350	
1230	-0.023			1625	-0.020		
		-0.419				-0.197	
1235	0.014			1630	0.010		
		-0.148				-0.553	
1240	0.032			1635	0.118		
		-0.973				-0.824	
1245	0.175			1640	0.322		
		1.720				0.561	
1250	-0.061			1645	0.176		
		0.089				1.041	
1255	-0.071			1650	-0.070		
		0.129				-0.382	
1300	-0.085			1655	0.017		
		-1.339				0.280	
1305	0.070			1700	-0.051		

TABLE 4.7.4: T-test for the France Telecom stock. This table reports the t-statistic when testing two adjacent means against each other during the period December 1, 1999 – March 31, 2000 for France Telecom price impact measure.

TIME	FRANCE TELECOM	VALUE OF DIFF	
905	0.584		
910	0.056	**2.603**	*
915	-0.094	0.858	
920	-0.195	0.493	
925	-0.116	-0.397	
930	0.128	-1.553	
935	0.199	-0.480	
940	-0.033	1.480	
945	-0.080	0.250	
950	0.045	-0.671	
955	0.041	0.029	
1000	0.045	-0.032	
1005	0.185	-0.957	
1010	0.100	0.550	
1015	0.102	-0.021	
1020	0.019	0.689	
1025	-0.039	0.411	
1030	0.002	-0.276	
1035	-0.052	0.398	
1040	-0.149	0.773	
1045	-0.040	-0.786	
1050	-0.201	1.169	
1055	-0.058	-1.148	
1100	-0.265	1.703	
1105	-0.167	-0.929	
1110	-0.113	-0.497	
1115	-0.055	-0.510	
1120	-0.123	0.597	
1125	-0.120	-0.030	
1130	-0.075	-0.359	
1135	-0.016	-0.455	
1140	0.000	-0.138	
1145	-0.050	0.513	
1150	0.012	-0.746	
1155	-0.003	0.139	
1200	-0.029	0.212	
1205	0.045	-0.564	
1210	0.032	0.106	
1215	0.079	-0.378	
1220	0.167	-0.629	
1225	0.053	0.886	
1230	0.029	0.172	
1235	-0.065	0.704	
1240	0.019	-0.779	
1245	0.011	0.072	
1250	-0.005	0.113	
1255	-0.024	0.119	
1300	0.166	-1.315	
1305	0.219	-0.424	

TIME	FRANCE TELECOM	VALUE OF DIFF	
1305	0.219		
1310	0.098	1.107	
1315	0.041	0.484	
1320	0.043	-0.013	
1325	-0.068	0.962	
1330	-0.126	0.612	
1335	-0.096	-0.296	
1340	-0.000	-0.696	
1345	-0.122	0.884	
1350	0.040	-1.349	
1355	-0.000	0.360	
1400	0.035	-0.308	
1405	0.079	-0.383	
1410	-0.249	**2.659**	*
1415	-0.117	-1.042	
1420	-0.092	-0.216	
1425	-0.001	-0.642	
1430	0.065	-0.434	
1435	0.034	0.211	
1440	-0.063	0.714	
1445	-0.079	0.136	
1450	-0.034	-0.373	
1455	-0.074	0.324	
1500	0.014	-0.604	
1505	0.092	-0.466	
1510	0.049	0.310	
1515	-0.097	1.323	
1520	-0.003	-0.722	
1525	0.035	-0.297	
1530	0.108	-0.526	
1535	0.072	0.241	
1540	0.120	-0.349	
1545	0.126	-0.034	
1550	0.134	-0.043	
1555	0.043	0.517	
1600	-0.031	0.427	
1605	-0.077	0.325	
1610	0.039	-0.795	
1615	0.022	0.096	
1620	-0.058	0.418	
1625	-0.271	1.389	
1630	0.117	**-2.714**	*
1635	0.015	0.511	
1640	-0.084	0.405	
1645	0.226	-1.182	
1650	0.263	-0.134	
1655	-0.044	1.216	
1700	-0.294	0.894	

TABLE 4.7.5: T-test for the Vivendi stock. This table reports the t-statistic when testing two adjacent means against each other during the period December 1, 1999 – March 31, 2000 for Vivendi price impact measure.

TIME	VIVENDI	VALUE OF DIFF		TIME	VIVENDI	VALUE OF DIFF
905	0.417					
		-0.076				
910	0.438			1305	-0.019	
		1.990	*			0.231
915	-0.049			1310	-0.045	
		-0.442				-0.098
920	0.047			1315	-0.034	
		-0.275				-0.304
925	0.102			1320	0.000	
		0.686				0.205
930	-0.041			1325	-0.025	
		-0.214				-0.135
935	0.003			1330	-0.006	
		0.084				0.163
940	-0.014			1335	-0.029	
		1.703				0.207
945	-0.326			1340	-0.054	
		-2.119	*			0.145
950	0.006			1345	-0.070	
		-0.368				0.034
955	0.060			1350	-0.073	
		0.045				0.366
1000	0.053			1355	-0.104	
		-0.067				-0.601
1005	0.065			1400	-0.047	
		-0.467				-0.611
1010	0.152			1405	0.017	
		1.041				-0.294
1015	-0.006			1410	0.045	
		1.904				-0.247
1020	-0.217			1415	0.069	
		-1.677				-0.026
1025	-0.073			1420	0.072	
		-0.236				-0.880
1030	-0.047			1425	0.197	
		-1.075				0.631
1035	0.105			1430	0.107	
		1.773				1.556
1040	-0.128			1435	-0.114	
		-1.469				-0.607
1045	0.066			1440	-0.033	
		0.490				0.774
1050	-0.003			1445	-0.105	
		0.039				-0.689
1055	-0.008			1450	-0.019	
		-0.998				0.362
1100	0.109			1455	-0.076	
		-0.204				-0.551
1105	0.132			1500	0.004	
		0.384				-0.900
1110	0.094			1505	0.125	
		1.668				0.155
1115	-0.059			1510	0.103	
		0.054				1.847
1120	-0.066			1515	-0.114	
		0.565				0.695
1125	-0.122			1520	-0.182	
		-3.251	*			1.243
1130	0.094			1525	-0.321	
		3.066				-0.461
1135	-0.118			1530	-0.263	
		-0.036				-0.029
1140	-0.114			1535	-0.259	
		-0.324				-1.379
1145	-0.066			1540	-0.088	
		-0.901				0.209
1150	0.058			1545	-0.115	
		1.314				-0.519
1155	-0.077			1550	-0.049	
		-1.232				0.502
1200	0.026			1555	-0.128	
		-0.014				-1.652
1205	0.027			1600	0.127	
		0.390				0.956
1210	-0.019			1605	0.020	
		-0.391				0.837
1215	0.029			1610	-0.100	
		-0.098				-1.067
1220	0.040			1615	0.077	
		-0.073				0.069
1225	0.048			1620	0.067	
		-0.531				0.534
1230	0.113			1625	-0.020	
		0.556				0.891
1235	0.047			1630	-0.159	
		-0.021				-1.817
1240	0.049			1635	0.281	
		1.039				0.740
1245	-0.070			1640	0.062	
		-0.764				-0.264
1250	0.035			1645	0.130	
		0.039				-0.986
1255	0.030			1650	0.427	
		2.429	*			0.795
1300	-0.195			1655	0.195	
		-1.682				1.175
1305	-0.019			1700	-0.099	

TABLE 4.7.6: Intraday relationship between quoted half spread and Market news. This estimation is based on the average trading data between the ratio of quoted half spread and the ratio of Market news from December 1, 1999 to March 31, 2000. From this sample I obtained 8352 observations of five minutes each for table 4.7.6.A and for table 4.7.6.B. Table 4.7.6.A represents the results of the regression between the ratio of CAC 40 quoted half spread (explained variable) and the following independent variables: ratio of Market news (RMARKET), a constant (C), and ARMA (3,3). The conditional variance equation of residuals follows a GARCH model including 2-lagged residuals coefficients, 1-lagged conditional variance (GARCH (1)) and a constant (C). Table 4.7.6.B represents the results of the regression between the ratio of Accor quoted half spread (explained variable) and the following independent variable: ratio of Market news for France (RMARKET_FR), a constant (C), and ARMA (2,2). The conditional variance equation of residuals follows a GARCH model including 2-lagged residuals coefficients, 1-lagged conditional variance (GARCH (1)) and a constant (C). In the Table 4.7.6.A. the value of parameters p and z are respectively: 3 and 3. In the Table 4.7.6.B. the value of parameters p and z are respectively: 2 and 2.

TABLE 4.7.6.A

	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.176	0.012	-14.414	0.000
RMARKET(-10)	-0.010	0.004	-2.642	0.008
AR(1)	1.570	0.191	8.204	0.000
AR(2)	-0.521	0.286	-1.825	0.068
AR(3)	-0.053	0.097	-0.543	0.587
MA(1)	-0.988	0.191	-5.173	0.000
MA(2)	-0.077	0.175	-0.439	0.661
MA(3)	0.110	0.022	4.978	0.000
		Variance Equation		
C	0.002	0.000	3.490	0.001
ARCH(1)	0.031	0.006	4.948	0.000
GARCH(1)	0.839	0.041	20.614	0.000
R-squared	0.484	**Mean dependent var**		-0.174
Adjusted R-squared	0.483	**S.D. dependent var**		0.152
S.E. of regression	0.110	**Akaike info criterion**		-1.587
Sum squared resid	99.866	**Schwarz criterion**		-1.568
Log likelihood	6636.049	**F-statistic**		371.722
Durbin-Watson stat	2.004	**Prob(F-statistic)**		0.000
Inverted AR Roots	0.990	0.660	-0.080	
Inverted MA Roots	0.950	0.360	-0.320	

TABLE 4.7.6.B

	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.246	0.032	-7.766	0.000
RMARKET_FR(-7)	0.040	0.015	2.619	0.009
RMARKET_FR(-8)	0.035	0.015	2.327	0.020
AR(1)	1.302	0.049	26.656	0.000
AR(2)	-0.347	0.042	-8.329	0.000
MA(1)	-0.714	0.050	-14.323	0.000
MA(2)	-0.077	0.024	-3.171	0.002
		Variance Equation		
C	0.022	0.007	3.018	0.003
ARCH(1)	0.083	0.013	6.463	0.000
ARCH(2)	-0.053	0.013	-3.963	0.000
GARCH(1)	0.885	0.034	25.894	0.000
R-squared	0.429	**Mean dependent var**		-0.215
Adjusted R-squared	0.428	**S.D. dependent var**		0.675
S.E. of regression	0.511	**Akaike info criterion**		1.486
Sum squared resid	2171.797	**Schwarz criterion**		1.504
Log likelihood	-6173.979	**F-statistic**		312.369
Durbin-Watson stat	1.999	**Prob(F-statistic)**		0.000
Inverted AR Roots	0.930	0.370		
Inverted MA Roots	0.810	-0.100		

TABLE 4.7.7: Intraday relationship between QHS_WAS and Industrial News. This estimation is based on the average trading data between the ratio of quoted half spread from the WAS file and the ratio of Industrial news from December 1, 1999 to March 31, 2000. From this sample I obtained 8352 observations of five minutes each for table 4.7.7.A and for table 4.7.7.B. Table 4.7.7.A represents the results of the regression between the ratio of market quoted half spread for the Alstom stock, obtained from the weighted average spread file (explained variable) and the following independent variables: ratio of Industrial news (RINDU), a constant (C), and ARMA (2,2). The conditional variance equation of residuals follows a GARCH model including 2-lagged residuals coefficients, two for all the residuals (ARCH (2)), lagged conditional variance (GARCH (1)) and a constant (C). Table 4.7.7.B reports the similar regression, but Industrial news for France and Lagardere stock are used. The conditional variance equation also follows a GARCH(1,2) model. In the Table 4.7.7.A. the value of parameters p and z are respectively: 2 and 2. In the Table 4.7.7.B. the value of parameters p and z are respectively: 2 and 2.

TABLE 4.7.7.A

	Coefficient	Std. Error	z-Statistic	Prob.
C	0.023	0.025	0.916	0.360
RINDU(-8)	-0.006	0.003	-1.710	0.087
RINDU(-9)	-0.011	0.003	-3.639	0.000
RINDU(-10)	-0.010	0.003	-3.500	0.001
AR(1)	1.654	0.032	51.066	0.000
AR(2)	-0.663	0.031	-21.398	0.000
MA(1)	-0.689	0.033	-20.719	0.000
MA(2)	-0.122	0.012	-10.004	0.000
Variance Equation				
C	0.000	0.000	17.226	0.000
ARCH(1)	0.309	0.012	25.513	0.000
ARCH(2)	-0.263	0.012	-22.256	0.000
GARCH(1)	0.937	0.003	367.745	0.000
R-squared	0.865	Mean dependent var		-0.050
Adjusted R-squared	0.865	S.D. dependent var		0.358
S.E. of regression	0.132	Akaike info criterion		-1.387
Sum squared resid	144.177	Schwarz criterion		-1.370
Log likelihood	5804.322	F-statistic		2666.929
Durbin-Watson stat	2.060	Prob(F-statistic)		0.000
Inverted AR Roots	0.970	0.680		
Inverted MA Roots	0.830	-0.150		

TABLE 4.7.7.B

	Coefficient	Std. Error	z-Statistic	Prob.
C	0.026	0.030	0.861	0.389
RINDU_FR(-5)	0.011	0.005	2.177	0.030
AR(1)	1.655	0.028	58.605	0.000
AR(2)	-0.663	0.027	-24.537	0.000
MA(1)	-0.794	0.031	-25.318	0.000
MA(2)	-0.064	0.017	-3.793	0.000
Variance Equation				
C	0.002	0.000	15.001	0.000
ARCH(1)	0.255	0.013	18.997	0.000
ARCH(2)	-0.145	0.013	-11.097	0.000
GARCH(1)	0.846	0.007	113.610	0.000
R-squared	0.842	Mean dependent var		-0.075
Adjusted R-squared	0.842	S.D. dependent var		0.451
S.E. of regression	0.179	Akaike info criterion		-0.782
Sum squared resid	266.850	Schwarz criterion		-0.764
Log likelihood	3279.796	F-statistic		2223.535
Durbin-Watson stat	2.126	Prob(F-statistic)		0.000
Inverted AR Roots	0.970	0.680		
Inverted MA Roots	0.870	-0.070		

TABLE 4.7.8: Intraday relationship between market cumulated trading volume and All Alerts News. This estimation is based on the average trading data between the ratio of cumulated traded volume and the ratio of All Alerts news from December 1, 1999 to March 31, 2000. From this sample I obtained 8352 observations of five minutes each for table 4.7.8.A and for table 4.7.8.B. Table 4.7.8.A represents the results of the regression between the ratio of Canal Plus cumulated traded volume (explained variable) and the following independent variables: ratio of All Alerts News (RAA) and ratio of average Canal Plus return (RABSRET_CANAL), a constant (C), and ARMA (1,2). The conditional variance equation of residuals follows a TARCH model including 2-lagged residuals coefficients, one for all the residuals (ARCH (1)), the other only for negative residuals being a dummy variable (RESID<0)*ARCH(1), lagged conditional variance (GARCH (1)) and a constant (C). Table 4.7.8.B reports a similar regression, but cumulated traded volume of AGF stock and All Alerts news for France are used instead. In the Table 4.7.8.A. the value of parameters p, q and z are respectively: 1, 0 and 2. In the Table 4.7.8.B. the value of parameters p, q and z are respectively: 2, 0 and 2.

TABLE 4.7.8.A

	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.635	0.071	-8.927	0.000
RAA(-1)	0.097	0.035	2.817	0.005
RABSRET_CANAL	-0.182	0.016	-11.458	0.000
AR(1)	0.970	0.004	257.289	0.000
MA(1)	-0.726	0.012	-58.742	0.000
MA(2)	-0.077	0.012	-6.527	0.000
		Variance Equation		
C	0.040	0.005	8.639	0.000
ARCH(1)	0.023	0.005	4.812	0.000
(RESID< 0)*ARCH(1)	0.048	0.007	6.989	0.000
GARCH(1)	0.907	0.007	122.092	0.000
R-squared	0.357	**Mean dependent var**		-0.581
Adjusted R-squared	0.356	**S.D. dependent var**		1.191
S.E. of regression	0.956	**Akaike info criterion**		2.703
Sum squared resid	7604.922	**Schwarz criterion**		2.720
Log likelihood	-11247.950	**F-statistic**		231.264
Durbin-Watson stat	2.037	**Prob(F-statistic)**		0.000
Inverted AR Roots	0.970			
Inverted MA Roots	0.820	-0.090		

TABLE 4.7.8.B

	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.966	0.061	-15.899	0.000
RAA_FR(-8)	-0.084	0.042	-2.006	0.045
RABSRET_AGF	-0.641	0.023	-28.163	0.000
AR(1)	0.127	0.179	0.712	0.477
AR(2)	0.793	0.169	4.685	0.000
MA(1)	-0.070	0.176	-0.396	0.692
MA(2)	-0.756	0.157	-4.810	0.000
		Variance Equation		
C	0.552	0.163	3.384	0.001
ARCH(1)	0.038	0.008	4.492	0.000
GARCH(1)	0.743	0.070	10.562	0.000
R-squared	0.122	**Mean dependent var**		-0.899
Adjusted R-squared	0.120	**S.D. dependent var**		1.693
S.E. of regression	1.588	**Akaike info criterion**		3.761
Sum squared resid	20972.010	**Schwarz criterion**		3.779
Log likelihood	-15658.520	**F-statistic**		57.715
Durbin-Watson stat	1.974	**Prob(F-statistic)**		0.000
Inverted AR Roots	0.960	-0.830		
Inverted MA Roots	0.900	-0.840		

TABLE 4.7.9: Intraday relationship between return and Economic news. This estimation is based on the average trading data between the ratio of return in absolute terms and the ratio of Economic news from December 1, 1999 to March 31, 2000. From this sample I obtained 8352 observations of five minutes each for table 4.7.9.A and for table 4.7.9.B. Table 4.7.9.A represents the results of the regression between the ratio of Vivendi return in absolute terms (explained variable) and the following independent variables: ratio of Economic news (RECO), ratio of cumulated Vivendi traded volume (RSUMVOL_VIVENDI), a constant (C), and ARMA (3,3). The conditional variance equation of residuals follows a GARCH model including 2-lagged residuals coefficients for all the residuals (ARCH (1)), lagged conditional variance (GARCH (2)) and a constant (C). Table 4.7.9.B reports a similar regression, but cumulated traded volume of Aventis stock and Economic news for France are used instead. In the Table 4.7.9.A. the value of parameters p, q and z are respectively: 3, 0 and 3. In the Table 4.7.9.B. the value of parameters p, q and z are respectively: 3, 0 and 3.

TABLE 4.7.9.A

	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.138	0.076	-1.812	0.070
RECO(3)	0.029	0.009	3.136	0.002
RSUMVOL_VIVENDI	-0.109	0.006	-18.290	0.000
AR(1)	1.332	0.161	8.266	0.000
AR(2)	-0.025	0.273	-0.093	0.926
AR(3)	-0.308	0.114	-2.699	0.007
MA(1)	-1.065	0.159	-6.687	0.000
MA(2)	-0.172	0.227	-0.758	0.449
MA(3)	0.251	0.075	3.329	0.001
	Variance Equation			
C	0.000	0.000	2.067	0.039
ARCH(1)	0.058	0.011	5.413	0.000
ARCH(2)	-0.055	0.010	-5.362	0.000
GARCH(1)	1.531	0.110	13.947	0.000
GARCH(2)	-0.535	0.109	-4.917	0.000

R-squared	0.276	**Mean dependent var**	-0.125
Adjusted R-squared	0.274	**S.D. dependent var**	0.514
S.E. of regression	0.438	**Akaike info criterion**	1.160
Sum squared resid	1596.303	**Schwarz criterion**	1.181
Log likelihood	-4811.371	**F-statistic**	132.320
Durbin-Watson stat	1.985	**Prob(F-statistic)**	0.000

Inverted AR Roots	1.000	0.750	-0.410
Inverted MA Roots	0.980	0.550	-0.470

TABLE 4.7.9.B

	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.285	0.028	-10.069	0.000
RECO_FR(-1)	0.020	0.010	1.999	0.046
RSUMVOL_AVENTIS	-0.110	0.006	-18.066	0.000
AR(1)	0.805	0.090	8.962	0.000
AR(2)	0.323	0.079	4.082	0.000
AR(3)	-0.169	0.048	-3.545	0.000
MA(1)	-0.518	0.091	-5.682	0.000
MA(2)	-0.391	0.062	-6.346	0.000
MA(3)	0.049	0.045	1.087	0.277
	Variance Equation			
C	0.000	0.000	2.135	0.033
ARCH(1)	0.061	0.010	5.993	0.000
ARCH(2)	-0.059	0.010	-5.906	0.000
GARCH(1)	1.515	0.106	14.332	0.000
GARCH(2)	-0.519	0.105	-4.960	0.000

R-squared	0.195	**Mean dependent var**	-0.187
Adjusted R-squared	0.193	**S.D. dependent var**	0.627
S.E. of regression	0.563	**Akaike info criterion**	1.676
Sum squared resid	2634.732	**Schwarz criterion**	1.698
Log likelihood	-6963.448	**F-statistic**	84.106
Durbin-Watson stat	2.000	**Prob(F-statistic)**	0.000

Inverted AR Roots	0.960	0.350	-0.500
Inverted MA Roots	0.890	0.110	-0.490

TABLE 4.7.10: Intraday relationship between volatility and All Alerts News. This estimation is based on the average trading data between the ratio of volatility and the ratio of Corporate news from December 1, 1999 to March 31, 2000. From this sample I obtained 8352 observations of five minutes each for table 4.7.10.A and for table 4.7.10.B. Table 4.7.10.A represents the results of the regression between the ratio of volatility of Accor stock, measured as a log range (explained variable) and the following independent variables: ratio of Corporate news (RCORP), a constant (C), and ARMA (2,2). The conditional variance equation of residuals follows a GARCH model including 2-lagged residuals coefficients for all the residuals (ARCH (2)), 1-lagged conditional variance (GARCH (1)) and a constant (C). Table 4.7.10.B reports a similar regression, but Total Fina stock and Corporate news for France are used instead. In the Table 4.7.10.A. the value of parameters p and z are respectively: 2 and 2. In the Table 4.7.9.B. the value of parameters p and z are respectively: 2 and 2.

TABLE 4.7.10.A

	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.286	0.036	-7.938	0.000
RCORP(-10)	0.034	0.014	2.435	0.015
AR(1)	1.501	0.029	51.575	0.000
AR(2)	-0.517	0.028	-18.782	0.000
MA(1)	-1.172	0.031	-37.424	0.000
MA(2)	0.240	0.026	9.101	0.000
		Variance Equation		
C	0.012	0.002	5.287	0.000
ARCH(1)	0.119	0.014	8.255	0.000
ARCH(2)	-0.096	0.014	-6.747	0.000
GARCH(1)	0.951	0.007	131.657	0.000
R-squared	0.230	**Mean dependent var**		-0.233
Adjusted R-squared	0.228	**S.D. dependent var**		0.784
S.E. of regression	0.689	**Akaike info criterion**		2.063
Sum squared resid	3946.005	**Schwarz criterion**		2.081
Log likelihood	-8578.897	**F-statistic**		124.028
Durbin-Watson stat	2.045	**Prob(F-statistic)**		0.000
Inverted AR Roots	0.970	0.530		
Inverted MA Roots	0.910	0.260		

TABLE 4.7.10.B

	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.149	0.026	-5.731	0.000
RCORP_FR(-2)	0.020	0.011	1.753	0.080
AR(1)	1.410	0.045	31.162	0.000
AR(2)	-0.431	0.043	-10.074	0.000
MA(1)	-1.140	0.047	-24.014	0.000
MA(2)	0.209	0.041	5.138	0.000
		Variance Equation		
C	0.006	0.003	2.078	0.038
ARCH(1)	0.036	0.011	3.232	0.001
ARCH(2)	-0.025	0.011	-2.257	0.024
GARCH(1)	0.966	0.014	67.702	0.000
R-squared	0.146	**Mean dependent var**		-0.140
Adjusted R-squared	0.144	**S.D. dependent var**		0.554
S.E. of regression	0.513	**Akaike info criterion**		1.501
Sum squared resid	2186.576	**Schwarz criterion**		1.518
Log likelihood	-6235.003	**F-statistic**		71.167
Durbin-Watson stat	1.997	**Prob(F-statistic)**		0.000
Inverted AR Roots	0.960	0.450		
Inverted MA Roots	0.910	0.230		

TABLE 4.7.11: Intraday relationship between Air Liquide price impact and public information. This estimation is based on the average trading data between the ratio of price impact and the ratio of public information from December 1, 1999 to March 31, 2000. From this sample I obtained 8352 observations of five minutes each for table 4.7.11.A and for table 4.7.11.B. Table 4.7.11.A represents the results of the regression between the ratio of Air Liquide price impact (explained variable) and the following independent variables: ratio of All Alerts news France (RAA_FR), a constant (C), and ARMA (2,1). The conditional variance equation of residuals follows a GARCH model including 1-lagged residuals coefficients, 1-lagged conditional variance (GARCH (1)) and a constant (C). Table 4.7.11.B represents the results of the regression between the ratio of Air Liquide price impact (explained variable) and the following independent variables: ratio of Corporate news France (RCORP_FR), a constant (C), and ARMA (2,1). The conditional variance equation of residuals follows a GARCH model including 1-lagged residuals coefficients, 1-lagged conditional variance (GARCH (1)) and a constant (C). In the Table 4.7.11.A. the value of parameters p and z are respectively: 2 and 1. In the Table 4.7.11.B. the value of parameters p and z are respectively: 2 and 1.

TABLE 4.7.11.A

	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.698	0.057	-12.257	0.000
RAA_FR(3)	0.091	0.036	2.518	0.012
AR(1)	0.783	0.058	13.536	0.000
AR(2)	-0.035	0.028	-1.256	0.209
MA(1)	-0.478	0.056	-8.492	0.000
		Variance Equation		
C	1.039	0.272	3.814	0.000
ARCH(1)	0.039	0.009	4.340	0.000
GARCH(1)	0.324	0.170	1.903	0.057
R-squared	0.151	**Mean dependent var**		-0.632
Adjusted R-squared	0.149	**S.D. dependent var**		1.387
S.E. of regression	1.280	**Akaike info criterion**		3.330
Sum squared resid	13620.490	**Schwarz criterion**		3.346
Log likelihood	-13863.330	**F-statistic**		82.344
Durbin-Watson stat	2.013	**Prob(F-statistic)**		0.000
Inverted AR Roots	0.740	0.050		
Inverted MA Roots	0.480			

TABLE 4.7.11.B

	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.745	0.054	-13.797	0.000
RCORP_FR(1)	0.074	0.028	2.670	0.008
RCORP_FR(2)	0.099	0.029	3.413	0.001
RCORP_FR(3)	0.084	0.029	2.925	0.003
AR(1)	0.777	0.058	13.296	0.000
AR(2)	-0.032	0.028	-1.168	0.243
MA(1)	-0.472	0.057	-8.284	0.000
C	1.029	0.269	3.829	0.000
ARCH(1)	0.039	0.009	4.301	0.000
GARCH(1)	0.329	0.169	1.954	0.051
R-squared	0.153	**Mean dependent var**		-0.632
Adjusted R-squared	0.151	**S.D. dependent var**		1.387
S.E. of regression	1.279	**Akaike info criterion**		3.328
Sum squared resid	13600.020	**Schwarz criterion**		3.344
Log likelihood	-13857.290	**F-statistic**		83.164
Durbin-Watson stat	2.013	**Prob(F-statistic)**		0.000
Inverted AR Roots	0.730	0.040		
Inverted MA Roots	0.470			

TABLE 4.7.12: Intraday relationship between Axa price impact and public information. This estimation is based on the average trading data between the ratio of price impact and the ratio of public information from December 1, 1999 to March 31, 2000. From this sample I obtained 8352 observations of five minutes each for table 4.7.12.A and for table 4.7.12.B. Table 4.7.12.A represents the results of the regression between the ratio of Axa price impact (explained variable) and the following independent variables: ratio of Corporate news for France (RCORP_FR), a constant (C), and ARMA (2,1). The conditional variance equation of residuals follows an ARCH model including 1-lagged residuals coefficients and a constant (C). Table 4.7.12.B represents the results of the regression between the ratio of Axa price impact (explained variable) and the following independent variables: ratio of Market news for France (RMARKET_FR), a constant (C), and ARMA (2,1). The conditional variance equation of residuals follows an ARCH model including 1-lagged residuals coefficients and a constant (C). In the Table 4.7.12.A. the value of parameters p and z are respectively: 2 and 1. In the Table 4.7.12.B. the value of parameters p and z are respectively: 2 and 1.

TABLE 4.7.12.A

	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.770	0.051	-15.084	0.000
RCORP_FR(9)	0.096	0.031	3.080	0.002
RCORP_FR(10)	0.062	0.029	2.144	0.032
RCORP_FR(11)	0.055	0.029	1.893	0.058
AR(1)	0.828	0.058	14.190	0.000
AR(2)	-0.062	0.026	-2.357	0.018
MA(1)	-0.538	0.057	-9.426	0.000
		Variance Equation		
C	1.684	0.012	140.729	0.000
ARCH(1)	0.017	0.007	2.392	0.017

R-squared	0.126	**Mean dependent var**	-0.637
Adjusted R-squared	0.124	**S.D. dependent var**	1.403
S.E. of regression	1.313	**Akaike info criterion**	3.381
Sum squared resid	14347.750	**Schwarz criterion**	3.396
Log likelihood	-14076.720	**F-statistic**	70.585
Durbin-Watson stat	2.039	**Prob(F-statistic)**	0.000

Inverted AR Roots	0.740	0.080
Inverted MA Roots	0.540	

TABLE 4.7.12.B

	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.717	0.043	-16.507	0.000
RMARKET_FR(9)	0.121	0.038	3.150	0.002
AR(1)	0.832	0.058	14.391	0.000
AR(2)	-0.064	0.026	-2.440	0.015
MA(1)	-0.542	0.057	-9.583	0.000
		Variance Equation		
C	1.686	0.012	146.476	0.000
ARCH(1)	0.017	0.007	2.357	0.018

R-squared	0.126	**Mean dependent var**	-0.637
Adjusted R-squared	0.124	**S.D. dependent var**	1.403
S.E. of regression	1.314	**Akaike info criterion**	3.381
Sum squared resid	14354.150	**Schwarz criterion**	3.397
Log likelihood	-14078.340	**F-statistic**	66.420
Durbin-Watson stat	2.040	**Prob(F-statistic)**	0.000

Inverted AR Roots	0.750	0.090
Inverted MA Roots	0.540	

TABLE 4.7.13: Intraday relationship between France Telecom price impact and public information. This estimation is based on the average trading data between the ratio of price impact and the ratio of public information during December 1, 1999 and March 31, 2000. From this sample I obtained 8352 observations of five minutes each for table 4.7.13.A and for table 4.7.13.B. Table 4.7.13.A represents the results of the regression between the ratio of France Telecom price impact (explained variable) and the following independent variables: ratio of All Alerts news (RAA), a constant (C), and ARMA (2,1). The conditional variance equation of residuals follows an ARCH model including 1-lagged residuals coefficients, 1-lagged conditional variance (GARCH (1)) and a constant (C). Table 4.7.13.B represents the results of the regression between the ratio of France Telecom price impact (explained variable) and the following independent variables: ratio of Corporate news (RCORP), a constant (C), and ARMA (2,1). The conditional variance equation of residuals follows an ARCH model including 1-lagged residuals coefficients, 1-lagged conditional variance (GARCH (1)) and a constant (C). In the Table 4.7.13.A. the value of parameters p and z are respectively: 2 and 1. In the Table 4.7.13.B. the value of parameters p and z are respectively: 2 and 1.

TABLE 4.7.13.A

	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.771	0.036	-21.332	0.000
RAA(8)	-0.102	0.051	-2.012	0.044
AR(1)	0.791	0.077	10.318	0.000
AR(2)	-0.064	0.036	-1.785	0.074
MA(1)	-0.444	0.075	-5.890	0.000
C	1.157	0.306	3.779	0.000
ARCH(1)	0.034	0.010	3.405	0.001
GARCH(1)	0.327	0.172	1.905	0.057

R-squared	0.166	**Mean dependent var**	-0.749
Adjusted R-squared	0.164	**S.D. dependent var**	1.474
S.E. of regression	1.348	**Akaike info criterion**	3.435
Sum squared resid	15110.100	**Schwarz criterion**	3.451
Log likelihood	-14299.950	**F-statistic**	91.963
Durbin-Watson stat	2.021	**Prob(F-statistic)**	0.000
Inverted AR Roots	0.700	0.090	
Inverted MA Roots	0.440		

TABLE 4.7.13.B

	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.770	0.038	-20.489	0.000
RCORP(8)	-0.079	0.030	-2.631	0.009
AR(1)	0.802	0.075	10.668	0.000
AR(2)	-0.069	0.036	-1.931	0.054
MA(1)	-0.454	0.074	-6.147	0.000
C	1.126	0.307	3.666	0.000
ARCH(1)	0.033	0.010	3.322	0.001
GARCH(1)	0.346	0.173	2.006	0.045

R-squared	0.166	**Mean dependent var**	-0.749
Adjusted R-squared	0.164	**S.D. dependent var**	1.474
S.E. of regression	1.348	**Akaike info criterion**	3.435
Sum squared resid	15116.640	**Schwarz criterion**	3.451
Log likelihood	-14302.120	**F-statistic**	91.724
Durbin-Watson stat	2.021	**Prob(F-statistic)**	0.000
Inverted AR Roots	0.700	0.100	
Inverted MA Roots	0.450		

TABLE 4.7.14: Intraday relationship between Total Fina price impact and public information. This estimation is based on the average trading data between the ratio of price impact and the ratio of public information from December 1, 1999 to March 31, 2000. From this sample I obtained 8352 observations of five minutes each for table 4.7.14.A and for table 4.7.14.B. Table 4.7.14.A represents the results of the regression between the ratio of Total Fina price impact (explained variable) and the following independent variables: ratio of All Alerts news for France (RAA_FR), a constant (C), and ARMA (2,1). The conditional variance equation of residuals follows an ARCH model including 1-lagged residuals coefficients and a constant (C). Table 4.7.14.B represents the results of the regression between the ratio of Total Fina price impact (explained variable) and the following independent variables: ratio of Corporate news (RCORP), a constant (C), and ARMA (2,1). The conditional variance equation of residuals follows an ARCH model including 1-lagged residuals coefficients and a constant (C). In the Table 4.7.14.A. the value of parameters p and z are respectively: 2 and 1. In the Table 4.7.14.B. the value of parameters p and z are respectively: 2 and 1.

TABLE 4.7.14.A

	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.783	0.059	-13.208	0.000
RAA_FR(5)	0.109	0.037	2.922	0.004
AR(1)	0.932	0.060	15.554	0.000
AR(2)	-0.122	0.030	-4.103	0.000
MA(1)	-0.594	0.057	-10.372	0.000
C	1.614	0.025	64.653	0.000
ARCH(1)	0.026	0.009	2.970	0.003
R-squared	0.163	**Mean dependent var**		-0.673
Adjusted R-squared	0.162	**S.D. dependent var**		1.408
S.E. of regression	1.289	**Akaike info criterion**		3.347
Sum squared resid	13826.320	**Schwarz criterion**		3.362
Log likelihood	-13934.360	**F-statistic**		95.578
Durbin-Watson stat	2.012	**Prob(F-statistic)**		0.000
Inverted AR Roots	0.770	0.160		
Inverted MA Roots	0.590			

TABLE 4.7.14.B

	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.658	0.038	-17.500	0.000
RCORP(6)	0.055	0.027	2.010	0.044
RCORP(7)	0.060	0.028	2.166	0.030
AR(1)	0.926	0.060	15.430	0.000
AR(2)	-0.119	0.030	-3.989	0.000
MA(1)	-0.588	0.057	-10.245	0.000
C	1.617	0.025	65.557	0.000
ARCH(1)	0.025	0.009	2.889	0.004
R-squared	0.163	**Mean dependent var**		-0.673
Adjusted R-squared	0.161	**S.D. dependent var**		1.408
S.E. of regression	1.290	**Akaike info criterion**		3.348
Sum squared resid	13837.190	**Schwarz criterion**		3.363
Log likelihood	-13937.870	**F-statistic**		95.118
Durbin-Watson stat	2.011	**Prob(F-statistic)**		0.000
Inverted AR Roots	0.770	0.150		
Inverted MA Roots	0.590			

TABLE 4.7.15: Intraday relationship between Vivendi price impact and public information. This estimation is based on the average trading data between the ratio of price impact and the ratio of public information from December 1, 1999 to March 31, 2000. From this sample I obtained 8352 observations of five minutes each for table 4.7.15.A and for table 4.7.15.B. Table 4.7.15.A represents the results of the regression between the ratio of Vivendi price impact (explained variable) and the following independent variables: ratio of All Alerts news (RAA), a constant (C), and ARMA (2,1). The conditional variance equation of residuals follows an ARCH model including 1-lagged residuals coefficients and a constant (C). Table 4.7.15.B represents the results of the regression between the ratio of Vivendi price impact (explained variable) and the following independent variables: ratio of Economic News (RECO), a constant (C), and ARMA (2,1). The conditional variance equation of residuals follows an ARCH model including 1-lagged residuals coefficients and a constant (C). In the Table 4.7.15.A. the value of parameters p and z are respectively: 2 and 1. In the Table 4.7.15.B. the value of parameters p and z are respectively: 2 and 1.

TABLE 4.7.15.A

	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.796	0.036	-21.929	0.000
RAA(6)	0.132	0.052	2.527	0.012
RAA(7)	0.097	0.051	1.890	0.059
AR(1)	0.851	0.062	13.809	0.000
AR(2)	-0.082	0.029	-2.829	0.005
MA(1)	-0.530	0.060	-8.867	0.000
C	1.865	0.026	71.805	0.000
ARCH(1)	0.025	0.010	2.440	0.015
R-squared	0.152	Mean dependent var		-0.804
Adjusted R-squared	0.150	S.D. dependent var		1.502
S.E. of regression	1.385	Akaike info criterion		3.490
Sum squared resid	15950.350	Schwarz criterion		3.505
Log likelihood	-14530.550	F-statistic		87.500
Durbin-Watson stat	2.013	Prob(F-statistic)		0.000
Inverted AR Roots	0.740	0.110		
Inverted MA Roots	0.530			

TABLE 4.7.15.B

	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.788	0.039	-20.329	0.000
RECO(10)	0.082	0.030	2.715	0.007
AR(1)	0.859	0.061	14.028	0.000
AR(2)	-0.085	0.029	-2.979	0.003
MA(1)	-0.538	0.059	-9.065	0.000
C	1.864	0.026	71.647	0.000
ARCH(1)	0.025	0.010	2.470	0.014
R-squared	0.152	Mean dependent var		-0.804
Adjusted R-squared	0.150	S.D. dependent var		1.502
S.E. of regression	1.385	Akaike info criterion		3.490
Sum squared resid	15949.260	Schwarz criterion		3.505
Log likelihood	-14530.110	F-statistic		87.539
Durbin-Watson stat	2.013	Prob(F-statistic)		0.000
Inverted AR Roots	0.740	0.110		
Inverted MA Roots	0.540			

TABLE 4.7.16: Intraday relationship between intraday market liquidity proxy and All Alerts news. This table reports the R^2-adjusted for all the 43 stocks belonging to the CAC 40 index. The regressions are all executed between the five liquidity indicators (quoted half spread from the order file, quoted half spread from the weighted average spread file, cumulated traded volume and volatility measured as a log range) and All Alerts News. All significant results are bold faced and double underlined.

	QHS Adjusted R-squared	QHS_WAS Adjusted R-squared	Volume Adjusted R-squared	Return Adjusted R-squared	Volatility Adjusted R-squared
Accor	***0.429***	***0.654***	***0.261***	0.182	***0.228***
Aerospatia	0.439	0.854	0.154	***0.186***	***0.231***
Agf	***0.489***	0.676	0.119	***0.117***	0.114
Air Liquide	***0.314***	***0.800***	0.205	0.180	0.183
Alcatel	***0.246***	***0.855***	***0.443***	***0.200***	***0.277***
Alstom	***0.476***	0.865	***0.247***	0.204	***0.183***
Aventis	***0.313***	0.808	***0.344***	***0.193***	***0.222***
Axa	0.253	0.784	***0.242***	0.155	***0.146***
Bic	0.509	0.816	0.098	0.154	0.054
Bnp	0.311	0.806	0.279	***0.181***	***0.228***
Bouygues	***0.426***	0.774	0.165	0.143	0.177
Canal Plus	***0.358***	***0.757***	***0.356***	***0.219***	***0.297***
Cap Gemini	***0.340***	***0.899***	***0.311***	***0.160***	0.221
Carrefour	0.273	***0.835***	0.349	0.186	***0.259***
Casino	0.386	0.753	0.149	***0.108***	***0.010***
Credit Lyonnais	0.427	0.935	0.211	0.296	0.303
Thomson-csf	***0.497***	0.814	0.202	***0.179***	0.174
Danone	0.385	***0.827***	***0.201***	***0.261***	***0.216***
Dexia Sico	0.406	0.744	***0.147***	***0.070***	0.055
Equant	0.346	0.855	***0.292***	0.212	0.214
Eridania	***0.453***	0.578	0.113	***0.080***	0.053
France Telecom	***0.207***	***0.830***	***0.296***	0.156	0.194
Lafarge	***0.384***	***0.781***	***0.297***	***0.221***	0.198
Lagardere	***0.418***	***0.842***	0.382	***0.214***	0.288
Legrand	0.441	0.817	0.137	***0.099***	0.057
L'Oreal	0.277	0.772	0.187	***0.102***	***0.127***
Lvmh	0.351	***0.853***	0.223	***0.156***	0.174
Michelin	0.452	***0.758***	***0.160***	***0.158***	0.175
Thomson-Multimedia	***0.476***	0.894	***0.333***	***0.228***	0.246
Peugeot	***0.436***	0.786	***0.189***	***0.125***	0.133
Pinault Printemps	***0.342***	0.798	0.276	***0.199***	***0.155***
Renault	***0.425***	0.883	***0.254***	0.236	***0.258***
Saint Gobain	0.366	0.795	***0.238***	***0.146***	***0.164***
Sanofi Synthelabo	0.417	0.814	0.153	0.206	0.130
Schneider	***0.385***	0.824	***0.210***	***0.176***	0.189
Scociété Générale	***0.385***	0.852	***0.191***	0.188	***0.184***
Sodexho	***0.429***	0.715	0.189	0.170	0.108
Stmicroelectronics	***0.242***	***0.842***	0.345	***0.151***	0.212
Suez Lyonnaise des Eaux	0.261	0.751	***0.297***	0.181	0.199
TF1	0.493	0.767	***0.182***	***0.153***	0.194
Total	0.213	0.858	***0.334***	0.166	***0.144***
Valeo	0.449	0.766	0.225	0.241	0.238
Vivendi	0.295	***0.831***	***0.450***	***0.272***	***0.313***
Index	***0.483***	***0.933***	***0.546***	***0.545***	***0.471***

TABLE 4.7.17: Intraday relationship between five intraday market liquidity proxy and public information arrival. This table reports a X when a significant relationship is observed between a liquidity indicator of the CAC 40 index and a specific news category during the first period under study (December 1, 1999 – March 31, 2000).

	QHS	QHS_WAS	Volume	Return	Volatility
All Alerts	X	X	X	X	X
All Alerts France	X	X	X	X	
Political	X		X	X	
Political France	X	X	X		
Market	X	X	X		X
Market France	X	X		X	
Industrial	X	X			X
Industrial France					
General	X	X	X		
General France	X	X	X		
Economic	X				
Economic France	X		X	X	
Corporate	X	X	X		X
Corporate France					X
Firm-specific	X	X	X		

TABLE 4.7.18.A: Granger causality test results for the quoted half spread. This Table shows the results of the Granger causality test among the quoted half spread (QHS) for the CAC 40 index and the fifteen news categories considered in this study. This test covers the period between December 1, 1999 and March 31, 2000.

Null Hypothesis:	F-Statistic	Probability
TOT_AVERAGE does not Granger Cause AA	1.043	0.406
AA does not Granger Cause TOT_AVERAGE	1.963	0.024
TOT_AVERAGE does not Granger Cause AA_FR	1.128	0.331
AA_FR does not Granger Cause TOT_AVERAGE	0.581	0.860
TOT_AVERAGE does not Granger Cause POL	1.185	0.287
POL does not Granger Cause TOT_AVERAGE	2.704	0.001
TOT_AVERAGE does not Granger Cause POL_FR	1.295	0.213
POL_FR does not Granger Cause TOT_AVERAGE	0.950	0.495
TOT_AVERAGE does not Granger Cause MARKET	0.507	0.912
MARKET does not Granger Cause TOT_AVERAGE	2.034	0.018
TOT_AVERAGE does not Granger Cause MARKET_FR	2.136	0.012
MARKET_FR does not Granger Cause TOT_AVERAGE	1.274	0.226
TOT_AVERAGE does not Granger Cause INDU	1.708	0.058
INDU does not Granger Cause TOT_AVERAGE	0.868	0.580
TOT_AVERAGE does not Granger Cause INDU_FR	1.996	0.021
INDU_FR does not Granger Cause TOT_AVERAGE	1.077	0.375
TOT_AVERAGE does not Granger Cause GENERAL	1.973	0.023
GENERAL does not Granger Cause TOT_AVERAGE	0.610	0.835
TOT_AVERAGE does not Granger Cause GENERAL_FR	1.139	0.322
GENERAL_FR does not Granger Cause TOT_AVERAGE	0.576	0.863
TOT_AVERAGE does not Granger Cause ECO	1.134	0.327
ECO does not Granger Cause TOT_AVERAGE	1.753	0.050
TOT_AVERAGE does not Granger Cause ECO_FR	1.287	0.218
ECO_FR does not Granger Cause TOT_AVERAGE	0.422	0.956
TOT_AVERAGE does not Granger Cause CORP_FR	1.996	0.021
CORP_FR does not Granger Cause TOT_AVERAGE	1.077	0.375
TOT_AVERAGE does not Granger Cause CORP	0.611	0.835
CORP does not Granger Cause TOT_AVERAGE	1.041	0.407
TOT_AVERAGE does not Granger Cause CAC40	1.440	0.140
CAC40 does not Granger Cause TOT_AVERAGE	1.347	0.184

TABLE 4.7.18.B: Granger causality test results for the quoted half spread from the WAS file. This Table shows the results of the Granger causality test among the quoted half spread from the weighted average spread file (QHS_WAS) for the CAC 40 index and the fifteen news categories considered in this study. This test covers the period between December 1, 1999 and March 31, 2000.

Null Hypothesis:	F-Statistic	Probability
TOT_AVERAGE does not Granger Cause AA	1.526	0.107
AA does not Granger Cause TOT_AVERAGE	2.260	0.007
TOT_AVERAGE does not Granger Cause AA_FR	1.362	0.176
AA_FR does not Granger Cause TOT_AVERAGE	1.022	0.425
TOT_AVERAGE does not Granger Cause POL	1.830	0.038
POL does not Granger Cause TOT_AVERAGE	0.952	0.493
TOT_AVERAGE does not Granger Cause POL_FR	2.357	0.005
POL_FR does not Granger Cause TOT_AVERAGE	1.001	0.445
TOT_AVERAGE does not Granger Cause MARKET	2.311	0.006
MARKET does not Granger Cause TOT_AVERAGE	2.518	0.003
TOT_AVERAGE does not Granger Cause MARKET_FR	1.512	0.112
MARKET_FR does not Granger Cause TOT_AVERAGE	0.853	0.595
TOT_AVERAGE does not Granger Cause INDU	0.920	0.526
INDU does not Granger Cause TOT_AVERAGE	1.206	0.272
TOT_AVERAGE does not Granger Cause INDU_FR	1.307	0.206
INDU_FR does not Granger Cause TOT_AVERAGE	0.827	0.623
TOT_AVERAGE does not Granger Cause GENERAL	1.724	0.055
GENERAL does not Granger Cause TOT_AVERAGE	0.893	0.553
TOT_AVERAGE does not Granger Cause GENERAL_FR	1.394	0.160
GENERAL_FR does not Granger Cause TOT_AVERAGE	1.029	0.418
TOT_AVERAGE does not Granger Cause ECO	3.328	0.000
ECO does not Granger Cause TOT_AVERAGE	2.420	0.004
TOT_AVERAGE does not Granger Cause ECO_FR	1.494	0.118
ECO_FR does not Granger Cause TOT_AVERAGE	0.421	0.956
TOT_AVERAGE does not Granger Cause CORP	2.332	0.006
CORP does not Granger Cause TOT_AVERAGE	1.357	0.179
TOT_AVERAGE does not Granger Cause CORP_FR	1.307	0.206
CORP_FR does not Granger Cause TOT_AVERAGE	0.827	0.623
TOT_AVERAGE does not Granger Cause CAC40	2.537	0.002
CAC40 does not Granger Cause TOT_AVERAGE	0.935	0.510

TABLE 4.7.18.C: Granger causality test results for SUMVOL. This Table shows the results of the Granger causality test among the cumulated traded volume (SUMVOL) for the CAC 40 index and the fifteen news categories considered in this study. This test covers the period between December 1, 1999 and March 31, 2000.

Null Hypothesis:	F-Statistic	Probability
TOT_AVERAGE does not Granger Cause AA	3.773	0.000
AA does not Granger Cause TOT_AVERAGE	3.007	0.000
TOT_AVERAGE does not Granger Cause AA_FR	4.538	0.000
AA_FR does not Granger Cause TOT_AVERAGE	1.162	0.304
TOT_AVERAGE does not Granger Cause POL	2.119	0.013
POL does not Granger Cause TOT_AVERAGE	2.064	0.016
TOT_AVERAGE does not Granger Cause POL_FR	4.895	0.000
POL_FR does not Granger Cause TOT_AVERAGE	1.398	0.159
TOT_AVERAGE does not Granger Cause MARKET	4.689	0.000
MARKET does not Granger Cause TOT_AVERAGE	3.581	0.000
TOT_AVERAGE does not Granger Cause MARKET_FR	0.963	0.482
MARKET_FR does not Granger Cause TOT_AVERAGE	1.282	0.221
TOT_AVERAGE does not Granger Cause INDU	0.776	0.676
INDU does not Granger Cause TOT_AVERAGE	1.431	0.144
TOT_AVERAGE does not Granger Cause INDU_FR	1.911	0.029
INDU_FR does not Granger Cause TOT_AVERAGE	1.160	0.306
TOT_AVERAGE does not Granger Cause GENERAL	2.440	0.004
GENERAL does not Granger Cause TOT_AVERAGE	1.921	0.027
TOT_AVERAGE does not Granger Cause GENERAL_FR	4.523	0.000
GENERAL_FR does not Granger Cause TOT_AVERAGE	1.175	0.294
TOT_AVERAGE does not Granger Cause ECO	6.212	0.000
ECO does not Granger Cause TOT_AVERAGE	1.809	0.041
TOT_AVERAGE does not Granger Cause ECO_FR	2.543	0.002
ECO_FR does not Granger Cause TOT_AVERAGE	0.704	0.749
TOT_AVERAGE does not Granger Cause CORP_FR	1.911	0.029
CORP_FR does not Granger Cause TOT_AVERAGE	1.160	0.306
TOT_AVERAGE does not Granger Cause CORP	5.518	0.000
CORP does not Granger Cause TOT_AVERAGE	3.220	0.000
TOT_AVERAGE does not Granger Cause CAC40	4.315	0.000
CAC40 does not Granger Cause TOT_AVERAGE	0.875	0.572

TABLE 4.7.18.D: Granger causality test results for ABSRET. This Table shows the results of the Granger causality test among the average return in absolute terms (ABSRET) for the CAC 40 index and the fifteen news categories considered in this study. This test covers the period between December 1, 1999 and March 31, 2000.

Null Hypothesis:	F-Statistic	Probability
TOT_AVERAGE does not Granger Cause AA	3.773	0.000
AA does not Granger Cause TOT_AVERAGE	3.007	0.000
TOT_AVERAGE does not Granger Cause AA_FR	4.538	0.000
AA_FR does not Granger Cause TOT_AVERAGE	1.162	0.304
TOT_AVERAGE does not Granger Cause POL	2.119	0.013
POL does not Granger Cause TOT_AVERAGE	2.064	0.016
TOT_AVERAGE does not Granger Cause POL_FR	4.895	0.000
POL_FR does not Granger Cause TOT_AVERAGE	1.398	0.159
TOT_AVERAGE does not Granger Cause MARKET	4.689	0.000
MARKET does not Granger Cause TOT_AVERAGE	3.581	0.000
TOT_AVERAGE does not Granger Cause MARKET_FR	0.963	0.482
MARKET_FR does not Granger Cause TOT_AVERAGE	1.282	0.221
TOT_AVERAGE does not Granger Cause INDU	0.776	0.676
INDU does not Granger Cause TOT_AVERAGE	1.431	0.144
TOT_AVERAGE does not Granger Cause INDU_FR	1.911	0.029
INDU_FR does not Granger Cause TOT_AVERAGE	1.160	0.306
TOT_AVERAGE does not Granger Cause GENERAL	2.440	0.004
GENERAL does not Granger Cause TOT_AVERAGE	1.921	0.027
TOT_AVERAGE does not Granger Cause GENERAL_FR	4.523	0.000
GENERAL_FR does not Granger Cause TOT_AVERAGE	1.175	0.294
TOT_AVERAGE does not Granger Cause ECO	6.212	0.000
ECO does not Granger Cause TOT_AVERAGE	1.809	0.041
TOT_AVERAGE does not Granger Cause ECO_FR	2.543	0.002
ECO_FR does not Granger Cause TOT_AVERAGE	0.704	0.749
TOT_AVERAGE does not Granger Cause CORP	5.518	0.000
CORP does not Granger Cause TOT_AVERAGE	3.220	0.000
TOT_AVERAGE does not Granger Cause CORP_FR	1.911	0.029
CORP_FR does not Granger Cause TOT_AVERAGE	1.160	0.306
TOT_AVERAGE does not Granger Cause CAC40	4.315	0.000
CAC40 does not Granger Cause TOT_AVERAGE	0.875	0.572

TABLE 4.7.18.E: Granger causality test results for the VOLA. This Table shows the results of the Granger causality test among the volatility measured as a log range (VOLA) for the CAC 40 index and the fifteen news categories considered in this study. This test covers the period between December 1, 1999 and March 31, 2000.

Null Hypothesis:	F-Statistic	Probability
TOT_AVERAGE does not Granger Cause AA	1.915	0.028
AA does not Granger Cause TOT_AVERAGE	2.724	0.001
TOT_AVERAGE does not Granger Cause AA_FR	1.648	0.072
AA_FR does not Granger Cause TOT_AVERAGE	1.373	0.171
TOT_AVERAGE does not Granger Cause POL	1.763	0.048
POL does not Granger Cause TOT_AVERAGE	2.752	0.001
TOT_AVERAGE does not Granger Cause POL_FR	1.297	0.212
POL_FR does not Granger Cause TOT_AVERAGE	1.209	0.269
TOT_AVERAGE does not Granger Cause MARKET	1.414	0.151
MARKET does not Granger Cause TOT_AVERAGE	2.237	0.008
TOT_AVERAGE does not Granger Cause MARKET_FR	1.505	0.114
MARKET_FR does not Granger Cause TOT_AVERAGE	1.281	0.222
TOT_AVERAGE does not Granger Cause INDU	1.242	0.247
INDU does not Granger Cause TOT_AVERAGE	1.316	0.201
TOT_AVERAGE does not Granger Cause INDU_FR	2.499	0.003
INDU_FR does not Granger Cause TOT_AVERAGE	1.871	0.033
TOT_AVERAGE does not Granger Cause GENERAL	1.918	0.028
GENERAL does not Granger Cause TOT_AVERAGE	0.967	0.478
TOT_AVERAGE does not Granger Cause GENERAL_FR	1.643	0.073
GENERAL_FR does not Granger Cause TOT_AVERAGE	1.365	0.175
TOT_AVERAGE does not Granger Cause ECO	1.796	0.043
ECO does not Granger Cause TOT_AVERAGE	1.975	0.022
TOT_AVERAGE does not Granger Cause ECO_FR	1.102	0.353
ECO_FR does not Granger Cause TOT_AVERAGE	0.933	0.512
TOT_AVERAGE does not Granger Cause CORP	2.577	0.002
CORP does not Granger Cause TOT_AVERAGE	2.085	0.015
TOT_AVERAGE does not Granger Cause CORP_FR	2.499	0.003
CORP_FR does not Granger Cause TOT_AVERAGE	1.871	0.033
TOT_AVERAGE does not Granger Cause CAC40	1.223	0.260
CAC40 does not Granger Cause TOT_AVERAGE	1.587	0.088

SUMMARY AND CONCLUSIONS

This chapter analyses the results emerging from my thesis and tries to provide some useful considerations for future research. It is organized as follows: Section 5.1 is a brief summary of Chapter 1, which dealt with market structures. Section 5.2 critically reviews the results obtained in Chapter 2 containing an empirical analysis of the trading structure of the French Stock Exchange. Section 5.3 summarizes and discusses the empirical data on intraday public information patterns, while Section 5.4 analyses the impact of public information on the Paris Bourse. Finally, Section 5.5 gives some indications on the possible direction of future research work.

5.1. Market structures

The first chapter can be considered as a broad survey on various approaches to the topic of microstructure, and deals with some interesting features, namely market architecture and market microstructure models. First, I reported the definition of microstructure given by O'Hara (1995), i.e. the process and outcome of exchanging assets under explicit trading rules. I then surveyed the literature on the main characteristics of stock markets and on microstructure.

In the last two decades, stock markets worldwide changed drastically, in particular due to the technological progress, the European integration and the worldwide deregulation. Most stock exchanges abandoned the system based on call auctions in favour of a computerized limit-order market (among them the Paris Bourse and the Swiss Stock Exchange). In the late nineties the process of consolidation continued: many regional stock exchanges ceased to exist, while alternative trading systems, such as the Instinet and Island, gained in importance. We also witnessed the creation of new indexes for technology companies, such as the Neue Markt in Germany, New Market in Switzerland, and Nuovo Mercato in Italy. But the evolution of financial markets after the burst of the tech bubble in March 2000 was disappointing. Earnings manipulations, like in the cases of Enron and Worldcom, the terrorist attacks on September 11, 2001 in America, the worldwide recession and the recent war in Iraq led to a reduction in trading activity and the loss of trust in certain companies on the part of investors. Many companies went bankrupt, and some indexes related to the so-called New Economy ceased to exist (the last in time order was the Neue Markt). All these factors contributed to slowing down the process of consolidation we had seen at the end of the nineties. Certain projects have been suspended for the moment, such as the single stock exchange for the Euro-zone, but nevertheless the process of consolidation will probably continue in the years to come.

Chapter 1 also reviewed the organization and the main characteristics of financial markets. Three criteria were applied for distinguishing them:

a) The moment of the exchange. Two different approaches can be seen: the fixing market, where orders are batched together for simultaneous trade, and the continuous market, where orders may be submitted any time during trading hours.

b) The counterparts of the exchange. Here, we can distinguish between price-driven markets and order-driven markets. In the former, designated market makers supply the liquidity and maintain a fair and orderly trading. Their compensation is the difference between bid and ask. In the latter, there are no market makers, and orders are automatically and instantly matched with the orders currently outstanding in the limit order book.

c) The location of the exchange. On one hand there are centralized markets, where orders are routed to the same location, and on the other hand fragmented markets, where orders are routed through markets in different locations (multiple price for the same asset).

Other, secondary features characterizing the modern financial markets were briefly mentioned in Chapter 1, such as: the information available to market participants (the transparency concept); the process of price stabilization when the maximum set limit is exceeded (circuit breaker); the degree of exchange automation (floor vs. screen-based electronic systems); the minimum tick, i.e. the smallest stock price increment which can be quoted; the price discovery; and finally the allowed order form. All these features, however, leave the question open which trading structure is the best. Theoretical models (Glosten, 1994, Seppi, 1997 and Parlour and Seppi, 1998) suggest that there is no clearly superior market structure.

At the end of Chapter I, the relatively recent concept of "microstructure" was discussed. All the various models have as their central axis the bid-ask spread. However, two types of BAS are prominent in the literature, namely the quoted spread (the difference between the ask and bid price), and the effective spread (which reflects the reduction in trading costs attributable to trades executed within the quotes). The effective spread has two aspects: the price impact (the average information content of a trade), and the realized half spread (the effective gain after deduction of losses to better informed traders). Regarding the quoted spread, the literature shows that it must cover three types of costs incurred by the provider of immediacy: the order processing costs (compensation to market makers for providing liquidity services); the inventory holding costs (compensation to market makers for bearing the risk of holding unwanted inventories); and the adverse information costs (compensation to market makers for possible losses due to the presence of better informed investors). These costs are also studied in an order-driven market. Finally, I tried to show that access to high frequency data permits a better understanding of the price formation process and of the intraday movements on financial makets. Such an understanding is of fundamental importance for investors who wish to take frequent intraday positions.

5.2. Empirical analysis of the trading structure of the French Stock Exchange

Chapter 2 presented a number of original results on the intraday market liquidity of the French Stock Exchange during a one-year period (December 1, 1999 – November 30, 2000). The French Stock Exchange merged, in 2000, with the Amsterdam and Brussels Stock Exchanges in order to become the first European integrated transnational market called Euronext. In particular, the Paris Bourse had gradually shifted, since 1986, from a daily call auction to a computerized limit-order market in which trading occurs continuously. After the merger, Paris maintained its principal characteristics of an order-driven market with a central order book, and an auction before the opening and after closing.

In the literature, liquidity is defined as a multidimensional concept, and in particular Black (1971) claims that it has to meet 4 criteria: breadth, depth, resiliency and immediacy. Therefore, the analysis of intraday market liquidity cannot be based on one indicator only. For this reason, in my empirical analysis I calculated the common liquidity proxies which had already previously been used in the literature: the cumulated traded volume, the returns and the spread. However, I deepened the analysis by introducing relatively "new" measures in the intraday context:

(1) The quoted spread, calculated by using the weighted average spread file, which represents the price for blocks exceeding normal market size;

(2) The volatility, measured as log range;

(3) The waiting time between subsequent trades, originally introduced by Gouriéroux, Jasiak, LeFol (1997);

(4) The liquidity ratio, which had previously been used as an interday liquidity indicator (it represents the relation between the number or value of shares and price changes);

(5) The flow ratio (it represents the average number of shares traded in Euro, divided by the waiting time between subsequent trades).

All these proxies were applied to the 43 stocks belonging to the CAC 40 index during a one-year period (December 1, 1999 – November 30, 2000) and were calculated within successive intraday periods of 5 minutes. The results showed that:

(1) Spread measures (QHS, QHS_WAS, EHS) follow an inverse J-shaped pattern (wide spread at the beginning of the day, which then decreases constantly during the first hour of trading);

(2) Volume shows a J-shaped pattern;

(3) Volatility, measured ad log range, has a U-shaped pattern;

(4) Waiting time follows an inverse U-shape;

(5) Flow ratio has an inverse J-shaped pattern.

For each of these liquidity proxies, three peaks were observed in the afternoon, as previously reported by Ranaldo (2000) for the Swiss market and by Röder (1996), Röder and Bamberg (1996) and Kirchner and Schlag (1998) for the German market. The first peak occurs around 14:30, the second around 15:30 and the last around closing time. Three possible explanations are offered: the end of the lunch break; the adjustment of trader positions on the Paris Bourse before the US markets open, in particular following the release of US macroeconomic news, and finally, the linkage between European markets and US markets. Differently from other studies, I did not find any clear pattern in the average return and in the liquidity ratio measures.

Each liquidity component was also analysed with respect to the others, which led to interesting results. In particular, the depth in terms of trading volume showed a negative relation between ratio of cumulated traded volume and ratio of waiting time between subsequent trades, ratio of volatility of returns, whereas the relation was positive between the ratio of volume imbalance and the ratio of cumulated traded volume. The positive relation between cumulated traded volume and volume imbalance suggests that volume imbalance between counterparts tends to be transformed into trading volume, confirming that both indicators provide information on market depth. An increase in waiting time between subsequent trades is related a decrease in market depth. This relationship can be viewed as a proxy of trade frequency which is logically positively related to market depth. Ranaldo (2000), using the Glosten (1994) model, investigated different situations, according to the level of trading volume and the level of volatility, in order to find out the behaviour of market participants, i.e. when liquidity traders and informed traders are more likely to trade. Case 1: Informed traders are more present when the current level of trading volume and volatility is higher than normal. Case 2: Liquidity traders are present if the current level of trading volume is higher than normal and the current level of volatility is lower than normal. Case 3: The arrival of public and private information causes a price revision, which is particularly detectable when the current level of volatility is higher than normal, whereas the trading volume is lower. Case 4: Liquidity traders dominate trading activity, if volatility and trading volume are lower than normal. Following his interpretation, my results were explained as follows:

(1) Cumulated traded volumes can be caused, for example, by volume imbalance due to an ongoing price revision and strong liquidity trading;

(2) The negative relation between cumulated traded volume and waiting time may indicate the likely presence of discretionary liquidity traders and of small sized trades. It may also indicate that uninformed traders were able to protect themselves by reducing trade frequency and, inversely, that trading waiting time was used strategically by informed traders. Similar results have also been found by Madhavan and Sofianos (1998) with respect to the specialist market;

(3) The TARCH model, present in the majority of the regressions, shows evidence that positive and negative shocks have different effects, i.e. bad and good news affect

intraday market liquidity asymmetrically. If the residuals are interpreted as news arrival, as in Engle and Ng (1993), shocks create unexpected trading volume. The conditional variance equation shows that positive and negative ARCH components cancel each other when a negative shock is occurring, meaning that bad news reduces trading volumes, whereas good news increases them.

The depth in terms of order volume imbalance was also examined, and it showed evidence of a negative relation between volume imbalance, spread and waiting time. Lee et al. (1993) and Engle and Lange (1997) used this proxy to gauge market depth and found similar results, namely a negative relationship between spread and volume imbalance. This negative relationship supported the following assumptions: first, that the spread is wider during periods of high uncertainty, i.e. when a price revision is more likely (the demand or the supply is more rigid); and, second, that the behaviour of limit-order and market-order traders may be motivated by private information or liquidity reasons and that consequently, at certain moments, they tend to widen the spread, above all in moments of a higher presence of adverse selection.

The time dimension of intraday market liquidity showed, however, that the waiting time between subsequent trades follows an ARMA(1,1)-GARCH(1,1) model; it is negatively related to the trading volume and positively to volume imbalance and volatility. In some cases a TARCH model was also found. The residual can be interpreted as information arrival, which causes a change in trade frequency. Therefore it makes sense that the conditional variance has a TARCH structure, from which a negative shock simply eliminates the ARCH components and leaves only the GARCH effect. This overreaction to good news is similar to the variance equation found in the analysis of depth in terms of trading volume. I observed that a rise in market depth leads to a rise in trade frequency, expressed in terms of waiting time between subsequent trades, which means that informed traders may be more present, since they use trade frequency in order to act strategically.

The tightness of intraday market liquidity was measured in order to understand the behaviour of the BAS. The results showed a positive relation between spread and volume imbalance during the period December – March (an increase in volume imbalance was followed by a wider spread) and a negative relation during the period April – November (the activity may have been dominated by eager traders who traded within the quoted spread, thus reducing it). The quoted spread and the waiting time were also negatively related. Ranaldo (2000) found a significantly negative relation only when liquidity traders dominated the trading activity.

The intraday return volatility analysis showed a positive relation between spread and volatility and, on the other hand, a negative relation between volume imbalance and volatility. Return volatility may depend on traders' information, and, as reported in the literature, the positive relation between spread and volatility signals an increase in informed trading periods. The negative relation to volume imbalance can be interpreted in two ways: first, as a market depth proxy and second, as a signal of divergence between the bid and the ask side. Having found a negative relation, I interpreted the volume imbalance as a good indicator of market divergence between counterparts. A positive relation, however, has been interpreted in the literature as a more efficient proxy of intraday market depth. In this situation, it is possible that informed traders and liquidity traders are more present.

Finally, an empirical analysis was made concerning the relation between the quoted spread, calculated from the weighted average spread, and the volume imbalance, a subject not yet studied in this form in the microstructure literature. The results are quite intriguing and showed that there exists a negative relation between quoted spread, waiting time and imbalance, but a positive relation between volatility and spread. The negative relation between spread and volume imbalance has been interpreted in the literature as the ability of investors to observe the state of the order book and their corresponding aggressiveness (in order to trade promptly they trade within the quote, thus reducing the quoted spread); therefore, the volume imbalance has been considered as an indicator of the divergence between counterparts. My results showed, through very significant regression coefficients, that the WAS is actually a good illiquidity indicator. All this is a much debated issue in the microstructure literature. In fact, the WAS can also be related to the market depth, and in particular to the elasticity of demand and supply. If demand and supply are more rigid, then the WAS will widen, especially at the beginning and at the end of the trading day, as is also documented by the spread pattern. Brock and Kleidon (1992) claimed that at the beginning and at the end of the trading day demand and supply were more rigid, since prices couldn't adjust during the night or were not likely to do so in the following night. This reasoning explains the positive relation.

5.3. Intraday public information patterns

Chapter 3 dealt with the intraday information patterns, a subject rarely reported in the financial literature. My investigation is based on a broad range of intraday information items released during a one-year period by the Reuters 2000 News Alert System. The volume of news items constituted the proxy of information arrival. Differently from other studies, I tried to make a clearer distinction between types of news, considering not only specific announcements such as macroeconomic or earnings news. In fact, eight news categories were taken into consideration: All Alerts news (the headlines of important news), Political news (news related to political activities worldwide), Market news (news items related to the general market activity), Economic news (macroeconomic indicators), Industrial news (manufacturing sectors), Corporate news (news about companies, earnings, dividends etc.), Firm-specific news (news related to firms belonging to the CAC 40 index) and General news (culture, sports, crime, etc.). The news related to France only were also broken down into seven of these eight categories and form a separate subgroup. In fact Firm-specific news considers already news items related to France. This procedure is different from the one previously reported by Berry and Howe (1994).

Investors closely follow public information releases in order to update their expectations about risk and return. Therefore it is important to know when and which information is released. My straightforward question was whether there exists an intraday pattern of news, similarly to that found for intraday market liquidity proxies. Investors are flooded every day with news announcements, as is demonstrated by the more than 3.5 million news items I collected during the one-year period. In order to get a clearer picture of the news flow in the 8 categories, the 24 hours of the day were subdivided into 5 minutes periods. In this way, an intraday pattern emerged which showed that the highest information activity is concentrated around the pre-opening and opening of US markets, i.e. when all important trading places, except the Tokyo Stock Exchange, are open. As previously found, the news patterns more or less resemble an inverted U-shape, but each news category has its own particular shape. One or two peaks, depending on the news category, were observed shortly before and after the official market closing. Two explanations were given: first, news items which might have an important influence on the stock price are released shortly before or after trading hours and, second, news which might concern press release or news which might concern the opening and the closing of financial markets are released just shortly before and afterwards.

I also reported the news flow by day of the week, by month of the year and by trading hours. Unfortunately, technical problems with the Reuters Terminal did not allow to draw general conclusions because some categories are not complete. But considering all those months for which news has been completely collected, I observed that:

(1) Overall news flow is highest during the month of February, and for the French related news it is highest during March.

(2) Overall news flow is smallest in December.

(3) The results by day of the week showed that news items are concentrated on Wednesday, while they are lightest on Friday.

(4) News coverage concerning the stocks belonging to the CAC 40 index shows different results, and the hypothesis that higher capitalization means also higher coverage has not been confirmed.

Chapter 3 left open the question whether the Reuters Terminal is the best public information proxy, or whether it could be substituted by other information providers such as Bloomberg. If it were substituted, would the intraday information proxy change ? One has to bear in mind that Reuters has been used in most empirical studies so far, and is a press agency handling all types of news. Bloomberg however, concentrates mainly on news which is suitable as a tool for company analyses.

5.4. Public information impact on the Paris Bourse

Chapter 4 dealt with the public information concept, which in the literature has always been applied to market efficiency, and in particular the semi-strong form test carried out by Fama (1970), which claims that the prices fully reflect all publicly available information. In contrast to previous studies, my investigation looks at the amount of public information and examines its effects on intraday trading activity of 43 stocks belonging to the CAC 40 index. Such a procedure is relatively new and has first been adopted by Berry and Howe (1994). My study is based on four liquidity indicators: cumulated traded volume, return, volatility (log range) and spread. The news items are those described in chapter 3, and the intraday liquidity indicators were calculated as mentioned in Chapter 2. The analysis was conducted in two steps:

A. *Regression analyses*

(1) The quoted spread, calculated from the order data, was regressed on the news flow. The results showed a positive or negative relation with news announcements, depending on the stock chosen (similarly, no clear relation was found in the tightness measure of intraday market liquidity), meaning that spread may increase or decrease with higher (lower) information flow. In contrast, the quoted half spread shows in the majority of cases a negative relation, i.e. the spread widens when the information flow is lower, thus reducing trading activity. In this case the presence of informed traders may be higher, and liquidity traders tend to protect themselves by widening the spread through limit orders. If a trader knows that adverse selection is more severe, he will reduce his trading activity until more public information arrives at the market. This problem has also been raised by Glosten and Milgrom (1985) with respect to a price-driven market, where the market maker is confronted with asymmetric information. The model claims that if the adverse selection is too extreme, each market maker will expect to lose money on trade. The consequence is that the market shuts down until enough public information arrives to relieve the adverse selection problem. The authors suggested the presence of a monopolist specialist in order to reduce the adverse selection effect. In an order-driven market, however, liquidity traders may reduce trading activity by widening the spread through limit orders, and informed traders may not trade in order not to disclose themselves.

(2) The trading volume was regressed on a specific category and on the absolute value of returns. The results showed that a higher information flow (the independent variable might be significant until one hour lag) tends to be transformed into a higher transaction volume. The positive relation may be interpreted as agreement or disagreement which generates trading activity. Volume volatility followed, for certain shares, a TARCH model, implying that positive and negative shocks have an asymmetric impact; thus, as already explained

by Engle and Ng (1993) and by Lamoreux and Lastrapes (1990), the negative coefficient of the asymmetric effect induces a reduction in market activity if bad news arrives on the market;

(3) The relation between absolute price changes and news flow was calculated. The results were weaker than for other liquidity indicators, but still significant. In some cases I found that return anticipates information arrival, meaning that informed traders are active;

(4) The influence of news flow on volatility calculated as log range. The results showed that a higher information flow leads to higher volatility. Such a positive relation between volume and volatility had already been mentioned in Chapter 2. But although news items are important for determining volatility and volume, investors also trade for other reasons than informational, for liquidity or speculative desires, as shown by the constant term of the regression analysis, which was always significant.

B. Measurement of price impact

The measured suggested by Bessembinder and Kaufmann (1997) allows to measure the average information content of the trade. I applied their method in an order-driven market. The results were intriguing and showed that trades are much more informative before news release, i.e. private information anticipates (up to 40 minutes) the arrival of public information. The measurement of the intraday evolution of the price impact also showed that trades are more informative in the morning and, in some cases, during the pre-opening and opening of the US markets.

The theoretical and empirical analyses made in Chapter 1 to 4 lead to a number of surprising results which may shed new light on the concept of market efficiency. In practical terms, the findings might help investors to decide when and how to trade, and thus become a useful tool for asset management activities.

5.5. Research agenda

This dissertation left open a number of questions which require further investigations:

(1) The linear regression model may not be the optimal solution, but it constitutes a first step in order to analyse the impact of intraday information arrival on stock exchanges.

(2) It may be much more intriguing to analyse the bid-ask spread components around the public information arrival, similarly to Ranaldo (2002), but considering, instead of firm-specific news only, the overall information flow by categories. The models of Madhavan, Richardson and Roomans (1997) and Lin, Sanger and Booth (1997) seem to be good starting points.

(3) Investors may be much more interested in the option market evolution around the news flow. Since options have an higher leverage effect, the information impact may be different. The decomposition into order processing costs, inventory holding costs and adverse information costs in the option market might lead to a new understanding of the price formation process. The analysis may be even more interesting, if it considers both the equity market and the option market on the French Stock Exchange, since they have a different structure. The former is an order-driven market, whereas the latter is a price-driven market.

(4) The analysis in this dissertation were made only a few months after the burst of the tech bubble. It would be interesting to see how the market liquidity indicators (spread, volume, volatility) have changed during the recent market decline. Did investor behaviour change ?

(5) It might be a challenge to analyse the news released by different information providers contemporaneously. No doubt high frequency data has provided a better and deeper analysis of the price formation process. Today we have much easier access to tick-by-tick data, thanks to reduced costs of data collection, compared to about ten years ago when most empirical studies used daily data.

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