# Do Analysts Forecast a Mean-Reverting Pattern in Return on Equity?

## MASTER THESIS

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I opted to use personal pronouns to avoid unnecessarily complicated passive sentences structures. I used “we” rather than “I,” to direct readers’ attention to the subject matter and avoid any sense of self-centeredness.

Patrick Chardonnens, Fribourg, 12 January 2017

## Abstract

This thesis' purpose is to explore whether analysts forecast a mean-reverting pattern in return on equity (ROE). The academic fields of both, mean reversion in ROE and analysts' forecasts are well explored. However, literature did so far not connect those research fields. This is motivation enough for assessing the ROE pattern of analysts' forecasts. We answer the research question by sorting reported ROE values and analysts' ROE forecasts into 10 portfolios in descending order. The extensive dataset includes Worldscope's reported financial statement data and the Institutional Brokers' Estimate System (I/B/E/S) analysts' forecasts of all publicly traded firms in 16 European countries from 1986-2015. Further, a detailed guideline for combining fundamental Worldscope ROE data with earnings per share (EPS) data from the I/B/E/S is established. Our findings provide supportive evidence for mean reversion in reported ROE and approve the research question: Analysts predict a mean-reverting pattern in ROE. We demonstrate that analysts tend to overestimate past losers and that they are selective in forecasting equities. Past winners (losers) and larger (smaller) firms, measured in terms of net income and common equity, show a higher (lower) analyst coverage. Evidence is provided that analysts' picks imply a higher future ROE. We propose a novel approach to offset the analysts' bias and thus improving ROE predictions. Finally, this thesis suggests a formula which upcoming research can use to assess and compare the quality of existing ROE predictions models.

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## List of Abbreviations and Acronyms

| | |
|---|---|
| ATO | Asset Turnover |
| BPS | Book Value per Share |
| DAF | Dispersion in Analysts’ Forecasts |
| DPS | Dividend per Share |
| EPS | Earnings per Share |
| FLEV | Financial Leverage |
| I/B/E/S | Institutional Brokers' Estimate System |
| LTG | Long-Term Growth |
| OLS | Ordinary Least Squares |
| PM | Profit Margin |
| RNOA | Return on Net Operating Assets |
| ROA | Return on Assets |
| ROE | Return on Equity |

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# 1 Introduction

Fama and French (2000: 174) analyzed in their paper "Forecasting Profitability and Earnings" the mean-reverting pattern of profitability and concluded the following:

> *"There is also predictable variation in earnings. Much of it traces to the mean reversion of profitability. An important practical implication of this result is that forecasts of earnings (e.g., by security analysts) should exploit the mean reversion in profitability."*

To our knowledge, academic research has not yet assessed analysts' forecasts in relation to mean reversion in profitability. This was motivation enough to answer the following research question: Do analysts predict a mean-reverting pattern in return on equity (ROE)? This paper connects the research of both, mean-reverting pattern of ROE and analysts' earnings predictions, as it aims to reveal new findings of this nearly unexplored field. Ultimately, we propose two formulas contributing to future research. The first adjusts the observed bias in analysts' forecasts, whereas the second proposes a methodology to evaluate existing ROE prediction models.

Mean reversion originates from the economic principle that profitability reverts to a mean level in the long run. This is because market participants with below average returns are incentivized to move towards more profitable domains. The same mean-reversion pattern was also observed regarding firms' ROE and is a well-researched phenomenon. The research field of analysts' forecasts offers a larger variety. We limit ourselves to the evaluation of analysts' periodical forecasts concerning earnings and profitability predictions.

The thesis begins by offering a broad overview of the academic literature on the mean reversion of equities. We mainly focus on accounting earnings in terms of profitability and absolute earnings but exclude research regarding stock returns. Next, the thesis describes how we examined such a mean reversion process using a comprehensive dataset covering 16 European countries from 1982-2015. This mean reversion analysis followed von Arx's (2015) methodology. We graphically examined the mean reversion process for ROE by building 10 portfolios. Additionally, we sorted the portfolios by descending ROE, analyzed them over time, and compared the findings to von Arx's (2015) results. The first section ends by linking our results to the existing literature, such as works by

Penman (1991), Harris and Nissim (2004), Palepu et al. (2010), and particularly, von Arx (2015).

In a second section, we reviewed the academic literature on analysts' earnings forecasts. The scope is limited to papers evaluating the analysts' forecasts. Further, the thesis describes the retrieved Institutional Brokers' Estimate System (I/B/E/S) dataset and the extrapolation of the analysts' earnings forecasts on the basis of predicted long-term growth (LTG). As no conventional transmission or academic study has translated Worldscope ROE data into I/B/E/S earnings per share (EPS) forecasts, this paper provides such a method. Moreover, our approach to translating between the databases aims to identify and correct all possible mismatches. Further, we plotted analysts' forecasts in a similar way to the mean reversion data. Finally, the paper clarifies whether analysts exploit the mean reversion in profitability, as suggested by Fama and French (2000: 174).

In a third and final section, we graphically compared section two's mean reversion results with section three's ROE forecasts. Furthermore, we split the initial highest and lowest portfolio in terms of ROE into 10 sub-portfolios to carefully assess analysts' estimation errors when facing extreme ROE values. Next, we selected firms for which analysts had provided five-year forecasts. Again, we evaluated the highest and lowest initial portfolio in order to identify analysts' systematic forecasting errors. At the end of the thesis, we employed our findings to propose an alternative ROE forecasting model. Furthermore, we developed a new approach for assessing the quality of prediction models for profitability, in mind that future research builds on our findings.

# 2 Mean Reversion

This chapter discusses mean reversion in ROE and begins with a chronological literature review. The fact that the term 'mean reversion' has a clear definition in literature allowed us to structure the review chronologically instead of thematically. Afterwards, the chapter introduces the retrieved I/B/E/S dataset. Finally, a graphical analysis demonstrates whether we can confirm past findings from the literature, and particularly those of von Arx (2015).

## 2.1 Literature on Mean Reversion

Previous studies have analyzed deflated and non-deflated earnings. Therefore, the literature review presents both. In this context, non-deflated earnings are absolute earnings for a given period. In contrast, deflated earnings are absolute earnings divided by the book value of equity, and so this figure is expressed as a ratio. The advantage of the latter method is that it permits analysts to draw comparisons across firms, because a profitability ratio describes earnings in relation to invested capital. We treat EPS as non-deflated values for two reasons. Firstly, the number of shares is not related to the book value, but a firm's owners decide on the number of shares in an unsystematic manner. Secondly, a percentage increase in absolute earnings is identical to the increase in EPS if the number of shares remains unchanged. When using deflated earnings, non-distributed prior-year earnings become part of the deflated value, and so the effective profitability is measured. We also discuss research papers forecasting mean reversion in ROE based on regressions. Those results are relevant for Chapter 4.4, "Forecasting ROE."

The issue of measuring returns on invested capital has been a topic of discussion in the economic literature for more than 100 years. According to Webb (1888: 191), the analysis of rates of return was already applied to fields such as rents, profits, and wages. Early on, Fisher (1907) created the theory of interest. In the theory of economic development, Schumpeter (1934) stated that market participants are incentivized to take advantage of profit opportunities when the market is not in equilibrium. Therefore, long-term profitability will revert to normal levels. Boulding (1936) studied the rate of return over time, while Little (1962) analyzed firms' growth patterns in his work "Higgledy Piggledy Growth".

The first to indicate that mean reversion might apply to profitability was Nobel Prize winner George J. Stigler in 1963. With his vast (for the era) collection of data, Stigler (1963: 12 and 35) compared returns over time to the corresponding book values. His data (1963: 48) revealed that rates of return are relatively stable throughout the years and are closely correlated. To emphasize the importance of his findings, Stigler (1963: 54) opened with the following statement, which many researchers (e.g., Fama and French [2000], Soliman [2004], Allen and Salim [2005] and von Arx [2015]) have quoted either in full or in part:

> *"There is no more valuable proposition in economic theory than that, under competition, the rate of return on investment tends toward equality in all industries. Entrepreneurs will seek to leave relatively unprofitable industries and enter relatively profitable ones."*

Stigler (1963: 54) added that this process might happen over time due to market imperfections.

A few years later, Beaver (1970) defined the process of pure mean reversion and also established the pure random walk model. He argued that researchers knew far too little about accounting behavior and that accounting returns and security returns might exhibit different types of statistical behavior. To our knowledge, Beaver (1970) was the first to define the mean-reversion process with respect to the time series behavior of accounting earnings.

According to Beaver (1970), mean reversion describes the process by which the rate of return reverts to normal earnings over time. It includes the variance as a stochastic component in the error term. In the pure mean-reversion model, the expected rate of return is a constant and does not change over time, as it is the deterministic variable.

For his study, Beaver (1970) randomly selected 100 industrial firms listed on the New York Stock Exchange on December 31, 1954. All of these firms were included in Moody's Industrial Manual. Then, Beaver (1970) collected the available firm data of the selected firms from 1949-1968. He thought that the difference between industrial and non-industrial firms might be substantial and that a firm's sector might have an effect on the variables.

He concluded that deflated accounting earnings were more successfully approximated by the pure mean-reversion model rather than by the random walk model. Moreover, he found that undeflated accounting earnings better fit a random walk model with drift. These results were consistent with the studies of Ball et al. (1968), Ball et al. (1970), and Archibald (1967). Further, he confirmed that accounting returns tend to have a smoothing nature.

Brooks and Buckmaster (1976) used a different approach than previous researchers. They analyzed the change in earnings, applying stratification rules to find the best smoothing constant, which was 1. According to their findings, a submartingale process, which is similar to a random walk model, was the best fit for the data.

Lookabill (1976) discussed whether accounting earnings follow a random walk model over time, as Ball and Watts (1972) had previously found, or if they follow a mean-reverting model, as Beaver (1970) discovered. Additionally, he defined an autoregression and a moving-average process before analyzing his data. His sample contained 56 firms from the food, beverage, tobacco, chemical, and steel industries, and he sorted them according to their rate of return. The ROE was consistently calculated as this year's accounting earnings divided by last year's book value of equity. Unlike Beaver (1970), Lookabill (1976) found that the deflated earnings from the cross-sectional analysis did not revert to the mean but instead fit a moving average.

Around the same time, Albrecht et al. (1977) analyzed both deflated and undeflated earnings. They performed a cross-sectional analysis and also assessed individual time series. Taking into account different industry groups, they found that a random walk model with drift best fits the undeflated data, whereas deflated earnings followed a strict random walk model.

Mueller (1977) researched the persistence of profits above and below the norm, creating the first graphical approximations of an observed mean-reversion process. Additionally, he graphically represented the partial mean reversion of return on assets (ROA). Rather than examining the industry level, he assessed individual firm data, since products, margins, and other important determinants of the rate of return are not homogenous within industries and are therefore not comparable. He claimed that intra-industry above-average and below-average profits might simply cancel out each other.

Mueller (1977) analyzed a sample from Compustat covering 472 firms over a 24-year period from 1949-1972. He divided the firms into eight different portfolios ordered by their ROA in the initial year (1949). His results revealed that firms starting in the top (bottom) portfolio had the highest chance of ending up in the top (bottom) portfolio years later. Also, Mueller (1977: 372) managed to create a first illustration of the mean-reverting process of ROA:

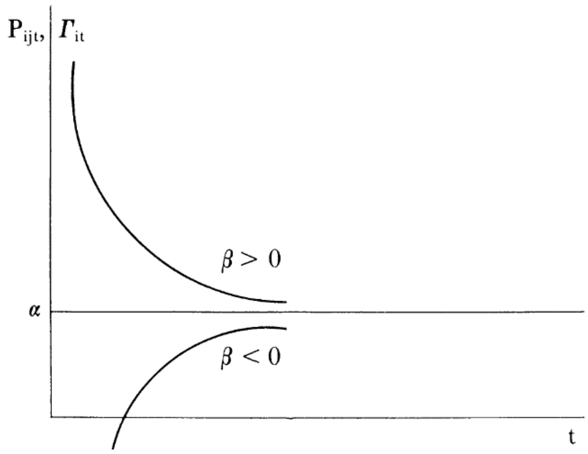


Figure 1: The mean reversion process, as illustrated by Mueller (1977)

In the above graph $P_{ijt}$ is the profitability, defined as the ROA; $r_{it}$ is the observed ROA; $\alpha$ is the mean return level of all firms; and $\beta$ is the rate at which returns revert to the mean. Thus, the concept of mean reversion in profitability had been established and illustrated in graphic form. However, the academic discussion continued.

Ball and Watts (1977) published a study assessing absolute net income, EPS, net income deflated by total assets, and absolute sales. They analyzed the Standard and Poor's Compustat tape over a 20-year period from 1947-1966 and excluded all firms that either dropped out of the index or joined it during that time frame. With a sample of almost 900 firms, they found that net income and sales were close to a submartingale process with a linear trend, or in other words, a random walk model with drift. For EPS and deflated net income, they found a submartingale process without drift. They concluded that the random walk model outperformed a mean-reverting model for deflated earnings.

Freeman et al. (1982) disagreed with the past literature stating that deflated earnings follow a random walk (e.g., Ball and Watts [1972] and Gonedes [1973]) and instead offered support for a mean-reversion process. They managed to prove the existence of the mean-reversion process that Beaver (1970) had informally observed. They analyzed Compustat data from 30 firms from 1946-1972. Their results indicated that the rate of return predicts earnings changes. The distribution of differences in earnings from one year to the next was not normally distributed. As a consequence, they analyzed whether an increase (decrease) in earnings was dependent on the actual rate of return. Furthermore, they mentioned that changes in the rate of return correlated with changes in earnings. After a year in which the rate of return increases (decreases), the following year is likely to see the rate further increase (decrease). They found that this effect was stronger the more that the rate of return deviated from the mean rate of returns. Moreover, the researchers discovered that a high (low) rate of return reverted to an average level. Freeman et al. (1982) saw an econometric problem in prior studies: The null hypothesis is hard to reject because of noisy data.

In his book, *Profits in the long run*, Mueller (1986) published parts of his 1977 article in which he had analyzed whether differences in profitability persist across firms in the long term. He assessed a larger sample, consisting of the 1’000 largest U.S. companies from 1950-1972, and found after the termination of the mean reversion process some persistent differences. He enforced his claim from 1977 by providing evidence that high (low) starting values do not completely revert to the mean but remain higher (lower).

Penman (1991) took a closer look at the components of ROE. In particular, he introduced the “Du Pont system” to disaggregate ROE. Like Lookabill (1976), he defined ROE as annual earnings divided by the previous year's book value of equity. Penman’s (1991) study utilize a sample from Compustat spanning 18 years (1969-1986), in which each year had an average of almost 2,000 data points. Consistent with previous studies, Penman (1991) classified the portfolios into 20 different portfolios on the basis of ROE. His findings showed similarities to those of Freeman (1982) who had assessed ROA. He concluded that firms with a high (low) starting ROE are likely to have a lower (higher) ROE in a few years’ time but do not completely revert to the median. Penman (1991) mentioned that the current ROE is not necessarily indicative of the future ROE. This effect could also origin from the price divided by book value and is possibly an indicator of the future ROE, due to market expectations for future and transitory earnings.

Brown (1993) confirmed the results of previous researchers, such as Ball and Watts (1972) and Albrecht et al. (1977), stating that absolute, non-deflated earnings follow a random walk model with drift, whereas deflated earnings adhere to a mean-reversion process. Brown (1993: 295) concluded that the topic of annual earnings behavior had been mostly resolved by the late 1970s.

Fairfield et al. (1996) disaggregated ROE from an accounting point of view to retrieve more information from financial statements. They were able to improve out-of-sample ROE forecasts, as well as one-year ahead ROE forecasts before special items. They applied a linear cross-sectional forecasting time-series model and found that operating earnings were the most important determinant of the future ROE, with non-operating earnings coming in second place. Other significant disaggregated variables were income taxes and special items.

Fama and French (2000) provided additional evidence for mean reversion and examined the process' characteristics more closely. They criticized the previous literature for conducting few formal tests and frequently basing them on time-series models. They also mentioned the emerging problem of survivor bias. Analyzing periods in excess of 20 years implies a considerable number of firms might leave the market. Further, they excluded the finance and utility industries due to heavy regulation. In their study, they forecasted profitability and earnings on a yearly basis using cross-sectional regressions. Moreover, Fama and French (2000: 169) created the following partial-adjustment model to forecast profitability:

$$\begin{aligned} CP_{t+1} = a + b_1 DFE_t + b_2 NDFE_t + b_3 SNDFE_t + b_4 SPDFE_t + c_1 CP_t + c_2 NCP_t \\ + c_3 SNCP_t + c_4 SPCP_t + e_{t+1} \end{aligned}$$

Here, $b_2, b_3,$ and $b_4$ measure the nonlinear adjustment speed of profitability to the expected value. The terms $c_2, c_3,$ and $c_4$ measure the nonlinear autocorrelation of profitability changes. The individual variables are constructed as follows: $CP_{t+1}$ is the change in profitability (earnings before interest and extraordinary items but after the year's taxes divided by the book value of assets in that same year) from one year to the next. The variable $CP_t$ is the realized change in profitability, while $DFE_t$ stands for the deviation from forecasted profitability at time *t*. Finally, *N (P)* captures negative (positive) deviations from profitability, and variables including *S* are squared values.

Fama and French (2000: 170) found evidence that the nonlinearity of the autocorrelation profitability changes was similar to that observed by Brooks and Buckmaster (1976) and Elgers and Lo (1994). Their computed rate of reversion was 38% per year, with higher (lower) reversion values when profitability was below (above) average. They offered a potential economic justification, claiming that a higher reversion rate is likely in cases of past negative profitability, because such firms might be prone to failure or takeover. Another possible explanation is the asymmetric timeliness that Basu (1997) described. Regulation standards require firms to declare or impair losses on short notice. Therefore, the profitability values can become highly negative in case of impairment and then quickly revert to the initial profitability level. Gains, on the other hand, are spread over several periods and have a less drastic impact on a firms' profitability.

Fairfield and Yohn (2001) disaggregated profitability into asset turnover (ATO) and profit margin (PM), and assessed whether they could predict changes in profitability. They found that decomposing ROA into ATO, and PM does not help to forecast the ROA one year ahead. However, disaggregating the one-year ROA change into ATO and PM contributes to predicting the one-year changes in ROA.

Nissim and Penman (2001) combined classical ratio analysis with equity valuation. They distinguished between operating activities and financial activities and completed a detailed profitability analysis. Their findings suggested that profitability and growth drive value. Furthermore, they observed accounting figures in detail and analyzed their behavior over time.

Harris and Nissim (2004) confirmed previous results indicating that ROE are mean reverting in a non-linear manner. They added that non-linearity is convex for a high initial ROE and concave a low initial ROE.

In addition, Soliman (2004) explored the mean reversion of profitability for industry-adjusting ratios. He argued that due to structural differences between industries not all firms might revert in the same way. Soliman (2004) used the Du Pont model to disaggregate the return on net operating assets (RNOA) per industry. Through this separation process, he managed to increase the predictive power of changes in RNOA. Due to structural differences, an industry-specific PM and ATO are better fits when measuring the RNOA. He advocated for the inclusion of industry variables in future RNOA analyses, because a high ATO might be better explained by industry-specific characteristics than firm-specific characteristics.

Allen and Salim (2005) replicated Fama and French's (2000) study and applied their methodology to UK companies. This study is of importance, because, to our knowledge, it was the first such analysis to use European firm data. They found a mean convergence rate of 23% rate directed to the median. However, their results were not significantly non-linear. Allen and Salim (2005) mentioned the divergent dividend taxation policies could potentially explain how their results differed from those of Fama and French (2000).

Altunbas et al. (2008) confirmed Allen and Salim's (2005) findings using a larger sample consisting of all listed firms in 15 European Union member states. Their sample, retrieved from the Worldscope Database, covered the period from 1990-2000 which sums up to an average of 3'281 firm-year observations. They found that EU firms demonstrated a mean-reverting tendency for profitability over several years. However, as in the case of Allen and Salim (2005), the researchers found no evidence of non-linearity. Further, the mean-reversion process, with a reversion speed of 27%, was slower than in the US. Altunbas et al. (2008) assessed whether the mean-reversion speed changed when they used the same industries as Fama and French (2000). This modification led the reversion rate to be 32%, closer to the 38% annual reversion rate found by Fama and French (2000). Altunbas et al. (2008) found slower reversion speeds for industries such as utilities, finance, and manufacturing, where heavy regulation might have been the cause. One of Altunbas et al.'s (2008) final conclusions was that the U.S. market might be more competitive and homogenous than the European market.

Nordal (2009) analyzed the mean-reversion process for non-listed Norwegian firms from 1988-2006. The mean rate of reversion was with 44% per year much higher than in other studies. The high reversion rate might have been due to Nordal's (2009) sample, which consisted of smaller and non-listed firms. Also, smaller companies might be more agile and therefore capable of moving more quickly to profitable segments, thus accelerating the mean-reversion rate.

Palepu et al. (2010: 277) retrieved their sample, which spanned the years from 1992-2008, from Thompson Financials' Worldscope database. They formed five portfolios sorted by descending ROE and observed the mean reversion effect, as in previous studies. After completion of the mean reversion process, the results revealed that the ROEs of the top initial portfolio and bottom initial portfolio differed by 11% in ROE. Palepu et al. (2010: 280) gave two possible explanations for why certain firms consistently have above-average annual profitability ratios. First, some companies possess a sustainable competitive advantage. Second, pharmaceutical companies, for instance, do not list research expenses on their balance sheets.

Canarella et al. (2013) focused on whether firm profitability follows a mean-reverting process or a random walk. They analyzed a large dataset consisting of publically listed U.S. companies from 2001-2010. They noted that most prior studies had ignored the cross-sectional dependences in industry data. Nevertheless, their research confirmed that profitability follows a mean-reverting process.

In his Ph.D. thesis, von Arx (2015) analyzed long-term ROE tendencies. He used a large dataset consisting of all stock quoted firms in 16 European countries from 1981-2010. In the portfolio formation year, he split the dataset into 10 portfolios sorted by descending ROE. Afterwards, he plotted the portfolios over a 10-year period beginning subsequent to the portfolio formation year. He analyzed the industry differences and developed an alternative approach with predefined ROE portfolio ranges. Ultimately, von Arx's (2015) results provided evidence in support of mean reversion in ROEs.

Since the time of Freeman et al. (1982) or, at latest, Mueller (1986), it had been uncontested that deflated accounting earnings follow a mean-reversion process and that portfolios do not fully revert. Since Fairfield et al. (1996), researchers had been building regression models that incorporated current knowledge on the mean-reversion process to predict the ROE one year in advance. Moreover, Allen and Salim (2005), Altunbas et al. (2008), and von Arx (2015) had confirmed these findings for the European market.

## 2.2 Worldscope Data

This subsection describes our retrieved Worldscope data in detail and compares it to von Arx's (2015) dataset. Our sample consisted of all listed dead or alive equity firms in 16 European countries from 1981-2015 (35 years). In alphabetical order, those countries were Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, and the UK. The sample included 13'272 individual firms that were retrieved from Thomson Reuters Worldscope.

The academic literature on mean reversion has provided little information when it comes to the exact definitions of these variables. Von Arx (2015: 207) clearly stated which Worldscope items codes he used to define the ROE. To provide consistency to von Arx's (2015) study, we used his method to compute the ROE.

To ensure comprehensiveness and avoid ambiguity, this paper consistently uses capital letters and includes the Worldscope item code in parentheses when using a definition from that database. Appendix 3 provides a detailed list with all Worldscope items. When employing other definitions, we consistently use lowercase letters.

The net income computed by von Arx (2015) consists of subtracting the Worldscope Items Income Tax (WC01451) from Pretax Income (WC01401). The deflating variable is the last year's book equity, which is the sum of the last year's Common Equity (WC03501) and the last years' Preferred Stock (WC03451). The following table displays the ROE composition, as applied by von Arx (2015):

**Composition of ROE according to von Arx [2015]**

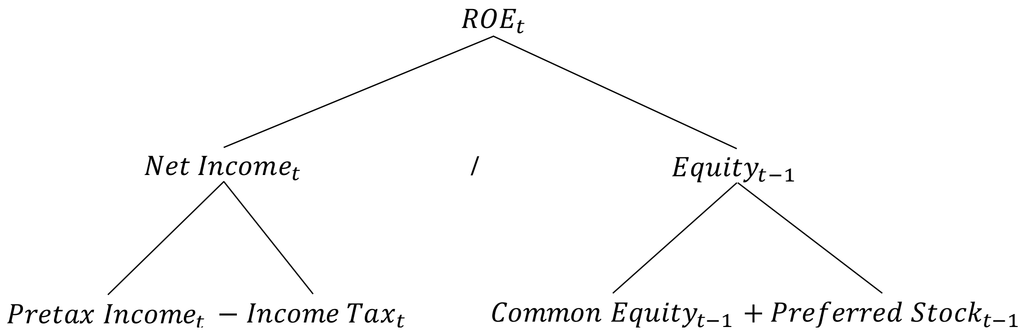


Figure 2: Composition of ROE, according to von Arx (2015)

Calculating ROE this way reduced the study’s time frame to 34 years, because we deflated the earnings variable by the previous year’s equity variable. To compute the 1982 ROE, for example, we divided net income for 1982 by the 1981 year-end equity value.

We excluded 2’230 financial firms, which had the Worldscope industry codes ranging from 4’300 to 4’395. Financial firms might have a slower conversion ratio due to heavy regulation and could therefore have significantly influenced the results, as mentioned by Altunbas et al. (2008). This methodological choice is also consistent with the studies of Fama and French (2000) and von Arx (2015). Additionally, we removed extreme outliers consisting of ROE values below -2 and above 2. In accordance with Nissim and Penman (2001), Harris and Wang (2013), as well as von Arx (2015), we excluded observations with negative equity. After applying these changes to the data, the final sample had 10’939 individual firms. The large data table in Appendix 1 displays the number of observations, median ROE, mean ROE, and standard deviation for every country in every year.

Overall, 36% of the firms in our full sample were listed on stock exchanges in the UK. Observations from the UK, France, and Germany comprised more than 60% of all observations. An analysis of the values for UK firms revealed consistently higher means and medians from 1982-1990 and lower mean and median ROE from 1997-2015. The standard deviation increased from 1982-1996 but remained below 0.3 during that time period. In contrast, it then crossed the 0.3 threshold and remained above it after 1996.

A comparison of our dataset with that of von Arx (2015: 22 - 25) demonstrates that our study included more firms. In particular, in 1998 we had 38% more observations than von Arx (2015). However, the percentage of additional observations did not remain stable over the period of study. Although both datasets consisted of Worldscope data retrieved from Datastream and included all stock quoted equities from the same 16 European countries, the two studies may have used different filters, thus resulting in varying numbers of firms. Von Arx (2015: 44) had 87’035 ROE observations, whereas our study had 121’130 ROE observations. Of note, however, is that our study included five more observation years, those from 2011-2015. Figure 3 depicts mean and median ROE in our sample over time:

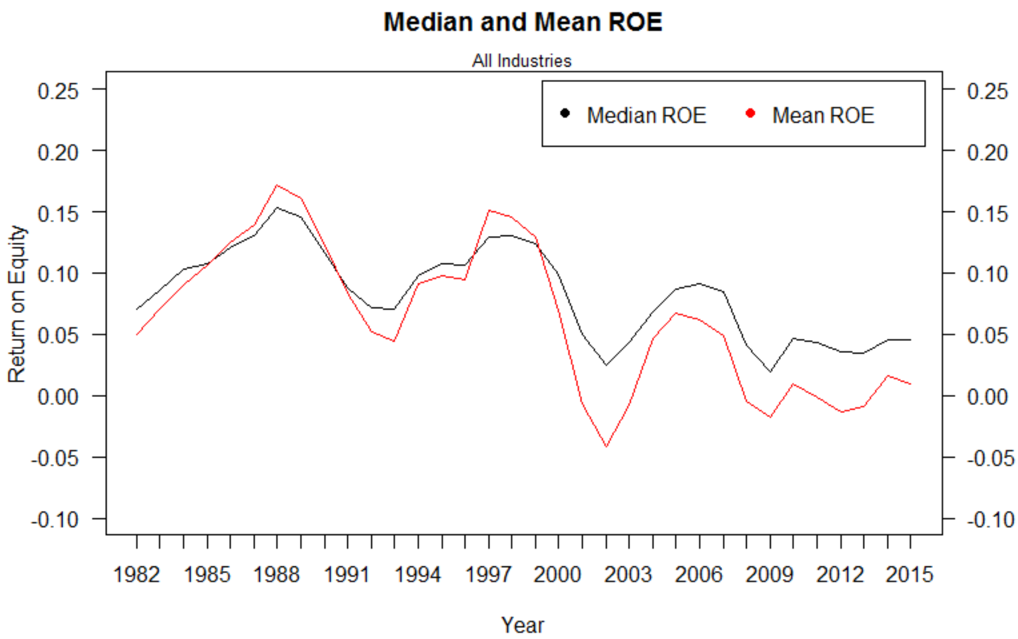


Figure 3: Median and mean ROE from 1982-2015

Obviously, we observed higher ROE values in periods of economic growth and lower ROE values during recessions. Until 1998, mean ROE values seemed to be more extreme during both economic upswings and downswings. From 1998, however, mean ROE values were lower than median ROE values. The dot-com crash and the subsequent recovery are a possible explanation for the more extreme values from 2001-2005. That timeframe was also the period for which our sample had noticeably more observations than von Arx's (2015) sample. In general, the mean ROE tended to be lower than the median ROE.

## 2.3 Graphical Analysis of ROE

This section graphically plots the mean reversion in profitability. We followed von Arx's (2015) methodology to ensure comparability between the two studies. First, we reproduced von Arx's (2015) methodological procedures and assessed whether we arrived at the same results for the period from 1982-2010. In a second step, we extended the time frame by five years, until 2015, so that we could include all available data. Finally, we evaluated whether our results confirmed or refuted the findings described in the literature review.

First, we sorted all firms with available 1982 ROE observations by ROE in descending order. Then, we subgrouped ROE observations building ten portfolios according to the portfolio formation year 1982. The composition of each portfolio remained the same over the next decade. Afterwards, we computed the median ROE for each portfolio over that 10-year period. Given that our timeframe of 34 years exceeded 11 years (the portfolio formation year and 10 following ROE observations years), we repeated the above process for each year until only 10 years of observations followed the final portfolio formation year. Since we had gathered ROE observations from 1982-2015, we were able to create 24 sets of portfolios, and each year from 1982-2004 established a portfolio formation year. Finally, we computed the mean ROE for each portfolio of those 24 processes. This approach is called the mean of medians method. According to von Arx (2015: 28), this method is advantageous due to its unaffectedness of a survivorship bias. If a firm goes bankrupt or leaves the stock market, it simply drops out of the sample.

Von Arx (2015: 33) also developed an alternative approach in which he formed 10 portfolios on the basis of predefined ROE ranges instead according to the number of firms per portfolio. His portfolios ranged from ROEs above 0.5, 0.5 to 0.4, and so forth, to end with ROE of below -0.3. Additionally, he analyzed the 90$^{th}$, 75$^{th}$, 25$^{th}$, and 10$^{th}$ quantiles. As all quantile distributions were stable and did not reveal any surprising results, we do not raise that approach again, as it is outside the scope of this thesis.

Lookabill (1976), Albrecht et al. (1977), Fama and French (2000), Soliman (2004), Altunbas et al. (2008), and von Arx (2015) analyzed the mean-reversion process by industry. As our dataset was similar to that of von Arx (2015), we did not examine industry classes in depth. Such an analysis would have been beyond the thesis' scope.

Researchers such as Penman (1991), Fama and French (2000), Palepu et al. (2010), and von Arx (2015) split the ROE into its components (e.g., RNOA, PM, ATO, and financial leverage [FLEV]). Their aim was to better understand the factors that drive the ROE and to predict future ROE or RNOA values using linear regressions. They wanted to use that information to develop investment strategies. Again, such analyses would have been beyond the scope of the thesis.

When plotting the portfolios over time, this thesis uses a consistent color pattern and notation scheme. The eight portfolios with the highest ROEs have been assigned the following colors, in descending order: pink, purple, blue, light blue, green, light green, yellow, and red. The two portfolios with the lowest ROEs use gray and black. The highest, or the tenth, portfolio is always visually depicted in pink. In contrast, the lowest, or first, portfolio is always illustrated in black. The following graph shows the mean reversion of ROE according to the preceding of von Arx [2015] with data from 1982 to 2010:

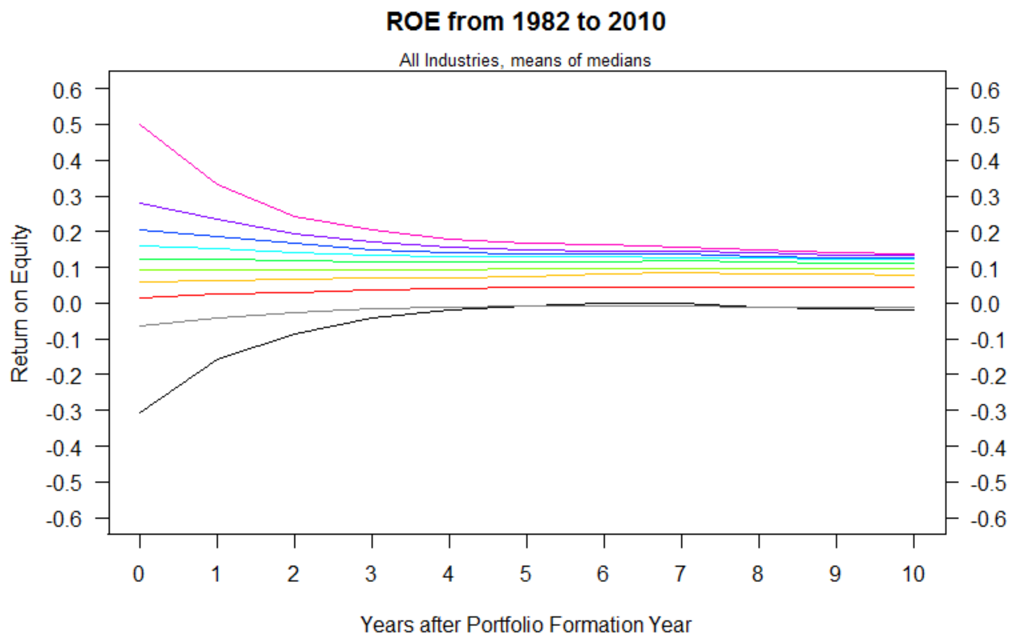


Figure 4: The ROE in 10 portfolios from 1982-2010

In the above graph, a pattern very similar to that detected by von Arx (2015: 29) is noticeable. As expected and as many researchers have found (e.g., Stigler [1963], Beaver [1970], Mueller [1977], Freeman [1982], Mueller [1986], Penman [1991], and Fama and French [2000]), profitability clearly reverted to the mean over time. Furthermore, we confirmed that the portfolios were not fully mean reverting. Finally, we noted that the mean-reversion process ended after approximately five years, at which point a steady state was achieved.

We identified 3 explanations why profitability differences persisted after 10 years, a finding that contradicted Schumpeter’s (1934) claim that market participants have an incentive to take advantage of profit opportunities. The first reason is that firms have different accounting policies. The management might actively reduce a firm's assets by writing off more assets than necessary and creating hidden reserves, which is known as conservative accounting. Secondly, firms' dividend payout policies constitute a second possible reason. A higher dividend payout ratio reduces the book equity, resulting in higher ROE values. The third reason involves accounting regulations. According to various accounting standards, internal research cannot be recorded as an asset but must be considered an expense. As a consequence, value-enhancing research investments increase the future profitability, due to a lower total asset value and therefore also a partially lower equity basis.

Compared to the graph of von Arx (2015: 29), our results were slightly different. The highest and the lowest portfolios had slightly more extreme values in the portfolio formation year (year 0). In the first year, our top portfolio had a ROE of 0.5, while the bottom portfolio had an ROE of -0.3. In contrast, von Arx's (2015) top portfolio started at 0.45, while his bottom one had an initial value of -0.27. Furthermore, after 10 years, the median ROE was slightly above 0.1 in von Arx's (2015) sample. On the other hand, our study had lower ending values, while the bottom two portfolios even had slightly negative ROE values. Our study's more extreme starting values, lower ROEs, and lower portfolio values likely arose from the extended dataset.

After reproducing von Arx's (2015) methodology, we extended the study's time frame, including five additional years (2011-2015), to evaluate whether the mean-reversion pattern had changed:

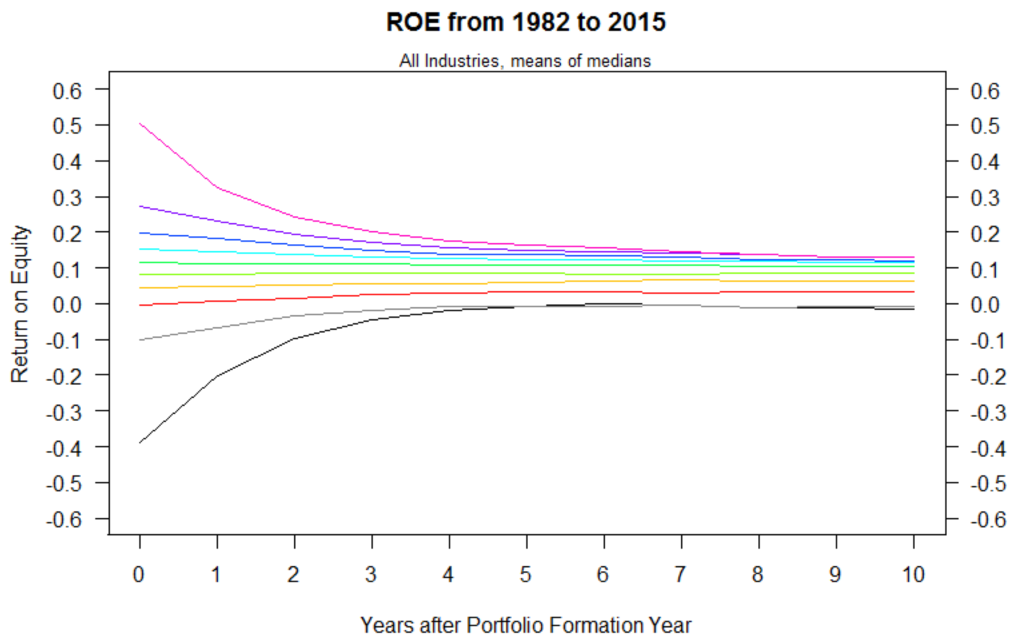


Figure 5: The ROE in 10 portfolios from 1982-2015

Overall, the graph appears very similar to the previous figure. The only notable change is that the top and bottom portfolios adopted slightly more extreme values in their formation years. Those differences thus stemmed from the more extreme ROE values in the portfolio formation years from 2000-2004.

While the mean-reversion process presented itself as very stable, three points of criticism are worth raising. Firstly, we did not have the same number of ROE observations in each year. However, averaging the 24 mean-reversion processes meant that each portfolio was equally weighted. This resulted in overweighting (underweighting) ROE values in years with fewer (more) observations. Secondly, von Arx (2015: 28) claimed that bankrupt firms removed from the stock market simply drop out and do not create a sample bias. We would expect that companies with negative ROE (those in the bottom portfolios) would have a higher likelihood of exiting the stock market, due to bankruptcy, takeover, or management and shareholder decisions. Fama and French (2000: 162) raised the same point. As the portfolios were not rebalanced, the remaining firms in the bottom portfolios had more influence than the firms in the top portfolios. Even though we used median values, this effect could have introduced a bias. In Chapter 4.3, “Analysts’ Selectivity,” we analyze this issue in detail. Thirdly, median values were provided for the portfolios. However, the ROE values for individual firms had much more variation. Using median values could have created the impression that individual firms' ROEs did not change much. Chapter 4.4, "Forecasting ROE" further assesses this issue.

This chapter started by reviewing the literature on mean reversion. Deflated earnings revert to the mean, as researchers had long expected. Stigler (1963) was the first to describe this phenomenon, and further research proved that he was correct. Sample sizes have increased over time, and many researchers have shifted from analyzing time series to applying cross-sectional methods. Recently, von Arx (2015) published his findings on mean reversion, and his work made use of an extensive dataset. We used the methods of von Arx (2015) and demonstrated that the mean-reversion process persisted between 2010-2015.

# 3 Analysts' Forecasts

This section contains an evaluation of analysts' earnings predictions. To be consistent with the last chapter, we begin with a literature review focusing on analysts' forecasts. We clearly delimit the scope of this review, concentrating on comparing analysts' predictions to the mean-reversion process. Subsequently, the chapter describes our analysis of the I/B/E/S dataset and offers descriptive statistics. Due to a mismatch in how the Worldscope and I/B/E/S datasets define different variables, we converted the Worldscope data into the I/B/E/S format. Additionally, we extrapolated EPS values using analysts' LTG forecasts and finally graphically assessed whether analysts exploit the mean reversion in profitability, as suggested by Fama and French (2000: 174).

## 3.1 Literature on Analysts' Forecasts

The literature review focuses on assessing analysts' EPS and ROE forecast performances. In this context, short-term predictions are generally forecasted of up to a year, and long-term predictions range from one year to several years. Furthermore, this section presents a selection of models for forecasting the EPS.

Humans have always been interested in forecasting upcoming events. Forecasting allows us to prepare for the future and limits possible outcomes to a discrete number of events or a certain range. Furthermore, those who use forecasts have an advantage over those who do not. Research on analysts' forecasts grew out of the same starting point as the research on mean reversion. Both fields emerged from early analyses of undeflated earnings time series, going back to early research by Little (1962), Stigler (1963), Beaver (1970), Ball and Watts (1972), Lookabill (1976), Brooks and Buckmaster (1976), and Albrecht et al. (1977). To avoid duplication, this section does not discuss the literature on deflated and undeflated earnings.

The introduction of the I/B/E/S in the U.S. market in 1976 and the international market in 1987 allowed analysts to access a large range of predictions in one database, making it the first of its kind. From then on, researchers could utilize a growing selection of estimates, and as a consequence, the academic literature on earnings forecasts deeply expanded.

The academic study of earnings predictions is both broad and fragmented. It is important to clearly distinguish whether forecasts are evaluated on the basis of accounting earnings or stock returns. The analysts' consensus forecast, consisting of mean EPS predictions, refers to accounting earnings. In the more recent literature, researchers have often assessed analysts' expectations with regards to stock prices. Therefore, this literature review is split into two sections to avoid confusion, one on accounting earnings and one on stock prices.

### 3.1.1 Literature on Accounting Earnings

At the early beginnings of this research field, Collins and Hopwood (1980) analyzed a sample of 50 firms' predicted earnings from 1951-1974. The Value Line Investment Survey provided the forecast data. They investigated whether analysts' quarterly earnings forecasts outperformed five different time-series models and found that the forecasts were superior to any of the selected models. Thus, Collins and Hopwood (1980: 404) concluded that analysts could react to sudden changes, whereas statistical models were either slow or unable to respond. Furthermore, they noted that analysts' superior predictive power might have stemmed from their information advantage, including their non-financial information advantage. In contrast, by definition, statistical models only include numeric data.

Brown and Rozeff (1978) assessed analysts' quarterly earnings predictions and compared them to univariate time-series models. They found that the analysts included qualitative information and more effectively exploited the available data than the time-series models. Additionally, analysts have a timing advantage over time-series models. They publish their forecasts in the months following the release of firms' year-end financial statements. Likely, new qualitative information becomes publicly available during the interim, giving the analysts an indication of firms' performances in the period directly following the release of year-end statements. Further, Brown and Rozeff (1978) found that analysts' timing advantage had a noticeable impact on the accuracy of their short-term forecasts.

Brown et al. (1987a) mentioned that the superiority of analysts' forecasts decreases as the forecast period increases. However, for long-term forecasts, this timing advantage decreases, and statistical models gained in predictive power.

Finally, Brown et al. (1987b) compared analysts' forecasts for different time periods to time-series models. They found that the larger the firm, the more accurate were the analysts' forecasts. Also, analysts' coverage of companies was non-random. These results led the authors to conclude that the more economically relevant the firm, the more information is available on it. Therefore, analysts' forecasts are more likely to cover economically relevant firms. The findings of Brown et al. (1987a) and Brown et al. (1987b) were confirmed by Kross (1990), who found that the more a firm was mentioned in *The Wall Street Journal*, the more accurate were the analysts' forecasts.

The literature is in consensus that analysts are overly optimistic. Indications of such a phenomenon were found by O'Brien (1988) and Francis and Philbrick (1993). Butler and Lang (1991), Francis et al. (2004), and Easton and Sommers (2007) later confirmed their findings. Additionally, Ali et al. (1992), Han et al. (2001), Elgers and Lo (1994), Jagannathan and Ma (2005), and Evans (2012) tried to offset analysts' optimism. We do not further explore the academic literature analyzing the reasons for analysts' optimism because this research field is outside of the thesis' scope.

Moreover, research on analysts' incentives, as described by Francis and Philbrick (1993) and Francis et al. (2004), is not included in this thesis' literature review. Such studies have neither focused on the reasons for analysts' optimism and nor validated their predictions.

Bradshaw et al. (2012) extensively re-examined the topic of accounting returns and their relation to analysts' forecasts. They noticed that past studies had relied on comparably small samples due to the limited available data. Furthermore, the studies mentioned above (with the exception of Brown et al. [1978b]) examined quarterly earnings for a one-year period but did not include longer forecast horizons. Finally, Bradshaw et al. (2012: 945) criticized time-series models for needing 10-20 years' worth of data to draw statistically significant conclusions, something previous studies had been unable to do. When investigating the mean reversion of ROE, researchers such as Lookabill (1976) and Albrecht et al. (1977) used cross-sectional models instead of times-series models. Bradshaw et al. (2012: 953) also stated that in earlier years, analysts only assessed few publicly traded firms, although analysts have been covering more and more firms in recent years. In 1980, the I/B/E/S did not cover 50% of listed firms. In contrast, in 2007, only 25% of firms remained uncovered for one- and two-years-ahead forecasts. The above-mentioned drawbacks of previous studies provided Bradshaw et al. (2012) with motivation to reassess a field of research in which few new findings had emerged in recent past years. The following paragraphs describe Bradshaw et al.'s (2012) subsequent research design, due to its relevance for later sections of this thesis.

Their sample, obtained from the I/B/E/S, consisted of analysts' earnings forecasts from 1983-2008. Bradshaw et al. (2012: 955) only included observations for which the following data was available: the previous year's EPS, one earnings forecast, the corresponding stock price, the realized EPS, the value of sales in the previous year, and positive earnings in the previous year. This implies that Bradshaw et al. (2012) excluded all observations for which forecasts from analysts were not available.

They compared the dispersion of these forecasts to a random walk model without drift. They computed the dispersion variable, which they used to assess the accuracy of the forecasts, by subtracting the realized $EPS_{t+1}$ from the forecasted $EPS_{t+1}$. The dispersion measurement for the random walk model was simply the $EPS_t$ values minus the realized $EPS_{t+1}$ value.

As Bradshaw et al. (2012: 959) did not have many three-year forecasts to analyze, they constructed third-year forecasts on the basis of analysts' two-year forecasts and LTG predictions. This approach is consistent with previous studies by Frankel and Lee (1998), Gebhardt et al. (2001), and Ali et al. (2003). Bradshaw et al. (2012: 946) found that with extended forecast horizons, analysts' EPS forecasts were not consistently more precise than time-series models, even though the analysts had timing and information advantages. Moreover, for the two-years-ahead forecast, the random walk model outperformed the analysts' projections in half of the forecast horizons. Furthermore, for the three-year-ahead forecasts, the random walk model strongly outperformed the analysts' forecasts. Finally, in the long run, the analysts only managed to outperform the time-series model if they forecasted negative changes or rather small absolute changes in EPS. Those findings contradicted those of Collins and Hopwood (1980), who found that analysts' forecasts outperformed various time-series models. Further, Bradshaw et al. (2012) discovered that analysts' forecasts outperformed the random walk model for short periods, but only for large, developed, and stable firms. Brown et al. (1987a) and Brown et al. (1987b) came to similar conclusions.

### 3.1.2 Literature on Stock Returns

Most academic researchers have analyzed earnings predictions with the goal of developing investment strategies based on stock prices rather than accounting earnings. Often, researchers have used accounting EPS predictions to assess the implications for stock prices. The empirical part of this thesis limits itself to analyzing accounting earnings. Nevertheless, reviewing the literature on how analysts' forecasts are related to stock returns yielded relevant and important insights. Therefore, this review discusses the literature on both accounting earnings and equity returns. While we more closely assess works with a direct link to our research topic, we also more generally examine other, less relevant, studies that provide key insights.

One topic of particular interest is forecast dispersion, which measures the degree to which analysts' forecasts diverge from actual values. Elgers and Lo (1994) analyzed the relation between analysts' EPS forecasts, on the one hand, and past earnings changes and stock returns, on the other hand. They measured earnings changes as the change in EPS divided by the stock price at the beginning of the same year. They used the Compustat and the Center of Research in Security Prices CRSP data tape from 1977-1989 and noted that mean forecasted earnings changes were higher than actual earnings changes for most years. They defined the forecast error as the mean squared error. Moreover, Elgers and Lo (1994) demonstrated that analysts' prediction errors were systematically related to prior earnings changes and prior security returns. Furthermore, they created a regression model to correct the bias by deflating the earnings by the share price, and they also included the earnings changes predicted by a random walk model and the I/B/E/S consensus forecast. The results indicated that both prior returns and earnings changes could help improve analysts' predictions for companies with poor previous performances.

Han et al. (2001) analyzed the dispersion in analysts' earnings forecasts from the future realized values. To our knowledge, they were the first to include the observed dispersion in ROE prediction models. Their study combined two datasets. First, to assess analysts' predicted earnings, Han et al. (2001) retrieved one-year-ahead EPS predictions made nine months before the end of the fiscal year end from the I/B/E/S. Their data covered the years from 1977-1990. Unfortunately, they did not mention the size of their sample or the number of EPS predictions. Secondly, they retrieved financial statement data from the 1993 Industrial Compustat tape. They computed the realized ROE by dividing net income by the previous financial year's common equity. Then, Han et al. (2001) calculated the future ROE by averaging the latest reported ROE and the one-year forecast for the ROE. The median predicted ROE was 15%, while the mean predicted ROE was 14.7%. Moreover, they measured the dispersion in analysts' forecasts (DAF) by computing the standard deviation deflated by the market price on the date on which the EPS values were published.

Han et al. (2001) split the firm observations into deciles and then sorted them according to the analysts' forecast dispersion, in contrast to the literature on ROE, which sorted the deciles by ROE. The DAF is the standard deviation of the analysts' EPS forecasts, deflated by the price at the date the forecast was released. They found evidence that as the DAF increased (decreased), the future ROE decreased (increased). Moreover, Han et al. (2001: 105) stated that a poor past performance was positively correlated to a higher DAF. Abarbanell (1991) came to similar conclusions, finding that analysts were more likely to overestimate future negative returns than to underestimate future positive returns.

Other researchers focused on analysts' equity selection patterns. According to Das et al. (1998), analysts can seemingly select those firms that later outperform others, and they can predict such firms' earnings. Das et al. (1998) observed that after an initial public offering, companies with high residual analyst coverage generated significantly higher returns than firms with low residual analyst coverage. Therefore, Das et al. (1998) concluded that analysts have predictive abilities. La Porta (1996), Hong et al. (2000), and Diether et al. (2002) found that analysts rarely cover financially distressed firms.

Dechow et al. (1997) reported that following analysts' earnings growth forecasts explains a substantial part of the above than normal returns. Many other researchers have also focused on the relationship between analysts' forecasts and stock prices. Barber et al. (2001) used analysts' recommendations to assess stock returns. They found that following the most favorable recommendations led to abnormal gross returns of more than 4%.

Jung et al. (2008) addressed the question of why analysts predict LTG for some firms but not others. They found that more LTG forecasts are available when investors have a demand for them. Such demand is positively correlated with the firm's growth opportunities, financial health, percentage of long-term investors, size, and age. On the other hand, this demand is negatively correlated with financial losses.

Researchers also examined analysts’ revised forecasts and their effects on stock prices. Gleason and Lee (2003) explored factors that explain market price changes after analysts released forecast revisions, while Burgstahler and Eames (2006) assessed the influence of analysts’ forecasts on stock prices. Fama and French (2006) computed the effect of stock valuation on expected returns by dividing the predicted EPS by the book equity. Scherbina (2004) provided evidence that biases in analysts’ earnings forecasts have implications for stock prices, and Jung et al. (2008) confirmed that equity markets react with sensitivity to revisions of LTG estimates. Gebhardt et al. (2001) used analysts’ LTG forecasts and calculated the dispersion in those forecasts to capture variations in the implied cost of capital.

Da and Warachka (2011) analyzed differences in long- and short-term earnings growth forecasts and investigated their relationship to stock price. They created different portfolios according to implied short-term growth and forecasted LTG. Their findings supported the strategy of buying low LTG and high short-term growth stocks and selling the opposite.

Others have concentrated on stocks’ short-term performances. For example, Easton et al. (2002) used short-term I/B/E/S earnings forecasts, the current book value of equity, and current stock prices to estimate ROEs and growth rates. Furthermore, Copeland et al. (2004) found that changes in long-term forecasts have a greater influence on stock prices than changes in short-term forecasts. Finally, Jegadeesh et al. (2004) differentiated between stocks with a recent high (low) performance and investigated how their performances affected share prices.

Bryan and Tiras (2007) analyzed how forecast dispersion and information asymmetry affect share prices. They found that when information asymmetry was high, analysts instead relied on non-accounting fundamentals when creating their projections. Researchers such as Jagannathan and Ma (2005) and Hui et al. (2013) measured the bias in analysts' predictions and its influence on the stock market. Likewise, Green et al. (2016) analyzed the reasons for persistent biases.

Hou et al. (2012) criticized analysts' coverage of small firms and developed a new approach to forecast the implied costs of capital up to five years ahead. Specifically, they used total assets, dividend payments, earnings, and accruals to forecast one-year-ahead earnings, and they used earnings predictions as a proxy for one-year-ahead cash flow estimation.

Their cross-sectional earnings forecast model captured more than 80% of earnings variance in the first three years. On average, their model was less accurate than analysts' forecasts, but it resulted in a lower forecast bias and an improved earnings response coefficient. Further, they managed to extend their model to firms for which analysts had not created forecasts. Therefore, they saw their model as a better proxy for future stock returns than the analysts' predictions, due to its improved coverage, lower forecast bias, and earnings response coefficient. Further, their model's earnings and implied cost of capital predictions outperformed analysts' implied cost of capital estimates based on I/B/E/S data.

Evans et al. (2012) compared in their preliminary paper analysts' projections to the mean reversion model in terms of their ability to forecast profitability. In a first step, they revised Fama and French's (2000) model. Evans et al. (2012: 6) used a cross-sectional model to forecast earnings. Later, they adjusted their model to $h$ periods ahead ($EPS_{t+h}$). Evans et al.'s (2012: 9) following model forecasts earnings for different periods in time:

$$\begin{aligned} EPS_{t+h} = \alpha_0 + \alpha_1 EPS_t + \alpha_2 LOSS_t * EPS_t + \alpha_3 \Delta EPS + \alpha_4 DEBT\_DIST_t \\ + \alpha_5 EQUITY\_DIST_t + \alpha_6 SPLIT\_DUM_t + \alpha_7 DIV\_DUM_t \\ + \alpha_8 SPEC\_ITEMS_t + \alpha_9 lnSIZE_t + \varepsilon_{t+h} \end{aligned}$$

Here, $EPS_t$ is the EPS, $LOSS_t$ is a dummy variable taking a value of 1 when the EPS is below 0, $\Delta EPS$ is the change in EPS from one year to the next, $DEBT\_DIST_t$ is the net distribution to debtholders, $EQUITY\_DIST_t$ is the net distribution to shareholders, $SPLIT\_DUM_t$ is a dummy variable for stock splits, $DIV\_DUM_t$ is a dummy for dividend payments, $SPEC\_ITEMS_t$ stands for "special and extraordinary items," and $lnSIZE_t$ is the natural log of total assets.

In a second step, Evans et al. (2012: 11) created a partial-adjustment model to identify the drivers of EPS changes:

$$EPS_{t+1} - EPS_t = \beta_0 + \beta_1 E[EPS_t] + \beta_2 EPS_t + \beta_3 (EPS_t - \mathrm{EPS}_{t-1}) + \varepsilon_{t+1}$$

Here, $E(EPS_t)$ is the fitted value representing the expected EPS. In their regression, they used the Least Absolute Deviation method instead of the Ordinary Least Squares (OLS). Contrary to Fama and French (2000), Evans et al. (2012) used the EPS instead of a profitability measure.

In addition to forecasting earnings, Evans et al. (2012) also assessed the analysts' forecasts. They reduced the analysts' forecast optimism by combining their predictions with the random walk model. The analysts' forecasts are known to be overly optimistic, while the opposite is true for the random walk model.

Finally, Evans et al. (2012) improved profitability predictions by utilizing the mean-reversion model rather than the random walk model or another statistical model. Their model performed better and exhibited less bias over a 5- to 20-quarter period using out-of-sample data than when it used analysts' forecasts. In particular, their models increased the forecast accuracy by 7% for one-year forecasts and by 27% for five-year forecasts.

When forecasting out-of-sample data, Evans et al. (2012) concluded that their model was more accurate than the random walk model, an auto-regressive model, and the cross-sectional model proposed by Hou et al. (2012). Further, their model outperformed analysts' two- to five-year forecasts, and so they suggested that their model could be used for firms for which analyst forecasts are unavailable.

Harris and Wang (2013) used the Ashton and Wang (2013) model to generate earnings forecasts, which they then compared to I/B/E/S earnings predictions. The Ashton and Wang (2013) model relies on three assumptions. First, capital markets do not have any arbitrage opportunities. Second, clean surplus accounting holds. Third, dividend payouts reduce the stock price by the distributed amount. Their sample of realized data was larger than their I/B/E/S sample. They noted that analysts inclined towards providing forecasts for large and healthy firms and that such predictions tended to be optimistic. Additionally, Harris and Wang (2013) assessed the predictive power of different accounting variables on future earnings. They found that the Ashton and Wang

(2013) model was superior to analysts' forecasts. However, they did not compare the Ashton and Wang (2013) model to a mean-reversion model.

The literature is in partial disagreement as to whether analysts outperform statistical models or researchers' forecasts. Collins and Hopwood (1980) and Brown and Rozeff (1978) found that analysts' forecasts were superior to time-series models. On the other hand, Elgers and Lo (1994), Han et al. (2001), Bradshaw et al. (2012), Hou et al. (2012), Evans et al. (2012), and Harris and Wang (2013) developed models that they claimed were able to outperform analysts' forecasts. However, those researchers (with the exception of Han et al. [2001]) analyzed earnings instead of profitability. To our knowledge, only Bradshaw et al. (2012) assessed the fundamental data on the basis of which analysts made one-year-ahead forecasts. The other researchers used fundamental firm data where analysts only partially predicted earnings.

Overall, none of the above researchers assessed firms for which analysts had provided multiple-year ROE forecasts. Further, none of those studies sorted portfolios by the realized ROE or assessed the accuracy of analysts' portfolios. Researchers analyzing forecast dispersion, such as Elgers and Lo (1994) and Han et al. (2001), sorted their portfolios according to the forecast dispersion, but not by firm profitability.

## 3.2 I/B/E/S Data

Assessing analysts' forecasts in a sophisticated and detailed manner requires a large dataset. We retrieved data from Thomson Reuters I/B/E/S. According to Thomson Reuters, the database covers more than 40'000 firms in 70 markets, and over 900 individual companies contribute data. We retrieved the available forecasted earnings estimates for the same firms used in the previous chapter about mean reversion. Again, that sample consisted of 10'939 individual companies from 16 European countries.

According to Brown and Rozeff (1978) and Brown et al. (1987a), analysts benefit from a timing advantage due to firms' release of financial statements following the end of the year. Our study examines analysts' earnings forecasts on a yearly basis. However, forecasts are renewed on a monthly basis or even more frequently. Using forecasts from the end of the financial year would have introduced considerable bias, because the financial reports are not available to analysts at that time. To omit this bias, we instead aimed to retrieve the first forecast published after the release of a firm's financial statement. However, Thomson Reuters Datastream requires a fixed date to retrieve data.

The end of a firm's fiscal year is often also the end of the calendar year, and firms publish accounting data in the subsequent months. Regulations require listed firms to disclose their financial statements in a timely manner. For instance, the Swiss Code of Obligations sets a six-month deadline (OR 958 | Digit 3). Furthermore, stock exchanges and international accountings standards also have established guidelines. Thus, a delay of three to four months after the fiscal year end appeared to be most suitable choice.

According to Thomson Reuters (2010: 16), monthly forecasts are updated on the Tuesday following the third Friday of the month. Thus, Thomson Reuters (2010: 17) recommended picking a start date between the 20th and the end of the month. Depending on the month, the Tuesday following the third Friday falls between the 19th and the 25th. The 26th allowed for possible delays due to different time zones and various possibles failures. Therefore, we retrieved the analysts' forecasts as of April 26th of each year. This seemed to be the best trade-off between (i) ensuring that almost all financial statements had been published and were available to analysts and (ii) ensuring that they did not have a noticeable timing advantage which might have permitted them to update their forecasts.

After downloading the full dataset, we adjusted the year. The forecasts published at the beginning of 1987 corresponded to the financial year end of 1986. For instance, the one-year forecasts on April 26 1987 were treated as a 1986 forecast predicting the EPS for 1987. As a consequence, the I/B/E/S data covered the period from 1986-2015, even though the data was published in the years 1987-2016.

According to Thomson Reuters' I/B/E/S Guide (2010: 120), the well-known I/B/E/S consensus forecast is the mean of all available analysts' EPS forecasts. Moreover, I/B/E/S also provides the median of the analysts' EPS forecasts. We preferred using the median EPS to prevent extreme outliers from influencing the forecasts. The mean and median values, however, were very similar. Appendix 2 provides a detailed data table with the realized EPS values, the number of forecasted values, and the median

EPS values for five prediction years. It also displays the LTG forecast for each observation given as a percentage of the expected annual EPS growth.

Similar to Appendix 1, the number of reported EPS forecasts increased until year 2000. After that, a small drop was followed by an increase from 2004-2007. The year 2007 saw the most EPS predictions (5'476). Moreover, 2015 was noteworthy, since it had drastically fewer observations than the year before. A possible explanation for this effect is that the number of outstanding shares had not been published when we retrieved the I/B/E/S data. This effect was not observable in the Worldscope Data described in Chapter 2.2 (p. 12), because the number of outstanding shares was not necessary for computing the ROE. Furthermore, calculating the EPS does not require any prior year values. As Appendix 2 demonstrates, neither the mean nor the median greatly increased over the study period. Analysts' median predicted LTG rate was 10%. While the number of analyst predictions per firm increased slightly, the absolute number of assessed firms grew notably. Figure 6 illustrates the number of analyst predictions per year as a percentage of all available realized EPS calculations:

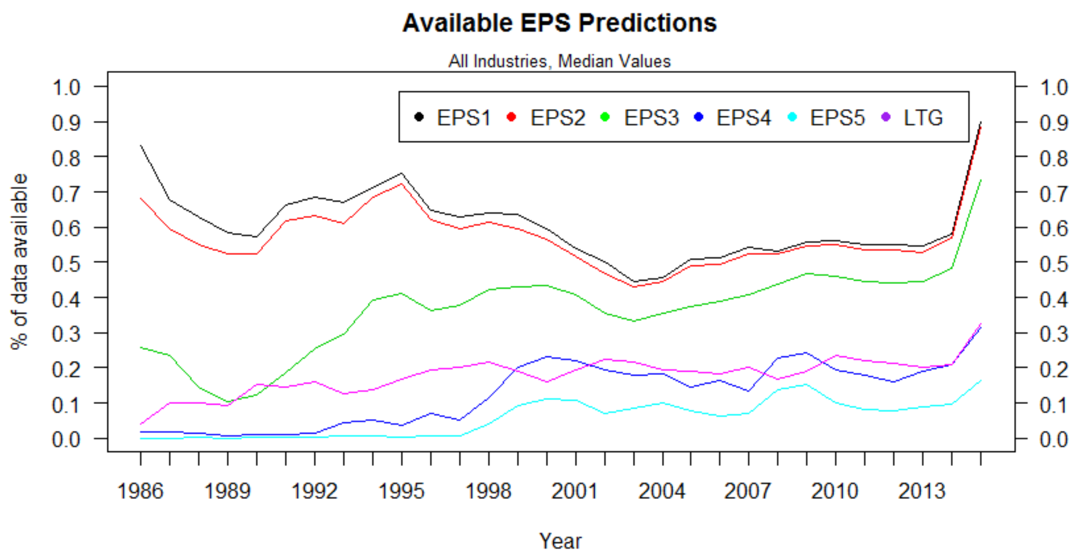


Figure 6: The ratio of forecasted EPS values to available EPS values

In the graph, "EPS1," "EPS2," and so on stand for the length of the forecast. For instance, the green line, "EPS3," is the ratio of available three-year forecasts to available realized EPS observations for the same year. The percentage of one- and two-years-ahead forecast coverage decreased overall. The exception was the very last year, since significantly fewer realized EPS observations were available. In contrast, the percentage of three-years-ahead predictions increased over time, reaching a similar level as the one- and two-years-ahead predictions. Four- and five-years-ahead estimates were very rare until the mid-1990s. From that point on, they increased, reaching a total of 10-20% of realized EPS observations in the remaining study years. Moreover, LTG coverage steadily increased in the early years, from 10% to more than 20%.

Our findings differed from those of Bradshaw et al. (2012: 953). They plotted the number of uncovered firms and found that the percentage of covered firms increased considerably for one- and two-year forecasts. Our sample selection method might explain this divergence. We included all firms in 16 European countries, only removing financial firms and firms with negative equity. On the other hand, Bradshaw et al. (2012: 954) had stronger data availability criteria for including firms in their dataset. Moreover, their study focused on the U.S. market, and one would expect that U.S. firms might be subject to higher level of analyst coverage.

## 3.3 Extrapolating EPS Predictions using LTG

The number of EPS predictions was not sizeable, as Appendix 2 demonstrates. In particular, there were noticeably fewer forecasts for lengths longer than two years. Fewer than 10’000 five-year EPS forecasts were available, whereas more than 130’000 realized EPS observations were available. The lack of multiple-year predictions constituted a drawback, and so we aimed to increase the number of estimates.

The Thomson Reuters I/B/E/S (2010: 125) database includes the variable “forecasted LTG.” Analysts directly contribute this variable, and it is not calculated on the basis of I/B/E/S data. It represents the expected annual growth in operating earnings as a percentage. Such forecasts should look three to five years ahead. Thomson Reuters I/B/E/S (2010: 121) recommends using the median value of long-term forecasts rather than the mean to avoid biases due to extreme outliers.

In the academic literature, Frankel and Lee (1998), Gebhardt et al. (2001), Ali et al. (2003), and Bradshaw et al. (2012) have applied this procedure to generate LTG forecasts of up to three years. Likewise, Evans et al. (2012) produced forecasts of up to five years. In contrast, we multiplied the last available median EPS prediction by the median LTG forecast. For example, when I/B/E/S provided a two-year forecast and a LTG forecast, we used the LTG forecast to extend the two-year forecast, thus generating the prediction for the next year. Again, we multiplied this prediction for the third year by the LTG forecast to obtain a fourth-year prediction, and so on. The following formula provides the formal notation:

$$EPS_{t+i} = EPS_{t+i-1} * (1 + LTG_t/100)$$

Where $EPS_{t+i}$ is the EPS prediction for year *t* forecasting $i$ years ahead and $LTG_t$ is the LTG forecast for year *t*. Throughout this thesis, *"t"* stands for the portfolio formation year, and it takes discrete values between 1982 and 2010. Further, *"i"* stands for the number of years in which a forecast was made in advance, and it can adopt discrete values from 1 to 5. Realized values from the Worldscope database are labeled with the prefix "R," which stands for "realized." Estimated values consistently contain the prefix "F" for "forecasted" when they originated from the I/B/E/S database.

After extrapolation, we obtained the following number of EPS observations. In Table 1, the letters "MD" at the end of a variable name signify that we consistently used median forecast values instead of means forecast values:

| **After extrapolation** | | **Before extrapolation** | |
|---|---|---|---|
| | **N** | | **N** |
| REPS | 133'165 | REPS | 133'165 |
| FEPS1MD | 75'609 | FEPS1MD | 75'609 |
| FEPS2MD | 72'044 | FEPS2MD | 71'925 |
| FEPS3MD | 51'319 | FEPS3MD | 48'575 |
| FEPS4MD | 30'216 | FEPS4MD | 18'073 |
| FEPS5MD | 25'946 | FEPS5MD | 8'434 |
| FLTGMD | 23'866 | FLTGMD | 23'866 |

Table 1: The number of available EPS predictions before and after extrapolation

Evidently, the number of one-year-ahead predictions did not change after we extrapolated additional EPS forecasts. However, the longer the forecast period, the more observations became available following that process. For instance, after extrapolation, the five-year forecast horizon had come close to 26'000 observations.

The above table indicates that extrapolating additional EPS predictions on the basis of analysts' LTG forecasts increased the number of two- to five-years-ahead EPS estimates. In particular, four- and five-years-ahead EPS predictions were clearly more numerous. We used these extrapolated values for the upcoming sections.

## 3.4 Transforming EPS into ROE

Analysts' forecasts are on a per-share basis. Consequently, the academic literature (e.g., Elgers and Lo [1994], Bradshaw et al. [2012], Hou et al. [2012], Evans et al. [2012], and Harris and Wang [2013]) has primarily assessed analysts' predictions by measuring the EPS. However, we saw two disadvantages of this method. First, it is impossible to compare EPS predictions across firms using absolute numbers, since firms have different earnings levels and book values for equity. A high EPS value does not imply high earnings or high profitability. Second, comparing a single firm's EPS over time is not ideal, because the owners and the management can easily modify the number of outstanding shares. Decreasing the number of shares results in a higher EPS. Therefore, past results would need to be reformulated to be useful. On the other hand, the ROE does not have any of these disadvantages, and numerous companies can be meaningfully evaluated using that metric. This thesis assesses analysts' ROE forecasts but not their EPS predictions. This choice is consistent with the methodology used in the first section, and it also allowed us to assess whether analysts predicted a mean-reversion effect in earnings.

For international markets, I/B/E/S EPS forecast data has been available since 1987. According to Thomson Reuters (2010: 28), ROE forecasts were introduced in May 1999. The consensus forecast is measured in EPS, and as ROE forecasts are less relevant, fewer analysts provide ROE predictions. Using analysts' ROE predictions would have severely restricted both, the horizon of the analysis and the data pool. On the other hand, it would have circumvented the task of manually transforming EPS data into ROE data. However, for the sake of data availability, we opted to calculate the forecasted ROE from the EPS predictions.

Researchers such as Gebhardt et al. (2001), Fama and French (2006), Evans et al. (2012), and Bradshaw et al. (2012) have all transformed I/B/E/S EPS forecasts into ROE values. For example, Gebhardt et al. (2001: 142) divided the forecasted EPS by last years' book equity. However, to our knowledge, no academic source has provided detailed and precise guidelines on how to match I/B/E/S EPS estimates with Worldscope ROE values. The different definitions used by these two databases could have introduced a substantial bias, thus rendering the results less meaningful. To ensure data comparability and increase the accuracy of the ROE values, we developed an extensive methodology for transforming EPS values into ROE values.

As stated in Chapter 2.2, we use capital letters to refer to predefined items from either Worldscope or I/B/E/S. Additionally, Worldscope item codes are included in parentheses. For all other variables, lowercase letters are used.

The transformation process had two stages. First, we decomposed ROE into its components. In a second step, we addressed the problems posed by the different definitions employed by Thomson Financials Worldscope and Thomson Reuters I/B/E/S.

The basic concept behind all methods for ROE calculation is to deflate the earnings component by the last years' invested capital component, thus yielding the profitability ratio. Penman (2013: 147) defined the ROE as follows:

$$ROCE_1 = Comprehensive\ earnings\ to\ common_1\ /\ Book\ value_0$$

Where $ROCE_1$ stands for return on common shareholders' equity in year 1. For our use we replace the return on common shareholders' equity by ROE, comprehensive earnings to common by net income and book value by common shareholders' equity. Also, the Arabic numerals are replaced by *t*. We extended the following formula by adding the common shares outstanding in the following formula:

$$ROE_t = (NI_t\ /\ CSO_t)\ /\ (CSE_{t-1}\ /\ CSO_t)$$

Where $NI_t$ stands for the net income in time *t*, and $CSO_t$ stands for the common shares outstanding in time *t*. By restating the above formulas, we obtain EPS and book value per share (BPS) definitions as follows:

$$EPS_t = NI_t\ /\ CSO_t$$

$$BPS_t = CSE_t\ /\ CSO_t$$

Where $EPS_t$ stands for the EPS in year *t* and $BPS_t$ stands for the BPS in year *t*. By using the EPS as the earnings component and the BPS as the invested capital component, we obtain an alternative definition of ROE:

$$ROE_t = EPS_t \,/\, BPS_{t-1}$$

Both the numerator and the denominator are on a per-share basis. The disadvantage is that the values are not absolute and are instead per-share deflated values. This renders any analyses of absolute net income and the book value less meaningful. Therefore, we carefully developed the following approaches for calculating the ROE and compared them among each other. First, von Arx's (2015) approach used in Chapter 2.2, "Worldscope Data". Second, the absolute method estimated ROE as: $NI_t \,/\, CSE_{t-1}$. Third, the deflated method computed ROE as: $EPS_t \,/\, BPS_{t-1}$.

To properly translate between the Worldscope and I/B/E/S definitions, we analyzed the composition of both data systems in detail, paying particular attention to net income, the book equity, and the BPS. After the transformation, the realized Worldscope values all follow I/B/E/S definitions. Of note is that the following sub-sections only include realized values. Analysts' forecasts are discussed in Chapter 3.5, "Adding Prediction Years."

### 3.4.1 Calculating Net Income

Von Arx (2015), Worldscope (2007), and I/B/E/S (2010) all use different definitions of net income. To illustrate this issue in a comprehensive way, the following table 2 contains an excerpt from Worldscope's (2007: 56-78) income statement metrics for industrial companies:

| **Worldscope Metric** | **WC Code** |
|---|---|
| Pretax Income | WC01401 |
| -Income Tax | WC01451 |
| =NI as used in the mean reversion part | |
| -Minority Interest | WC01501 |
| +Equity in Earnings | WC01503 |
| +After Tax other Income/Expenses | WC01504 |
| +Discontinued Operations | WC01505 |
| =Net Income before Extraordinary Items/Preferred Dividends | WC01551 |
| +Extraordinary Items & Gain/Loss Sale of Assets | WC01601 |
| =Net Income - Bottom Line = Net Income before Preferred Dividends | WC01651 |
| -Preferred Dividend Requirements | WC01701 |
| =Net Income After Preferred Dividends (Basic EPS) | WC01706 |
| =NI Used to Calculate EPS = NI Available to Common | WC01751 |

Table 2: Excerpt from the Worldscope-defined income statement

As described in Chapter 2.2, von Arx (2015: 207) computed net income as Pretax Income (WC01401) minus Income Tax (WC01451). Appendix 3 displays von Arx’s (2015) approach to using the Worldscope items in calculations. For the EPS calculation, Worldscope uses Net Income Used to Calculate EPS (WC01751), which was formerly Net Income Available to Common (WC01751).

The I/B/E/S Glossary (2000: 8) defines EPS differently than either Worldscope or von Arx (2015). Analysts providing data to I/B/E/S only consider the operating income, discontinued operations, and extraordinary items. However, I/B/E/S definitions are not based on Worldscope items. The I/B/E/S Glossary (2000: 8) mentions that the procedure is far from the ideal way to valuate a firm, and it might differ from other data providers. Nevertheless, we considered discontinued operations and extraordinary items of I/B/E/S to be the equivalent of Worldscope’s Discontinued Operations (WC01505) and Extraordinary Items & Gain/Loss Before Preferred Dividends (WC01701). Table 3 indicates the composition of analysts’ forecasted net income according to the I/B/E/S database:

| **Worldscope Metric** | **WC Code** |
|---|---|
| Pretax Income | WC01401 |
| -Income Tax | WC01451 |
| =NI as used in the mean reversion part | |
| +Discontinued Operations | WC01505 |
| +Extraordinary Items & Gain/Loss Sale of Assets | WC01601 |
| =Net Income as forecasted from Analysts | |

Table 3: Construction of net income according to the I/B/E/S structure

To maintain consistency between forecasted and realized net income values, we used the I/B/E/S methodology to compute net income using Worldscope data. Next, we compared our computed net income values to those of von Arx (2015) and those from Worldscope’s Net Income Used to Calculate EPS (WC01751) item. Table 4 contains the net incomes generated by these three methods. The mean and the median values vary slightly across the approaches:

| | N | Median | Mean | SD |
|---|---|---|---|---|
| **NI von Arx** | 135'006 | 1'935 | 71'975 | 810'872 |
| **NI Worldscope** | 137'535 | 2'629 | 83'787 | 830'321 |
| **NI I/B/E/S** | 137'622 | 2'416 | 80'483 | 841'397 |

Table 4: Data availability and key figures for three different approaches to calculating the ROE

### 3.4.2 Calculating Book Equity

The I/B/E/S Glossary does not indicate whether it includes preferred stock in the number of outstanding shares. Nevertheless, it (I/B/E/S Glossary, 2000: 6) consistently refers to common equity without mentioning preferred stock when discussing conventions for calculating the number of outstanding shares. We thus assumed that I/B/E/S forecasts do not include Preferred Stock (WC03451), as they do not include Preferred Dividends Requirements (WC01701) either. Therefore, we used Common Equity (WC03501) alone as the denominator when deflating the analysts’ forecasts. In contrast, von Arx (2015) defined the book equity as Common Equity (WC03501) plus Preferred Stock (WC03451). Figure 7 illustrates how to compute the ROE using I/B/E/S definitions in year *t* via the absolute method:

**Breakdown of ROE into Net Income and Common Equity**

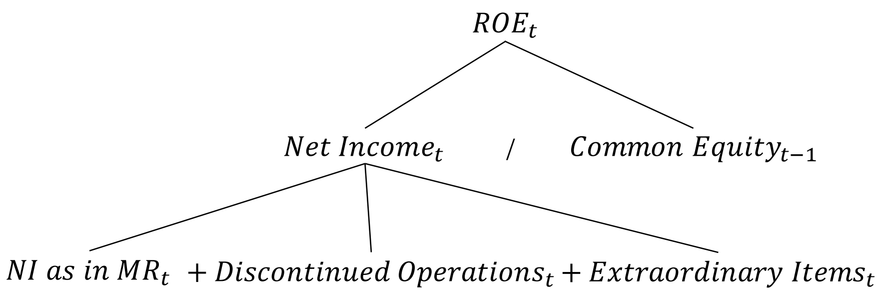


Figure 7: The absolute method for calculating the ROE according to I/B/E/S definitions

### 3.4.3 Calculating EPS and BPS

Computing the ROE via the deflated method requires not only the forecasted EPS but also the last years’ realized BPS. Again, I/B/E/S does not clearly define what should be included in the BPS.

The Worldscope definition of the Book Value Per Share (WC05476; 2010: 215) includes the items Common Equity (WC03501), Preferred Stock (WC03451), and other equity items. To be consistent with our previous methodological choices, we did not use the Worldscope definition of BPS. Instead, we used the above-mentioned method for computing the book equity, and divided Common Equity (WC03501) by Common Shares Outstanding (WC05301). We use the Worldscope definition for Common Shares Outstanding (WC05301) as they cancel each other out. Figure 8 decomposes the deflated ROE method according to I/B/E/S definitions by using Worldscope data:

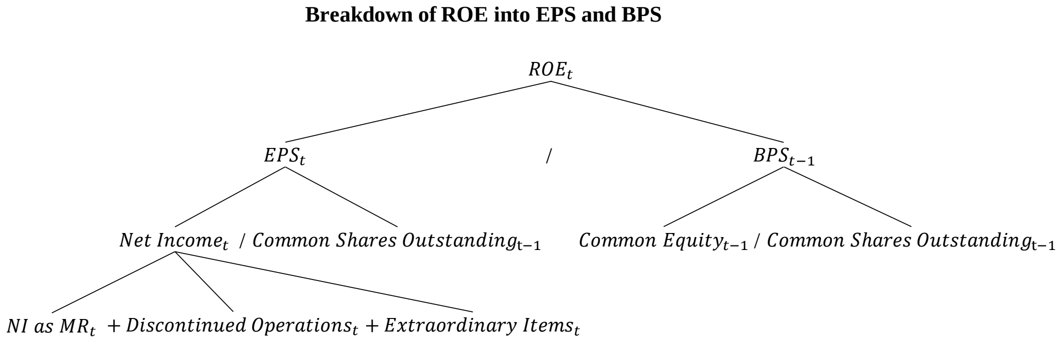


Figure 8: The deflated method for calculating the ROE according to I/B/E/S definitions

### 3.4.4 Descriptive Statistics

Figure 9 compares the three different approaches for calculating the ROE. The analyzed time frame ranges from 1982-2015:

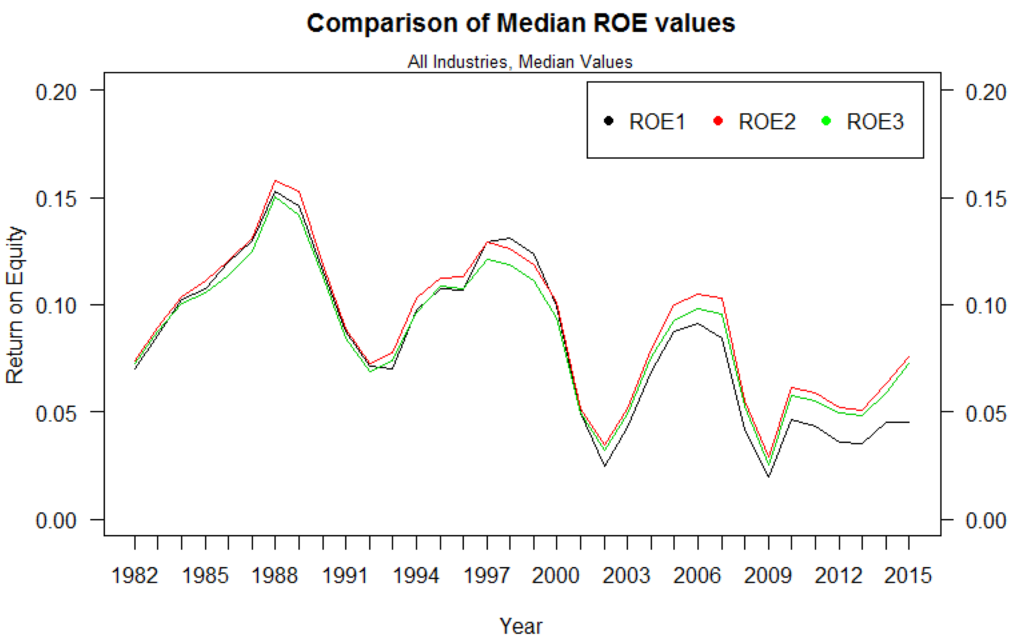


Figure 9: Comparison of three different ROE computation methods

First of all, “ROE1” corresponds to von Arx’s (2015) approach to calculating the realized ROE. Secondly, “ROE2” refers to the I/B/E/S approach (the absolute method), which is net income divided by Common Equity (WC3501). Finally, “ROE3” corresponds to the I/B/E/S approach of dividing the EPS by the BPS. This paper refers to this technique as the deflated method. Again, computed ROE values above 2 and below -2 were removed.

All three ROE definitions led to similar results. However, von Arx’s (2015) approach (“ROE1”) somewhat diverged from “ROE2” and “ROE3” between 2010-2015. Table 5 illustrates the amount of data that the three computation methods made available:

| | **N** | **Median** | **Mean** | **SD** |
|---|---|---|---|---|
| ROE1 | 117'963 | 0.0796 | 0.0513 | 0.3489 |
| ROE2 | 119'099 | 0.0876 | 0.0519 | 0.3622 |
| ROE3 | 119'455 | 0.0828 | 0.0526 | 0.3507 |

Table 5: Descriptive statistics for three different ROE computation methods

Constructing the ROE according to I/B/E/S definitions resulted in both more accurate ROE values and slightly improved data availability compared to von Arx’s (2015) method.

When comparing the ROE values to the realized EPS values in Table 1, it becomes clear that more EPS than ROE observations were available. This stems from the approach used to calculate the ratios. We calculated the ROE by dividing net income by the last year's book equity, whereas we computed the EPS by dividing net income by this year's number of shares. The need for the last year’s book equity reduced the number of ROE values.

## 3.5 Adding Predictions

After determining how to compute ROE values according to I/B/E/S definitions using Worldscope data, we added forecasted I/B/E/S values.

We compute the ROE forecasts using two different approaches. The first approach combines the absolute values defined above as “ROE2” using forecasted net income, realized common equity, and realized common dividends. The second utilized the deflated values as defined for “ROE3,” and it used forecasted EPS, realized BPS, and realized dividend per share (DPS).

### 3.5.1 Calculating the Number of Shares Outstanding

Analysts release their EPS predictions several years in advance assuming that the number of shares will remain constant. Consequently, we used a constant number of Common Shares Outstanding (WC05301) in year *t* for all prediction years *i*:

$$Common\ Shares\ Outstanding_t = Common\ Shares\ Outstanding_{t+i}$$

### 3.5.2 Calculating Forecasted Net Income

The below formula illustrates how we computed forecasted net income from the analysts' forecasted EPS:

$$FNI_{t+i} = FEPS_{t+\mathrm{i}} * Common\ Shares\ Outstanding_t$$

Where $FNI_{t+i}$ is the analysts' forecasted net income in year *t* for *i* years ahead and $FEPS_{t+i}$ is the analysts' forecasted EPS in year *t* for *i* years ahead.

### 3.5.3 Calculating Realized Common Equity

As described in Penman's (2013: 40) textbook, shareholders' equity only stays constant if net income is equal to net shareholder transactions. If not all positive net income is distributed to the shareholders, the book value rises. Also, it would be unrealistic to assume the book value would stay constant over the upcoming years. Penman (2013: 40) used the following formula to compute the shareholders' equity:

$$\begin{aligned} Shareholders'\ Equity_t \\ &= Shareholders'\ Equity_{t-1} + Comprehensive\ Incomes_t \\ &- Net\ Shareholder\ Transactions_t \end{aligned}$$

We adapted the formula for our purposes and replaced shareholders' equity with Common Equity (WC03501), comprehensive incomes with net income according to I/B/E/S definitions and net shareholder transactions with common dividends. Finally, we included the forecast years *i* and distinguished whether realized or forecasted values were used. This resulted in the following equation:

$$RCE_{t+i} = RCE_{t+i-1} + FNI_{t+i} - RCD_{t+i}$$

Where $RCE_{t+i}$ is the realized Common Equity (WC03501) in year *t* for *i* years ahead and $RCD_{t+i}$ is the realized common dividends in year *t* for *i* years ahead.

### 3.5.4 Calculating Realized Common Dividends

Furthermore, we needed to define the realized common dividends. With a varying $RCE_{t+i}$, $RCD_{t+i}$ is also expected to change. Gebhardt et al. (2001) faced a similar situation. To solve the issue, they used the current dividend payout ratio *k* and assumed it would remain constant over the coming years (Gebhardt et al., 2001: 142). Their approach was as follows:

$$B_{t+i} = B_{t+i-1} + FEPS_{t+i} - FEPS_{t+i} * k$$

Where $B_{t+i}$ is the BPS in year *t* for *i* years ahead, $FEPS_{t+i}$ is the forecasted EPS in year *t* for *i* years ahead, and *k* is the current dividend payout ratio. With:

$$FDPS_{t+i} = FEPS_{t+i} * k$$

Where $FDPS_{t+i}$ is the forecasted DPS in year *t* for *i* years ahead. Therefore:

$$B_{t+i} = B_{t+i-1} + FEPS_{t+i} - FDPS_{t+i}$$

Our formula was analogous to that of Gebhardt et al. (2001: 142) but used different notation. In addition, we preferred to use a different formula for realized common dividends, omitting the current dividend payout ratio *k* and replacing it with the forecasted net income growth ratio ($FNI_{t+i}$ / $FNI_{t+i-1}$):

$$RCD_{t+i} = RCD_{t+i-1} \ * \ FNI_{t+i} / FNI_{t+i-1}$$

After defining all relevant variables, we compiled Figure 10, which demonstrates how the absolute method utilizes the above-described variables:

**Breakdown of ROE into forecasted Net Income and Common Equity**

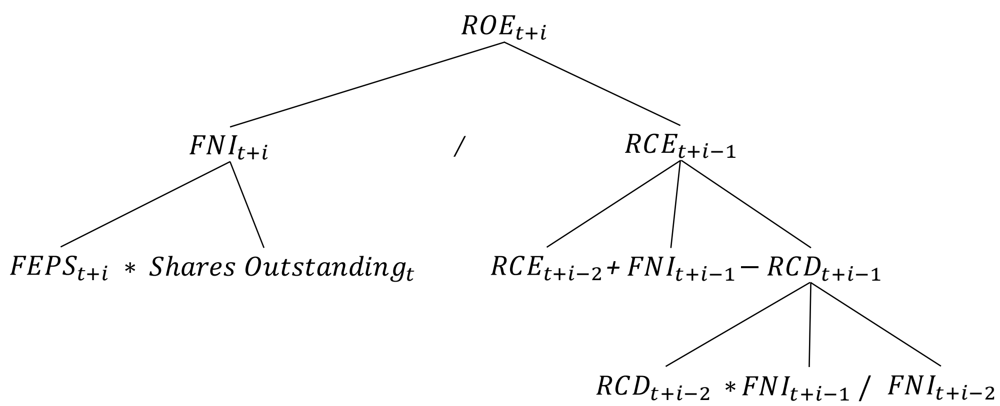


Figure 10: The absolute method for computing the ROE with forecast years and absolute numbers

The advantage of this approach is that it yielded absolute, undeflated values. The same formula construction can also be applied to deflated values. Since the methodology with deflated values was identical, the paper does not develop it again. Figure 11 illustrates how the deflated approach can be used to compute the ROE:

**Breakdown of ROE into EPS and BPS**

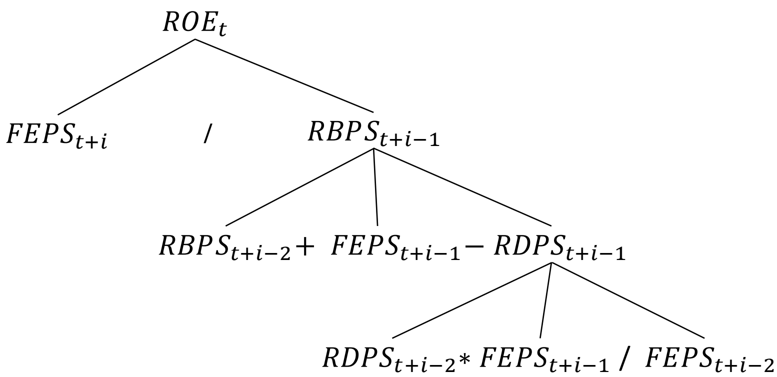


Figure 11: Computing the ROE with forecast years and deflated numbers

This method did not require the number of shares to compute the ROE. However, as mentioned above, the per-share basis method does not yield absolute values, because number of shares outstanding deflates them.

### 3.5.5 Unresolved Issues

By adapting the Worldscope data to I/B/E/S definitions, we faced two issues for which we could not account. The first involved the varying number of shares. Thomson Financial (2007: 21) is well aware that countries have different regulations concerning disclosures on shares. It (2007: 234) reports the number of outstanding shares at a firms' year-end. If the provided number of shares is determined by the beginning and the end of the year values (instead of using end-year values), Worldscope uses footnotes to point out the differences in disclosure. Also, in the case of more than one common or ordinary share type, the item Common Shares Outstanding (WC05301) represents adjusted and combined shares to reflect the par value of the share. According to the I/B/E/S Glossary (2000: 6), share disclosure for non-U.S. firms is only based on the predominant share type that the majority of analysts have covered. Moreover, I/B/E/S also considers if a type of share is available to non-nationals and which type of share has the highest public float. The irreconcilable differences between

Worldscope and I/B/E/S may have introduced a small bias for which we could not correct.

The second issue arises from the differentiation of basic and diluted shares. Thomson Financial (2007) has Worldscope codes for basic (non-diluted) and diluted numbers of shares. Earnings Per Share (WC05201) is equal to the basic EPS computation (Thomson Financial, 2007: 272). Precisely, Earnings Per Share (WC05201) is calcualted by dividing Net Income Used to Calculate EPS (WC01751) by Common Shares Outstanding (WC05301). However, the I/B/E/S Glossary (2000: 6) applies another policy regarding the dilution of shares. It does not instruct analysts on whether to disclose based on basic or diluted types of shares. I/B/E/S follows the majority and adjusts analysts' forecasts by a company-specific dilution factor when an analyst's methodology uses a different approach. This inconsistency could have led to slight differences.

### 3.5.6 Descriptive Statistics

This sub-section compares the absolute and deflated ROE computation methods. Table 6 summarizes the forecasted net income, forecasted common equity, forecasted common dividends and forecasted ROE according to the absolute method:

| | N | Median | Mean | SD |
|---|---|---|---|---|
| NofShares | 133'522 | 19'698 | 151'330 | 982'117 |
| RNI | 137'622 | 2'416 | 80'483 | 841'397 |
| FNI1MD | 69'291 | 45'038 | 2'075'280 | 20'745'105 |
| FNI2MD | 63'331 | 63'350 | 2'444'688 | 23'122'897 |
| FNI3MD | 44'611 | 90'310 | 3'461'679 | 28'774'896 |
| FNI4MD | 25'845 | 155'081 | 5'738'271 | 38'844'575 |
| FNI5MD | 21'392 | 223'178 | 7'131'100 | 45'494'011 |
| RCE | 131'746 | 53'533 | 820'811 | 5'178'025 |
| FCE1MD | 49'580 | 343'867 | 3'849'524 | 257'799'096 |
| FCE2MD | 45'648 | 513'242 | 7'039'555 | 597'267'159 |
| FCE3MD | 32'980 | 871'800 | 13'449'189 | 1'126'493'561 |
| FCE4MD | 20'583 | 1'425'842 | 26'740'020 | 2'006'829'000 |

| | N | Median | Mean | SD |
|---|---|---|---|---|
| RCD | 78'623 | 4'200 | 78'938 | 547'756 |
| FCD1MD | 49'587 | 29'238 | 550'457 | 257'695'880 |
| FCD2MD | 45'654 | 35'866 | 332'412 | 328'913'794 |
| FCD3MD | 32'984 | 47'596 | 318'078 | 423'896'797 |
| FCD4MD | 20'585 | 71'743 | 245'980 | 581'126'496 |
| RROE2 | 119'099 | 0.0876 | 0.0519 | 0.3622 |
| FROE1MD | 46'534 | 0.1159 | 0.1277 | 0.2634 |
| FROE2MD | 41'545 | 0.1711 | 0.4432 | 0.5952 |
| FROE3MD | 31'969 | 0.1694 | 0.3079 | 0.3985 |
| FROE4MD | 20'192 | 0.1624 | 0.2441 | 0.3096 |
| FROE5MD | 17'507 | 0.1599 | 0.2179 | 0.2773 |

Table 6: Realized and forecasted variables for the absolute computation method

As stated above, variable names starting with the letter "R" are realized values, and variables names starting with "F" are forecasted value. Again, the letters "MD" at the end of a variable name signify that we consistently used median forecast values instead of mean values.

The mean forecasted ROE value was significantly higher than the median value, particularly for two- and three-years-ahead forecasts. This indicated that more forecasted

ROE values were closer to 2 than to -2, which is plausible as ROE values below -1 are unrealistic. For consistency, outliers above 2 or below -2 were removed.

Forecasted net income, forecasted common equity, and forecasted common dividends all increased very rapidly in the predictions' first years, partially due to the construction of the above formulas. A high forecasted net income results in high common equity and dividend values. The following chapter returns to this issue.

As already seen, data availability decreased for longer forecasts. The number of forecasted ROE values was significantly lower than the number of EPS predictions. This was due to the fact that we omitted ROE values above 2 and below -2, and the large number of variables that the ROE computation required also played a role. If one of the necessary variables was missing, we were not able calculate the ROE.

Table 7 summarizes the forecasted EPS, forecasted BPS, forecasted DPS, and forecasted ROE, as calculated via the deflated method:

| | **N** | **Median** | **Mean** | **SD** | | **N** | **Median** | **Mean** | **SD** |
|---|---|---|---|---|---|---|---|---|---|
| REPS | 133'165 | 0.1376 | 129.7871 | 11'049 | RDPS | 78'287 | 0.2340 | 394.0248 | 56'093 |
| FEPS1MD | 75'609 | 1.7000 | 265.0020 | 284'395 | FDPS1MD | 51'046 | 1.1395 | 14.6435 | 1'243 |
| FEPS2MD | 72'044 | 2.2400 | 3'390.4851 | 522'281 | FDPS2MD | 48'862 | 1.3334 | 19.2778 | 1'904 |
| FEPS3MD | 51'319 | 2.5000 | -446.6797 | 110'458 | FDPS3MD | 35'675 | 1.3565 | 11.4242 | 386 |
| FEPS4MD | 30'216 | 2.9289 | 21.7998 | 354 | FDPS4MD | 22'589 | 1.4062 | 9.5711 | 269 |
| FEPS5MD | 25'946 | 3.6441 | 24.0697 | 389 | RROE3 | 119'455 | 0.0828 | 0.0526 | 0.3507 |
| RBPS | 133'486 | 2.8664 | 954.2738 | 56'616 | FROE1MD | 48'707 | 0.1185 | 0.1273 | 0.2619 |
| FBPS1MD | 50'925 | 9.9147 | 59.2334 | 1'873 | FROE2MD | 43'291 | 0.1813 | 0.4691 | 0.6185 |
| FBPS2MD | 48'748 | 14.1905 | 63.4451 | 3'407 | FROE3MD | 34'360 | 0.1855 | 0.3463 | 0.4214 |
| FBPS3MD | 35'593 | 18.3142 | 97.6511 | 1'950 | FROE4MD | 22'061 | 0.1797 | 0.2736 | 0.3240 |
| FBPS4MD | 22'531 | 21.4064 | 105.4410 | 2'079 | FROE5MD | 19'967 | 0.1802 | 0.2503 | 0.2911 |

Table 7: Realized and forecasted variables for the deflated computation method

The median forecasted ROE for two- to five-years-ahead forecasts remained very stable. The deflated approach to calculating the ROE yielded higher values than the absolute ROE computation method. In particular, the two- to five-year ROE forecast values were higher.

Both, the absolute and the deflated method, generated similar and stable mean as well as median ROE predictions. That said, the deflated approach's ROE predictions were slightly higher, and they were also more numerous.

In the absolute method, net income, common equity, and common dividends were comparable. The advantage of the deflated ROE computation was that it yielded more data. Although both methods had benefits, we judged the higher data availability as more essential. Therefore, the next section's graphs rely on ROE values generated via the deflated method.

## 3.6 Graphical Analysis of Forecasted ROE

This section analyses whether analysts predict that ROE reverts to the mean, as Fama and French (2000: 174) suggested. Since the I/B/E/S data only dated back to 1986, we replotted the initial ROE graph over a 22-year period from 1986-2015. Moreover, the remainder of this thesis uses the above-mentioned deflated definition of ROE: $FEPS_{t+i}$ / $RBPS_{t+i-1}$.

Additionally, we shortened the forecast period from 10 years to 5 years for 3 reasons. Firstly, as already mentioned in Chapter 2.3, the mean reversion process only takes five years and ROE from that point onwards falls into a steady state. Secondly, analysts forecast, at most, five years ahead. By plotting more years' worth of realized values, we would be unable to compare our results on mean reversion with von Arx's (2015) findings. Thirdly, by reducing the timespan to five years, the number of observations years increased, with portfolio formation years ranging from 1986-2010 rather than from 1986-2005. Figure 12 depicts the mean reversion of realized ROE computed according to the deflated method. The figure covers the period from 1986-2015:

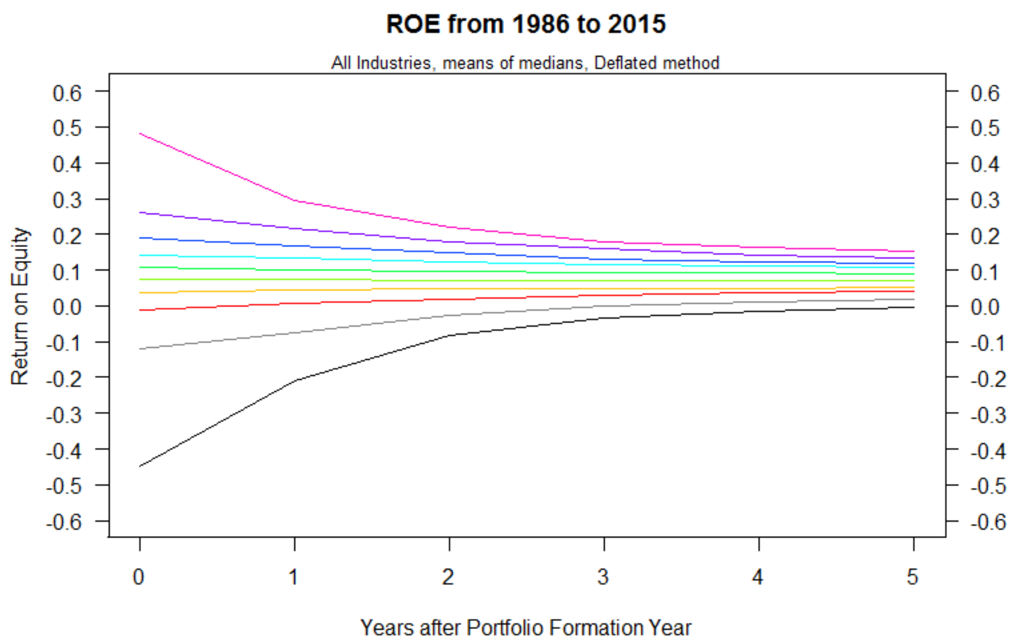

Figure 12: Mean of medians forecasted ROE in 10 predefined portfolios for a 5-year period ranging from 1986-2015

Compared to von Arx’s (2015: 29) results, our top portfolio had a slightly lower starting value. Our bottom portfolio also started lower, at -0.45 instead of -0.39. These differences could have been due to the divergent means of calculating the ROE and the different time periods. The years subsequent to the portfolio formation year did not notably differ.

Figure 13 compares realized and forecasted ROE values from 1982-2015. The realized ROE, labeled in the graph as “ROE,” were obtained since 1982. The one- to five-year ROE predictions (“ROE1” to “ROE5”) are analysts’ median ROE forecasts made in year $t$ for $i$ years ahead ($FEPS_{t+i}$ / $RBPS_{t+i-1}$). For instance, in 2009, where the realized ROE was 2.5%, analysts predicted a 5-year-ahead (year 2014) ROE of 17.7%:

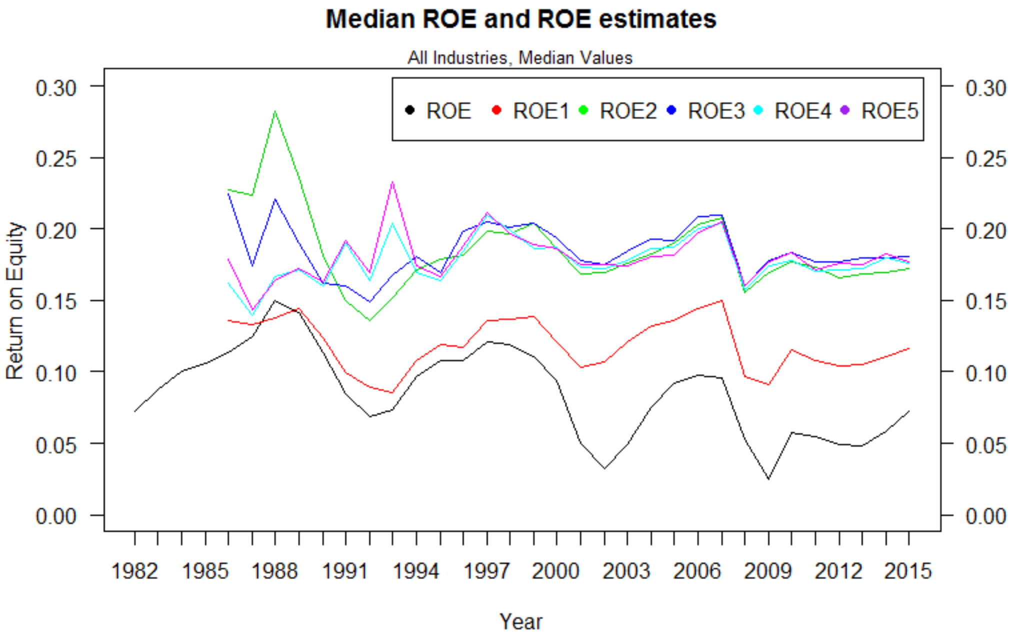


Figure 13: Analysts’ one- to five-year-ahead ROE forecasts

The two- to five-years-ahead predictions were clearly higher than the realized values. Our results confirm the findings of numerous researchers (e.g., O’Brien [1988], Francis and Philbrick [1993], Butler and Lang [1991], Francis et al. [2004], and Easton and Sommers [2007]) that analysts are overly optimistic.

In the above graph, we did not change the prediction horizon $i$ to forecast ROE development over time. Instead, we kept the prediction years constant. For instance, in the above graph, "ROE1" is the constantly one-year-ahead forecast. Figure 14 illustrates how we constructed the above plot:

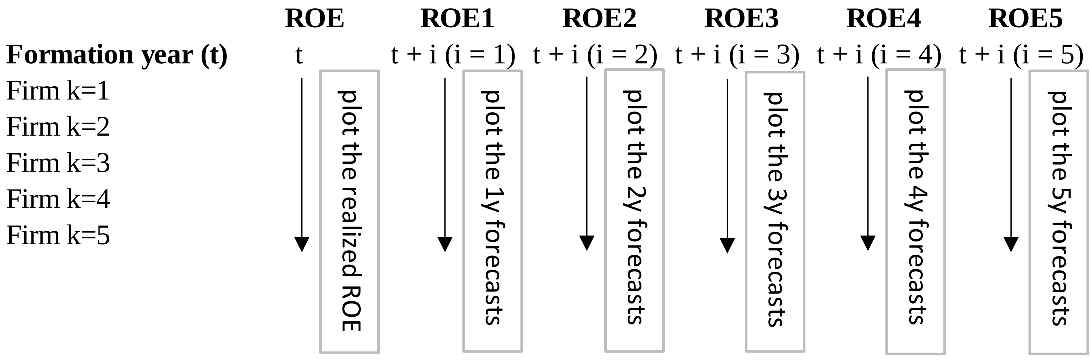


Figure 14: Structure of the constant ROE forecast years

When evaluating the analysts' forecasts, we were particularly interested in whether their forecasts were accurate. Thus, we matched the forecasted ROE values with the realized ROE values. In every year after portfolio formation year, $i$ increased by 1. Therefore, we plotted the data horizontally instead of vertically, using a similar approach to Bradshaw et al. (2012). Figure 15 clarifies the new structure:

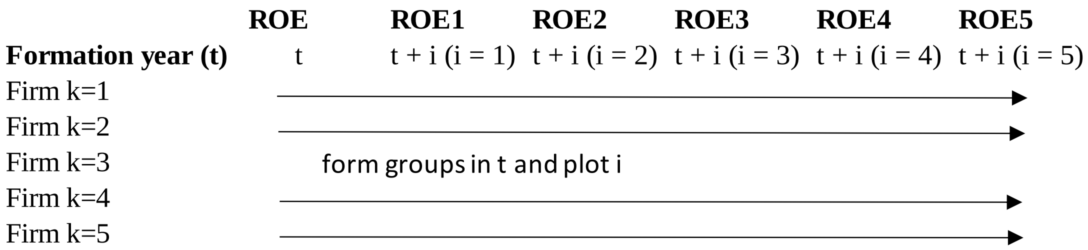


Figure 15: New structure for plotting analysts' forecasts. "*i*" adopts values from 1 to 5 as in the mean-reversion section

Figure 16 graphically displays the analysts' forecasts. The starting values (portfolio formation year $t_0$) are identical to those in the mean-reversion plot at the beginning of this sub-section because the portfolio formation year uses realized ROE values. In year $t_1$, the portfolios remained unchanged, we but used the analysts' one-year-ahead forecast made in year $t_0$. We applied the same method to years $t_2$ to $t_5$. For instance, $t_5$ signifies the analysts' five-year ROE forecast for each of the portfolios determined in year $t_0$:

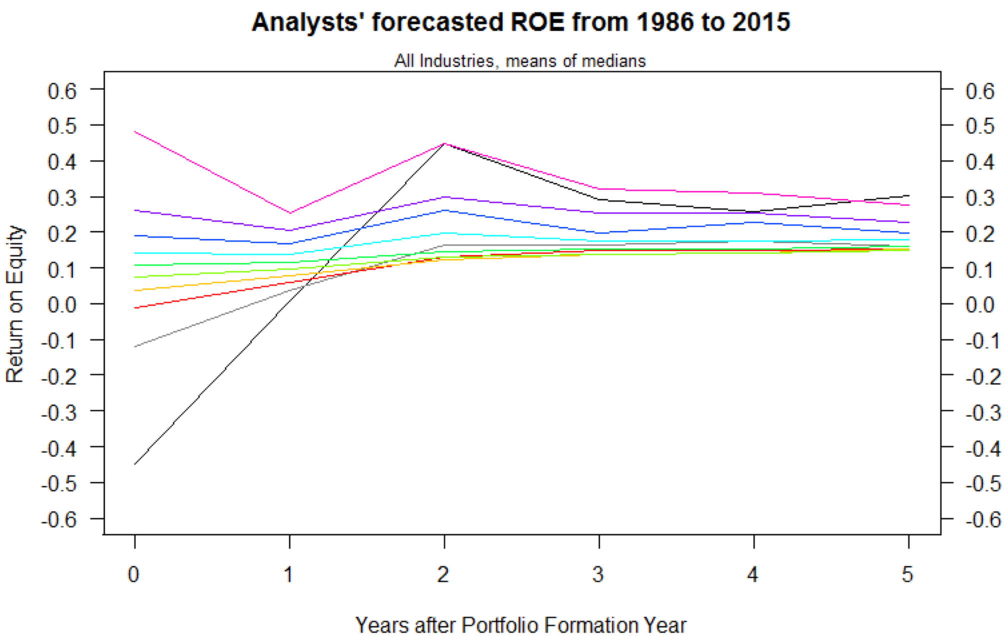


Figure 16: Mean of medians forecasted ROE in 10 predefined portfolios for a 5-year period ranging from 1986-2015

Overall, the graph's shape is quite surprising. First, the portfolios intersect, which did not occur when we used realized values. Secondly, in the final year ($t_5$), the bottom portfolio had the highest ROE forecasts. Thirdly and most importantly, analysts forecasted a mean reversion in year $t_1$. However, this effect does not hold for the subsequent years.

A high level of analyst optimism was expected, as it was already noted in previous tables. For the five-year forecasts, all of the portfolios ended with forecasted ROE values higher than 0.1. The initial bottom portfolio predicts the highest ROE of 0.3. In other words, analysts expected the firms with the most negative ROE values to be the most profitable firms in five years' time.

By closely assessing the individual portfolios, it becomes visible that in year one the top and the bottom portfolios strongly reverted to the mean. The top portfolios' ROE shrank, falling from 0.48 to 0.25. In contrast, the bottom portfolio displayed a steep increase, growing from -0.45 to 0. Moreover, none of the portfolios predicted a negative ROE in any prediction year. As early as the two-year forecasts, all analysts' ROE predictions were above 0. The initial bottom portfolio experienced the steepest increase, and it reached the same level as the top portfolio in year $t_2$. In the final forecast year ($t_5$), the initial top and bottom portfolios closed with the highest predicted values. This steep increase is surprising, and it contradicts previously observed mean-reversion patterns.

The above plot confirms that analysts predict a mean reversion in ROE in $t_1$. This partially answers our main research question, which Fama and French (2000: 174) inspired. However, opposed to the realized values, analysts do not predict a strict mean-reversion process. In the two-year forecasts, the upper portfolios experienced an increase in predicted ROE values. Clearly, the mean reversion of forecasted values only partially reflects the mean reversion of realized values. This finding constituted sufficient motivation for us to further compare the realized ROE values and the analysts' predicted ROE values in terms of their mean-reversion processes. The next chapter turns to that topic.

# 4 Mean Reversion versus Analysts’ Forecasts

This chapter compares Chapter 2’s findings on mean reversion findings with Chapter 3’s results on analysts’ forecasts. First, we subtracted the mean-reversion portfolios from the analyst forecast portfolios. Then, we meticulously analyzed the top and bottom portfolios with the goal of explaining differences between them. The final section of the chapter solely focuses on those forecasts for which analysts had estimated values for all five years. Finally, we propose an alternative model for forecasting ROE.

## 4.1 Graphical Comparisons of ROE

For clarity’s sake, Figure 17 contains a side-by-side comparison of graphs from the previous section. The left-hand graph depicts the realized ROE portfolios, while the right-hand graph provides the forecasted ROE portfolios. All of the following graphs consistently calculate ROE as $EPS_t/BPS_{t-1}$:

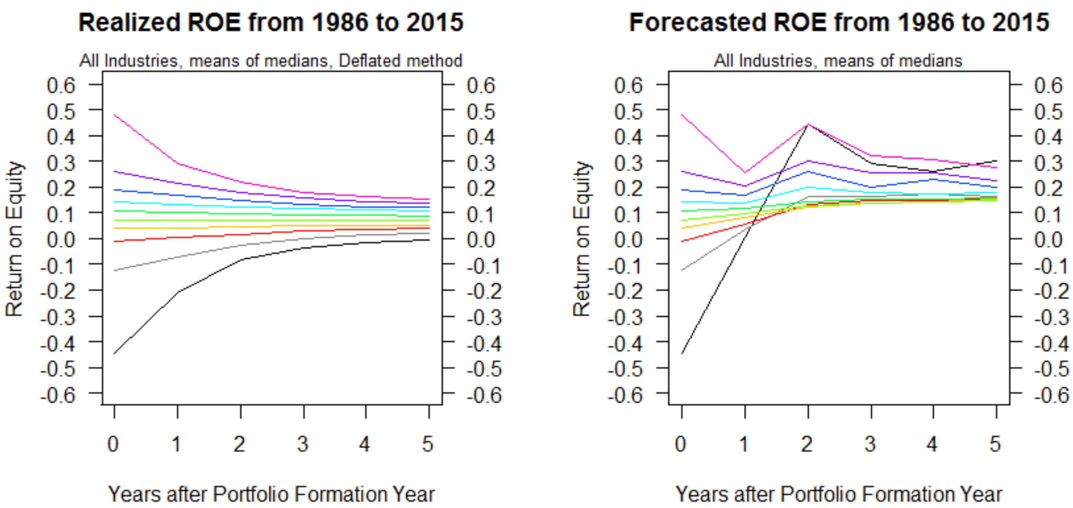


Figure 17: Left side: Mean of medians realized ROE in 10 predefined portfolios for a 5-year period ranging from 1986-2015. Right side: Mean of medians realized ROE in 10 predefined portfolios for a 5-year period ranging from 1986-2015.

By subtracting the obtained realized ROE portfolios from the analysts’ ROE prediction portfolios, we obtained a graph (see Figure 18, below) demonstrating the analysts’ error in predicting the ROE. Positive (negative) values imply that analysts were too optimistic (pessimistic) in their forecasts:

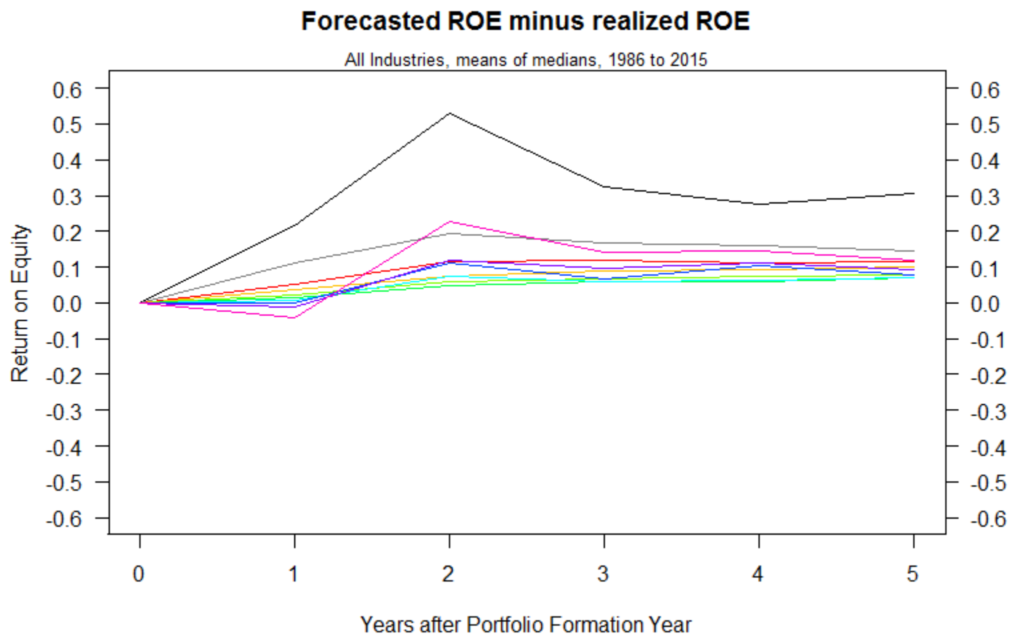


Figure 18: Difference in mean of medians between forecasted ROE and realized ROE in 10 predefined portfolios for a 5-year period ranging from 1986-2015

Analysts strongly overvalued the original bottom portfolio, and this effect persisted throughout all five years. The same pattern surfaced in the second-lowest portfolio, albeit to a lesser extent. Analysts undervalued the initial top portfolio, and had the lowest ROE values in year $t_1$. However, in year $t_2$ that portfolio experienced a steep increase and was the second-highest portfolio. Initially, the middle portfolios exhibited the least bias, but the analysts' optimism pervaded all of the portfolios. The top and the bottom 2 portfolios tended to be the most overrated. Overall, all 10 portfolios were overrated in the second to fifth year.

The above procedure is similar to the forecast dispersion method used by Elgers and Lo (1994) and Han et al. (2001). However, those studies sorted the portfolios according to the forecast dispersion. Our results indicated that analysts assessed past losers less accurately, which resulted in highly dispersed forecasts. Also, the results supported Han et al.'s (2001: 194) claim that a poor past performance is possibly correlated to a higher forecast dispersion. Furthermore, we confirmed Abarbanell's (1991) claim that analysts are more likely to overestimate future negative returns. To gain a deeper understanding of these differences, the following section examines the portfolios in a more detailed manner.

## 4.2 Portfolio Analysis

We expected to gain additional information by selecting individual portfolios and further splitting them into 10 sub-portfolios. Von Arx (2015: 36) followed a similar approach. However, instead of building 10 new portfolios for each existing portfolio, he plotted the initial portfolios' 90%, 75%, 25%, and 10% confidence intervals, as well as the mean and median for each portfolio. He then noticed that the top portfolio and the two bottom ones exhibited more variance over time.

### 4.2.1 Bottom Portfolio

We split the initial bottom portfolio into 10 sub-portfolios. Each sub-portfolio includes 1% of the initial data and accounts for approximately 1'200 ROE values. For the bottom portfolio, Figure 19 depicts the realized ROE values on the left-hand side and the forecasted ROE values on the right-hand side. We have adapted the scale of the y-axis to fit the graph's characteristics.

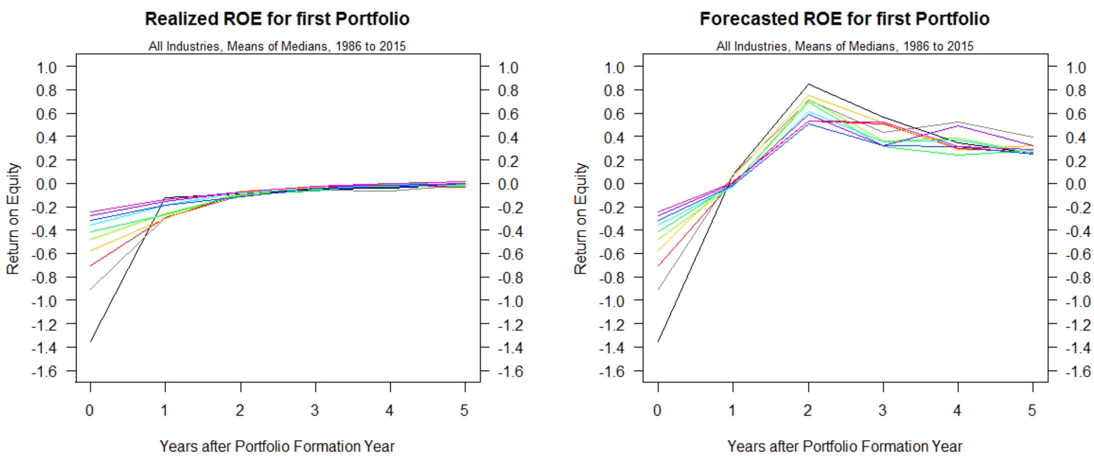


Figure 19: Left side: Mean of medians realized ROE for the predefined bottom portfolio for a five-year period ranging from 1986-2015. Right side: Mean of medians forecasted ROE for the predefined bottom portfolio for a five-year period ranging from 1986-2015.

All realized ROE sub-portfolios increased steadily. After $t_2$, all of the portfolios' realized ROE values fell within a small range, increasing to 0.0 in the following years. The bottom sub-portfolio for realized ROE in $t_0$ experienced a critical performance increase and became the best-performing portfolio in $t_1$, albeit still with negative values. This was a rather surprising finding as our analysis of the 10 initial realized ROE portfolios did not indicate that the portfolios switched rankings.

In general, ROE values below -1 are unrealistic because they imply a loss that is greater than last years' equity. In such cases, the only way a firm could prevent going bankrupt would be if net shareholder transactions were positive and accounted for part of the firm's losses. Therefore, we expected for the bottom portfolio that most firms went bankrupt in $t_0$. As a consequence, this portfolio contains only a few survivors.

On the right-hand side, the lowest forecasted sub-portfolio saw even greater increases than the realized portfolio. For the one-year-ahead forecasts, all 10 portfolios had very similar values. For $t_2$, analysts predicted high positive values for all portfolios. The initial bottom sub-portfolio experienced a particularly sharp increase and evolved into the portfolio with the highest predicted values. Then, its predictions proceeded to decrease slightly for the years $t_3$ to $t_5$. Figure 20 displays the difference between realized ROE and forecasted ROE for the bottom portfolio:

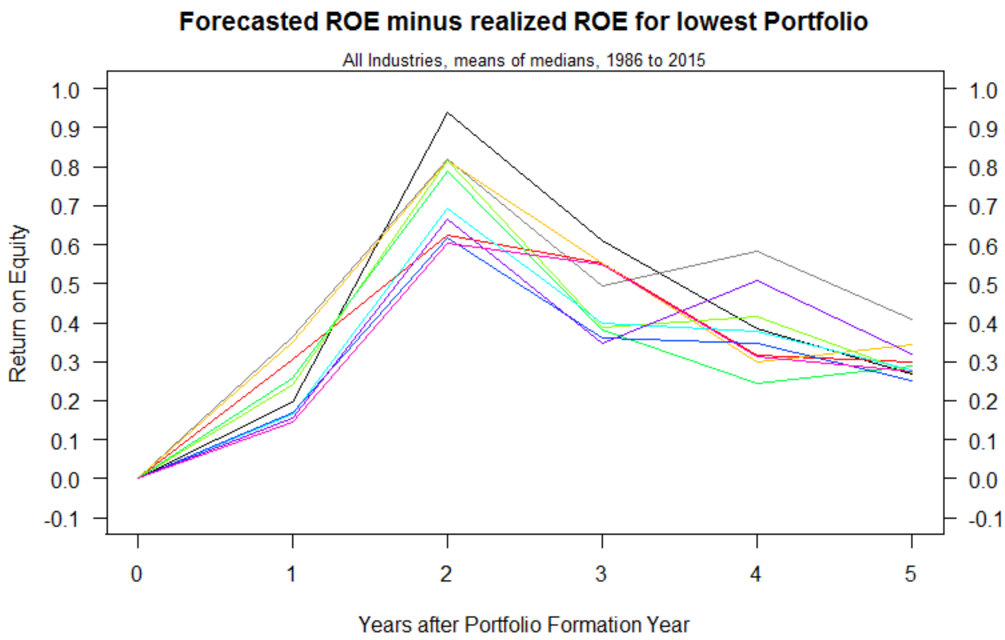


Figure 20: Difference in mean of medians between forecasted ROE and realized ROE for the predefined bottom portfolio for a five-year period ranging from 1986-2015

Again, all of the sub-portfolios had a starting point of 0.0. Moreover, the y-axis was again adapted to fit the data. Overall, the massive analysts' optimism is clearly visible. In $t_1$ and $t_2$, all sub-portfolios saw sharps increases. In $t_2$, analysts' deeply overestimated the initial bottom sub-portfolio. This was also true of the other portfolios, although to a lesser extent. In $t_{5,}$ the analysts overestimated all portfolios' ROE values by at least 0.25 and were overoptimistic.

### 4.2.2 Top Portfolio

In this sub-section, we split the initial top portfolio into 10 sub-portfolios, as Figure 21 demonstrates. Again, the left-hand side graph contains realized values, and the right-hand graph contains analysts' predictions:

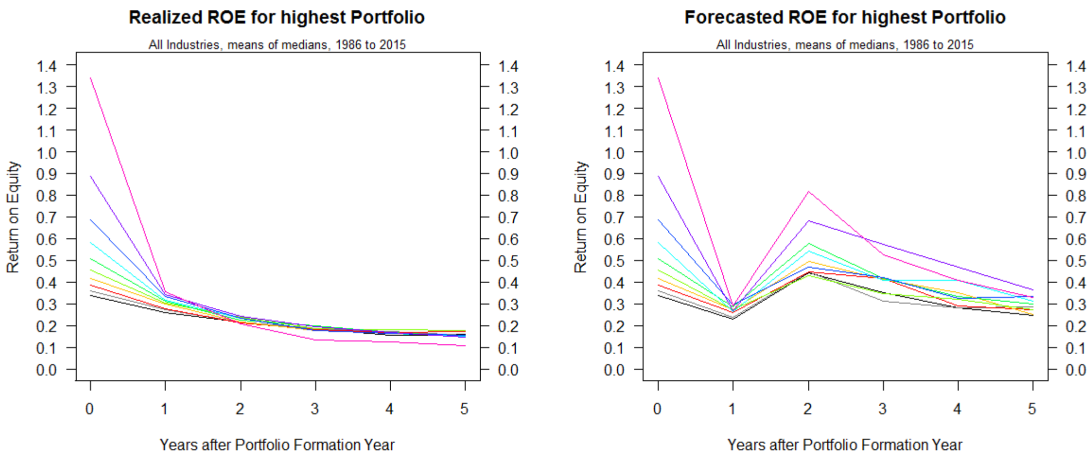


Figure 21: Left side: Mean of medians realized ROE for the predefined top portfolio for a five-year period ranging from 1986-2015. Right side: Mean of medians forecasted ROE for the predefined top portfolio for a five-year period ranging from 1986-2015.

A reversion process is clearly visible. Interestingly, the top sub-portfolio had the lowest realized ROE five years after portfolio formation. Although it remained the top portfolio in $t_1$, it then proceeded to drop below all the other portfolios. This finding is surprising, because so far in the theory of mean reversion, past winners remained the most profitable.

The forecasted plot shows strong mean-reversion tendency in $t_1$. Moreover, the analysts predicted higher ROE values in $t_2$ than $t_1$. This contradicts previously observed mean-reversion distributions in which top portfolio decreased in a consistent manner. Figure 22 (below) again plots the difference between the two sets of sub-portfolios:

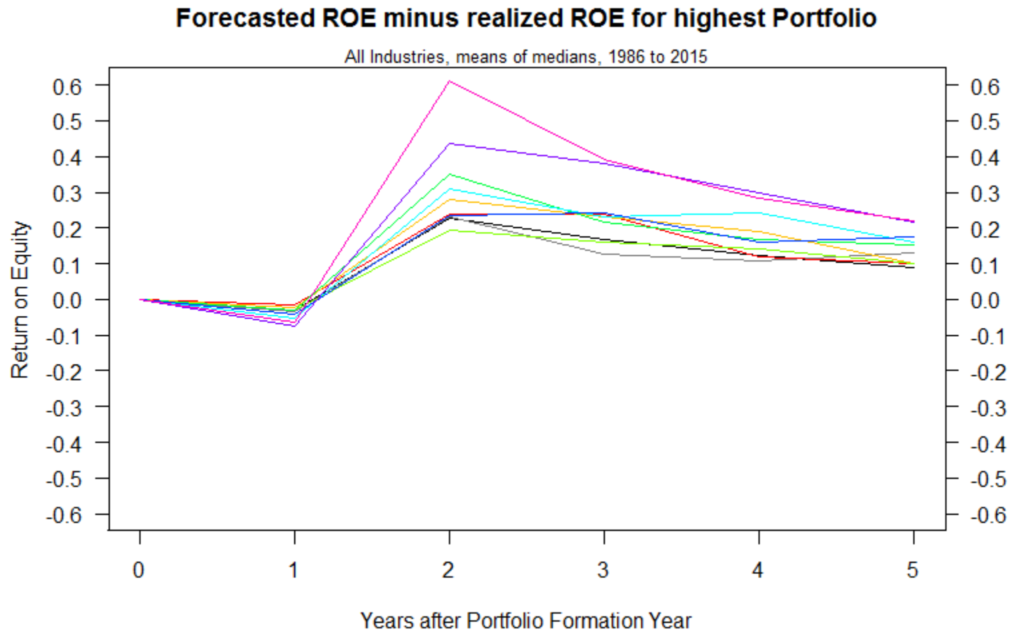


Figure 22: Difference in mean of medians between forecasted ROE and realized ROE for the predefined bottom portfolio for a five-year period ranging from 1986-2015

In $t_1$, analysts tended to undervalue the initial top sub-portfolio. The initial high (low) sub-portfolio was more (less) undervalued, although $t_2$ saw a reversal of this effect. The initial top sub-portfolio, as well as the second- and third-highest sub-portfolios were heavily overvalued, but this effect decreased over time. After five years, the sub-portfolios were arranged in a manner similar to their initial positions. Compared to the graph plotting the differences between the bottom sub-portfolios, the analysts' forecast error was less extreme but still persistent in the top portfolio.

## 4.3 Analysts' Selectivity

The previous findings lent support to the claim that analysts fail to accurately forecast ROE. However, as previously mentioned in the discussion of mean reversion (p. 18), the dataset might be prone to bias. Firms with high negative equity are more likely to drop out of the stock market or go bankrupt. As established in Chapter 3.2 (p. 31), significantly less data was available for the forecasted ROE than the realized ROE. In particular, three- to five-years-ahead forecasts often covered less than 30% of all available realized EPS observations.

To test whether analysts' firm selections adhered to a pattern, we analyzed realized net income and common equity. Table 8 provides the number of total observations, median, mean, and standard deviation for those variables using the absolute method. Again, "MD" signifies that forecast medians were used rather than means:

| | **N** | **Median** | **Mean** | **SD** |
|---|---|---|---|---|
| RNI | 137'622 | 2'416 | 80'483 | 841'397 |
| FNI1MD | 69'291 | 45'038 | 2'075'280 | 20'745'105 |
| FNI2MD | 63'331 | 63'350 | 2'444'688 | 23'122'897 |
| FNI3MD | 44'611 | 90'310 | 3'461'679 | 28'774'896 |
| FNI4MD | 25'845 | 155'081 | 5'738'271 | 38'844'575 |
| FNI5MD | 21'392 | 223'178 | 7'131'100 | 45'494'011 |
| | | | | |
| RCE | 131'746 | 53'533 | 820'811 | 5'178'025 |
| FCE1MD | 49'580 | 343'867 | 3'849'524 | 257'799'096 |
| FCE2MD | 45'648 | 513'242 | 7'039'555 | 597'267'159 |
| FCE3MD | 32'980 | 871'800 | 13'449'189 | 1'126'493'561 |
| FCE4MD | 20'583 | 1'425'842 | 26'740'024 | 2'006'829'229 |

Table 8: Descriptive statistics for realized and forecasted net income and common equity, with calculated absolute values

Both mean and median values indicated abnormally high growth rates for forecasted net income and forecasted common equity, even as the number of predictions quickly declined. Firm growth could not explain the massive increase in net income and common equity. This led to the conclusion that analysts tend to release forecasts for firms with high net income and high common equity. We use them in the following as proxies, as both are indicators for size. To assess this issue in a more detailed manner, Table 9 provides the number of available forecasts for each portfolio from 1986-2015:

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| **All Portfolios** | | | **Portfolio 1** | | | **Portfolio 2** | | |
| RROE | 119'455 | | RROE | 11'563 | 9.68% | RROE | 11'549 | 9.67% |
| FROE1MD | 48'707 | | FROE1MD | 2'708 | 5.56% | FROE1MD | 3'961 | 8.13% |
| FROE2MD | 43'291 | | FROE2MD | 676 | 1.56% | FROE2MD | 1'522 | 3.52% |
| FROE3MD | 34'360 | | FROE3MD | 452 | 1.32% | FROE3MD | 975 | 2.84% |
| FROE4MD | 22'061 | | FROE4MD | 260 | 1.18% | FROE4MD | 555 | 2.52% |
| FROE5MD | 19'967 | | FROE5MD | 245 | 1.23% | FROE5MD | 506 | 2.53% |
| **Portfolio 3** | | | **Portfolio 4** | | | **Portfolio 5** | | |
| RROE | 11'544 | 9.66% | RROE | 11'549 | 9.67% | RROE | 11'550 | 9.67% |
| FROE1MD | 4'481 | 9.20% | FROE1MD | 4'737 | 9.73% | FROE1MD | 4'982 | 10.23% |
| FROE2MD | 2'507 | 5.79% | FROE2MD | 3'539 | 8.17% | FROE2MD | 4'397 | 10.16% |
| FROE3MD | 1'777 | 5.17% | FROE3MD | 2'606 | 7.58% | FROE3MD | 3'472 | 10.10% |
| FROE4MD | 1'089 | 4.94% | FROE4MD | 1'512 | 6.85% | FROE4MD | 2'192 | 9.94% |
| FROE5MD | 966 | 4.84% | FROE5MD | 1'343 | 6.73% | FROE5MD | 1'984 | 9.94% |
| **Portfolio 6** | | | **Portfolio 7** | | | **Portfolio 8** | | |
| RROE | 11'543 | 9.66% | RROE | 11'544 | 9.66% | RROE | 11'549 | 9.67% |
| FROE1MD | 5'469 | 11.23% | FROE1MD | 5'637 | 11.57% | FROE1MD | 5'595 | 11.49% |
| FROE2MD | 5'438 | 12.56% | FROE2MD | 6'118 | 14.13% | FROE2MD | 6'558 | 15.15% |
| FROE3MD | 4'453 | 12.96% | FROE3MD | 5'113 | 14.88% | FROE3MD | 5'500 | 16.01% |
| FROE4MD | 2'886 | 13.08% | FROE4MD | 3'376 | 15.30% | FROE4MD | 3'689 | 16.72% |
| FROE5MD | 2'608 | 13.06% | FROE5MD | 3'092 | 15.49% | FROE5MD | 3'358 | 16.82% |
| **Portfolio 9** | | | **Portfolio 10** | | | | | |
| RROE | 11'544 | 9.66% | RROE | 11'560 | 9.68% | | | |
| FROE1MD | 5'157 | 10.59% | FROE1MD | 3'773 | 7.75% | | | |
| FROE2MD | 6'385 | 14.75% | FROE2MD | 4'670 | 10.79% | | | |
| FROE3MD | 5'359 | 15.60% | FROE3MD | 3'851 | 11.21% | | | |
| FROE4MD | 3'577 | 16.21% | FROE4MD | 2'529 | 11.46% | | | |
| FROE5MD | 3'248 | 16.27% | FROE5MD | 2'266 | 11.35% | | | |

Table 9: Realized and forecasted ROE by portfolio, thus demonstrating the data availability for each portfolio

Again, we computed the ROE using the deflated ROE computation ($EPS_t/BPS_{t-1}$). The top left-hand graph provides summary figures for all portfolios, which correspond to the initial dataset. The remaining graphs provide the number of available forecasts per portfolio. Portfolios 1-10 correspond to the previously mentioned portfolios, with portfolio 1 as the bottom portfolio and portfolio 10 as the top portfolio. The percentage values demonstrate the share of total observations. If the forecasts were evenly distributed across the portfolios, each would contain 10% of the total forecasts. Notably, the analysts predicted considerably fewer values for portfolio 1. The number of predictions increased steadily from portfolio 1 to portfolio 8, which had an above-average number of forecasts. Portfolio 9 and 10 again had a smaller share of forecasts.

On the basis of the above, we concluded that analysts rarely create forecasts for firms with negative realized ROE values. In the case of a realized loss (portfolios 1 to 3) analysts only made predictions for a range of selected firms. The longer the forecast horizon, the stronger was this effect. All 10 portfolios were equally weighted, but the number of firms assigned to each portfolio decreased in an irregular manner, with firms in the bottom portfolios overrepresented. More profitable firms were the subject of more forecasts.

To suppress the analyst's selection, avoid a sample bias and to increase the validity, we only selected firms for which five-year predictions were available. If any one- to five-year predictions were missing, we excluded that firm's realized and the forecasted ROE values. This procedure ensured that we could meaningfully compare the forecasted and realized ROE values. Table 10 analyses the remaining subset of 15'073 firms. Again, ROE values above 2 and below -2 were excluded:

| | N | Median | Mean | SD | | N | Median | Mean | SD |
|---|---|---|---|---|---|---|---|---|---|
| RROE | 15'073 | 0.1372 | 0.1611 | 0.1664 | RCE | 15'054 | 641'722 | 4'036'044 | 13'248'647 |
| FROE1 | 15'073 | 0.1491 | 0.1793 | 0.1515 | RCE1MD | 14'267 | 723'320 | 4'465'591 | 18'972'681 |
| FROE2 | 15'073 | 0.1552 | 0.1792 | 0.1389 | RCE2MD | 14'013 | 802'467 | 4'865'381 | 31'702'454 |
| FROE3 | 15'073 | 0.1587 | 0.179 | 0.1384 | RCE3MD | 13'649 | 895'168 | 5'353'151 | 48'947'736 |
| FROE4 | 15'073 | 0.1597 | 0.1775 | 0.1382 | RCE4MD | 13'138 | 1'012'897 | 5'883'944 | 69'434'021 |
| FROE5 | 15'073 | 0.16 | 0.1818 | 0.1539 | FLTGMD | 14'427 | 10.00 | 11.86 | 16.77 |
| RNI | 15'073 | 66'083 | 527'786 | 2'172'546 | | | | | |
| FNI1MD | 15'073 | 90'051 | 648'341 | 2'389'208 | | | | | |
| FNI2MD | 14'769 | 103'887 | 738'333 | 2'747'367 | | | | | |
| FNI3MD | 14'363 | 116'265 | 825'201 | 3'183'401 | | | | | |
| FNI4MD | 13'791 | 130'463 | 911'410 | 3'878'516 | | | | | |
| FNI5MD | 13'126 | 145'428 | 1'013'138 | 4'382'719 | | | | | |

Table 10: Descriptive statistics for ROE, net income, common equity, and LTG forecasts after filtering for analyst predictions

We computed the ROE values via the deflated approach. In the above table, we observe a reasonable increase in net income and common equity over time, which corresponded to the analysts' growth forecasts ($ROE_{t+i}$ / $ROE_{t+i-1}$) and LTG. More importantly, we notice that the realized ROE is significantly higher. This confirms that analysts tend to forecast profitable firms.

We then matched each realized ROE value with the corresponding forecasted value for the next five years. This method thus eliminated sample bias. Using a similar approach to that employed in previous sections, Figure 23 plots these 15'073 realized ROE values:

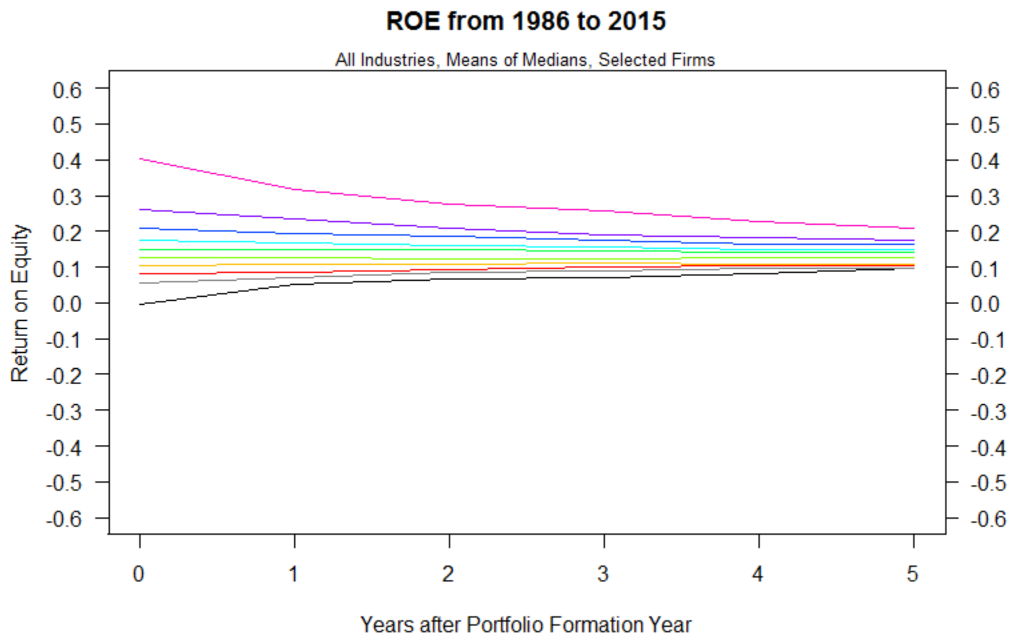


Figure 23: Mean of medians realized ROE in 10 predefined portfolios for a 5-year period ranging from 1986-2015 for selected firms

Surprisingly, the mean-reversion pattern substantially differs from the previous graphs. Overall, a mean-reversion process was observable, but in a much weaker form. The values in the portfolio formation years were much less extreme, and the lines did not intersect. The top portfolio started with a ROE value of 0.41, while in the original graph, including all realized observations, the first ROE value was 0.55. Even more surprisingly, the bottom portfolio started slightly below 0 (as compared to -0.6) and became positive as early as $t_1$. After five years, the portfolios' dispersion range became narrower (0.09 to 0.22). Also, the portfolios ended with a considerably higher ROE.

One of the implications of these findings could be that analysts rarely make predictions for current losers, and if they do, the values are only slightly negative. Furthermore, the average median realized ROE of 0.16 was clearly higher for this subset than when all ROE values were included (0.08). Das et al. (1998) provided evidence that analysts seem to be able to select and predict earnings for firms that will outperform others, and our results support this statement. Moving on, Figure 24 plots the analysts' forecasted ROE values.

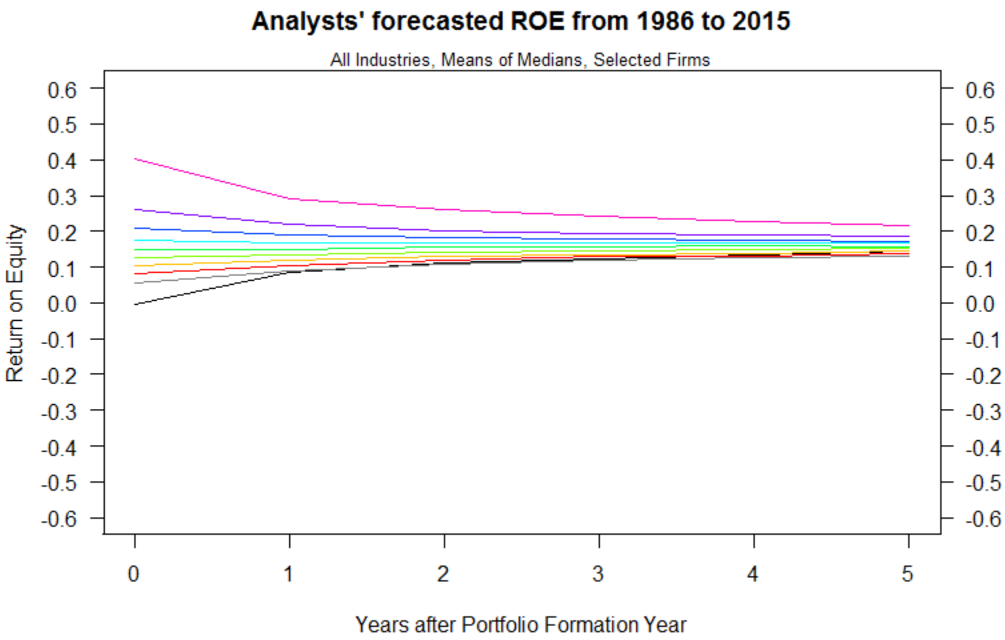


Figure 24: Mean of medians forecasted ROE in 10 predefined portfolios for a 5-year period ranging from 1986-2015 for selected firms

The above graph indicates that analysts' forecast a mean-reversion process. Therefore, our results confirmed Fama and French's (2000: 174) proposition. In $t_1$, the top and bottom portfolios seemed to revert slightly more quickly than the realized values. Further, the ending values had an even narrower range (0.12 to 0.21). Except for the bottom portfolios, none of the portfolios intersected each other.

Researchers such as Brown et al. (1987a) and Das et al. (1998) found that analysts' superiority over statistical models decreased as the forecasting period increased. The superiority may originate from the analysts' information advantage. According to their findings, we could expect two effects: (i) an increasing bias (more deviation from the overall forecasted median ROE than from the realized values) as the forecasting period becomes longer and (ii) a higher dispersion among the portfolios at longer forecast horizons. To be consistent with the previous procedure, we subtracted the analysts' predicted values from the realized ones. Figure 25 plots the differences between realized ROE and forecasted ROE for selected portfolios:

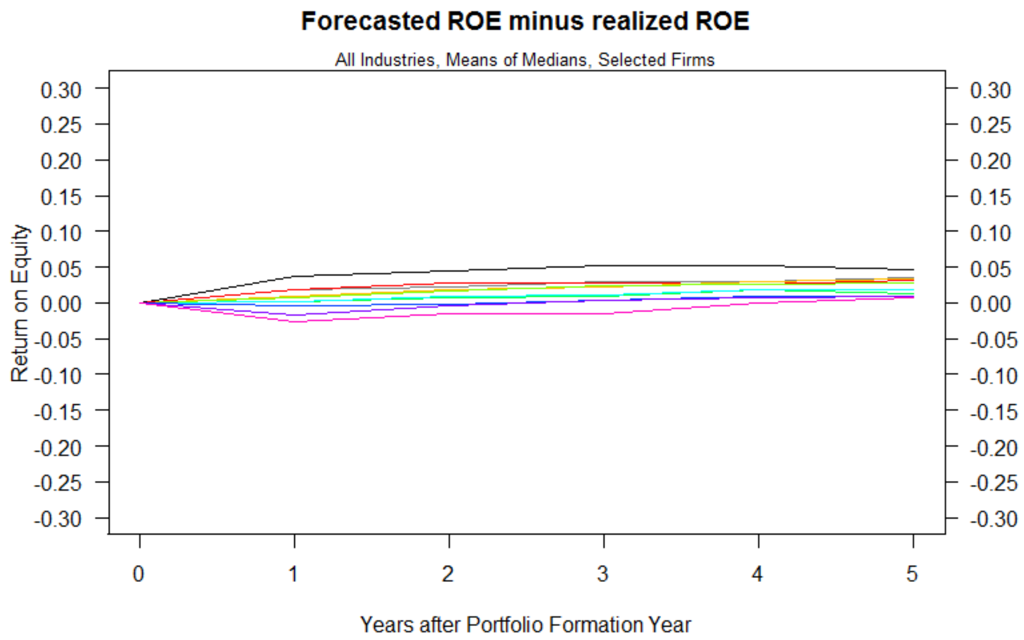


Figure 25: Difference in mean of medians between forecasted ROE and realized ROE for the predefined bottom portfolio of selected firms for a five-year period ranging from 1986-2015

When plotting the difference, the portfolios all fell very close to each other. There was considerably less dispersion when analysts selected the firms. To visualize these differences, we adjusted the y-axis to fit a narrower range. Nevertheless, the initial bottom portfolios were slightly overvalued. Portfolios 9 and 10, which had the highest starting values, became slightly negative, signifying that analysts undervalued them. Surprisingly, the total dispersion among the portfolios slightly decreased from $t_1$ to $t_5$. If analysts had a qualitative or quantitative information or timing advantage, we would expect the bias and dispersion to grow as the duration increased.

After reconsidering the new findings, we confirm the research question, whether analysts predict a mean-reverting pattern. The mean reversion of forecasted ROE is slightly stronger than the mean reversion of realized values. This overvaluation (undervaluation) of past losers (winners) remains throughout the prediction years. The analysts' optimism becomes increasingly noticeable in later forecast years, so that all of the portfolios were slightly overvalued in $t_5$. Nevertheless, analysts' general ability to predict ROE was surprisingly accurate.

Das et al. (1998) and Kross (1990) indicated that forecast accuracy grows as analyst coverage increases. If we consider years of consecutive forecasts as a proxy for increased analyst coverage, our results support the findings of Das et al. (1998) and Kross (1990).

Further, our results confirmed the findings of Brown et al. (1987b) and Harris and Wang (2013) that analysts' forecast accuracy increases as firm size increases. In our sub-sample, the firm size, measured in terms of net income and common equity, was clearly higher, as was the accuracy of the forecasts. Likewise, the analysts' coverage of firms was non-random.

As noted above, a weaker form of analyst optimism was still observable. Compared to when all analysts' forecasts were included in the sample (p. 52) the bias was much lower. O'Brien (1988), Butler and Lang (1991), Elgers and Lo (1994), Harris and Wang (2013), and Francis et al. (2004) all claimed that analysts are overly optimistic. Although their optimism was notable after five years, the analysts did undervalue the initial winners for the years $t_1$ to $t_4$. Based on the above findings, we would not conclude that analysts are overly, but to some extent optimistic.

Han et al. (2001) did not mention size of their study's I/B/E/S sample. Nevertheless, they compared the I/B/E/S sample to the relatively large 1993 Compustat tape. Moreover, they stated that poor past performance is positively correlated with higher forecast dispersion (Han et al., 2001: 105). When taking all firms and all analysts' forecasts into account, our findings support this statement, because the initial bottom portfolio deviated the most from the realized portfolio. However, when we only analyzed firms for which analysts had provided five-year forecasts, our results did only partially align with those of Han et al. (2001). Their unequal sample might have explained their high observed forecast dispersion for past losers.

To our knowledge, academic literature has not yet applied the above approach of solely including realized observations corresponding to analysts' predictions for the entire study period. Only Bradshaw et al. (2012) required, at minimum, a one-year earnings prediction as criterion for including fundamental data. Just as we did for the in the previous section, we analyze both the top and bottom portfolios in greater detail.

### 4.3.1 Bottom Portfolio

First, we split the bottom portfolio into 10 sub-portfolios. It is important to note that the sample size was much smaller. One sub-portfolio accounted for 1% of the data, or approximately 150 observations. In Figure 26, the left-hand graph provides realized ROE values for the 10 sub-portfolios, whereas the right-hand graph contains the forecasted values. Again, we adapted the scale to make the graphs more readable.

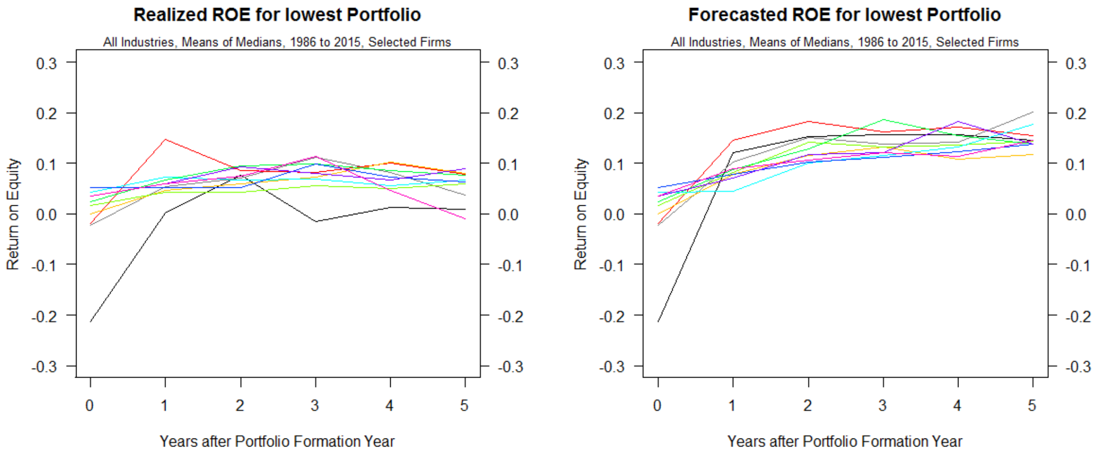


Figure 26: Left side: Mean of medians realized ROE for the predefined bottom portfolio for a five-year period for selected firms from 1986-2015. Right side: Mean of Medians forecasted ROE for the predefined bottom portfolio for a five-year period for selected firms from 1986-2015.

Compared with the complete sub-sample, in which a clear pattern could be identified, we faced a much more chaotic structure with numerous intersections between the portfolios. In portfolio formation year $t_0$, the initial values were closer to 0. The median value for the lowest 150 observations was slightly below -0.2. This result significantly differs from the previous results. When including all realized ROE values the lowest sub-portfolio started at -1.4. The initial top sub-portfolio was the lowest portfolio by $t_5$, with the initial bottom sub-portfolio in second-to-last place.

On the right-hand side in Figure 26, the initial bottom sub-portfolio experiences a steep increase. Also, the forecasted ROE values in $t_5$ ranged from 0.1 to 0.2. The sub-portfolios appear to be ordered rather randomly within a certain range. As in the other subsections, Figure 27 plots the differences between the bottom sub-portfolios:

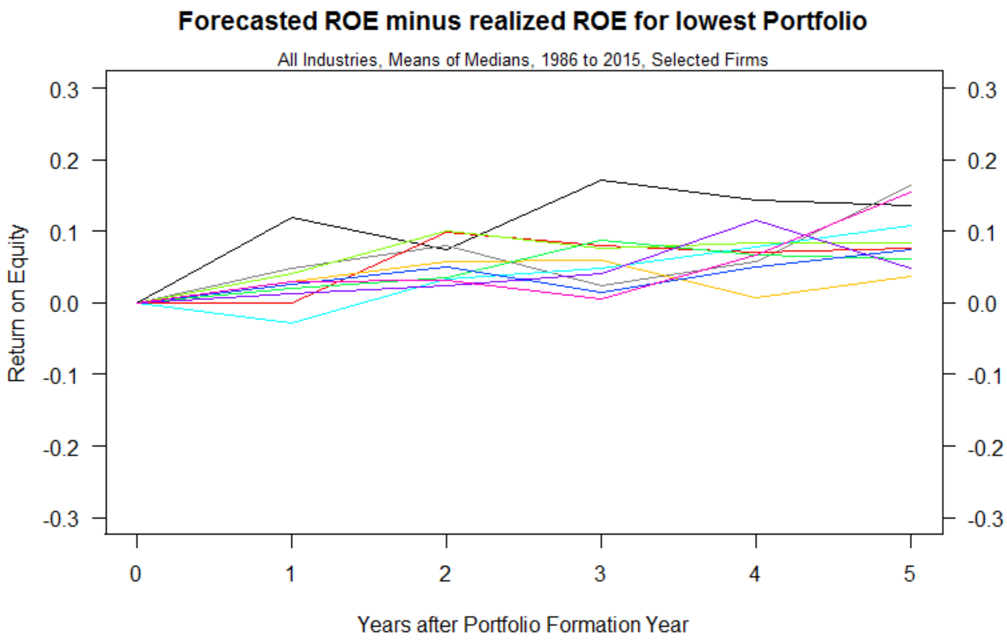


Figure 27: Difference in mean of medians between forecasted ROE and realized ROE for the predefined bottom portfolio of selected firms for a five-year period for selected firms ranging from 1986-2015

The differences among the sub-portfolios appear rather random. The top and bottom portfolios were the most overvalued at $t_5$. This difference could also be random, as the variance between the portfolios was high, and the sample size was rather small. The only consistent and visible factor in all of the sub-portfolios was the analysts' optimism.

### 4.3.2 Top Portfolio

Likewise, we divided the top portfolio into 10 sub-portfolios. In Figure 28, the left-hand graph represents the realized ROE values, whereas the right-hand graph provides the forecasted ROE values. Again, we have adapted the y-axis:

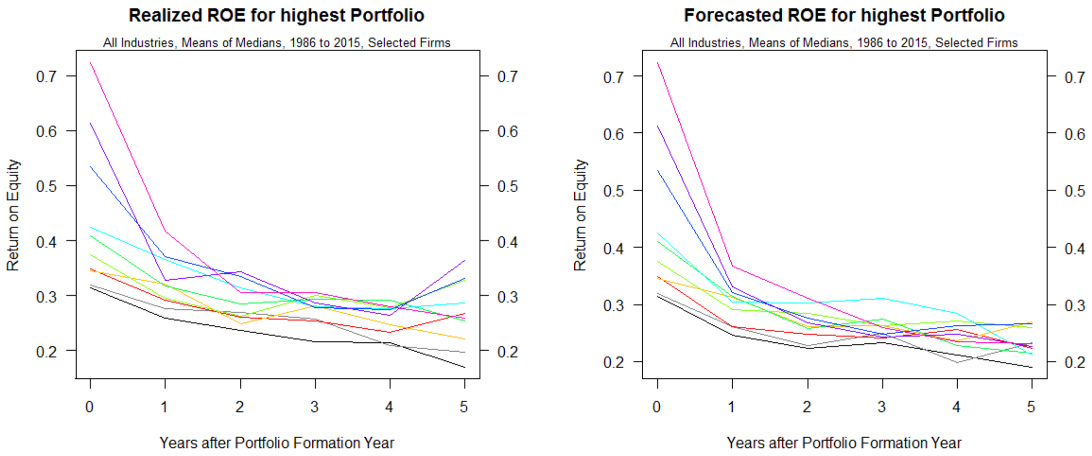


Figure 28: Left side: Mean of medians realized ROE for the predefined top portfolio for a five-year period for selected firms from 1986-2015. Right side: Mean of medians forecasted ROE for the predefined top portfolio for a five-year period for selected firms from 1986-2015.

In terms of realized ROE, the top sub-portfolios portfolios had fewer intersections than did the bottom sub-portfolios. Moreover, the order of the sub-portfolios did not vary much.

For forecasted ROE, a slightly stronger mean-reversion tendency was observable in $t_1$ is. In $t_2$, the forecasted sub-portfolios had slightly lower values. In $t_5$, the forecasted sub-portfolios had less variance than the realized values. However, this could have been a random effect due to the rather small sample size. The next step was to subtract the realized ROE from the forecasted ROE, resulting in Figure 29:

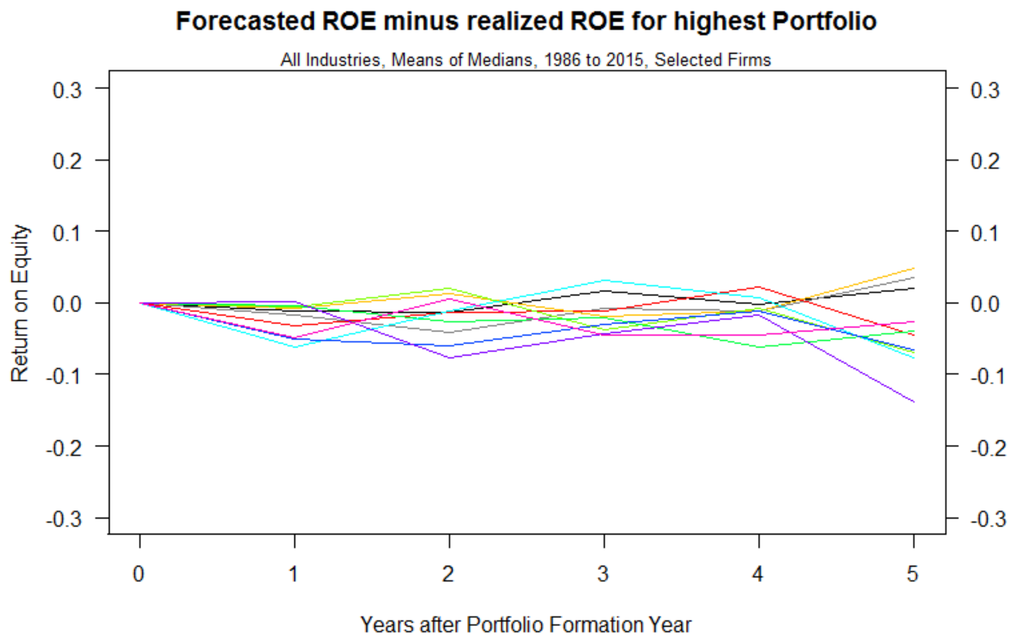


Figure 29: Difference in mean of medians between forecasted ROE and realized ROE for the predefined top portfolio of selected firms for a five-year period ranging from 1986-2015

Overall, the sub-portfolios were quite accurate. In $t_1$, almost all sub-portfolios are slightly underestimated the ROE. This effect persisted over the following years but in a weaker form. The dispersion increased as the forecast horizon grew.

## 4.4 Forecasting ROE

Many researchers have tried to predict future ROE or improve analysts' forecasts by using quantitative financial statement metrics in their regressions. The literature review presented the models used by Fama and French (2000) and Evans et al. (2012). However, these models proved only partially applicable when forecasting ROE. After all, Palepu et al. (2010: 278) mentioned that the actual ROE is not useful for predicting the one-year-ahead ROE. Researchers' ROE prediction models include quantitative data but fail to utilize qualitative data and cannot predict sudden swings in ROE. As seen in the graphical analysis of ROE, results remain extremely stable when the yearly median of a portfolio with numerous observations is used. This delivers the impression that a firm's ROE does not vary much over time. However, when analyzing the sub-portfolios (see Chapter 4.3), we found that they had a considerable amount of variance, with a drastically changing ROE from one year to the next. As analysts provide individual forecasts for each firm with all available qualitative and quantitative information, they might be capable of more accurately predicting sizeable changes in ROE.

Therefore, an alternative approach to predicting ROE could be to correct analysts' forecasts for the individual portfolios' observed bias. We propose the following formula for forecasting ROE:

$$AFROE_{t+i}^{k} = FROE_{t+i}^{k} - DAF_{t+i}^{p}$$

Where $AFROE_{t+i}^{k}$ is the alternative forecasted ROE for every individual firm *k* in year *t* for *i* years ahead, $FROE_{t+i}^{k}$ is the analysts' forecasted ROE for every individual firm *k* in year *t* for *i* years ahead, and $DAF_{t+i}^{p}$ is the observed portfolio dispersion in analysts' forecasts ($FROE_{t+i}^{p} - RROE_{t+i}^{p}$) for the observed portfolio *p* in formation year *t* for *i* years ahead.

Our above model uses analysts' forecasts, which presumably includes all available qualitative and quantitative information. Additionally, it corrects for the still unknown bias of the individual portfolios, as presented in the previous sections. In other words, the above model reduces the forecast bias by the absolute median error of each portfolio. For instance, the analysts' the five-year forecasts for all firms in the bottom portfolio would be reduced by 5%.

We are not aware of a formula for assessing the accuracy of ROE prediction models. Therefore, we propose the following model for evaluating the forecast accuracy of existing ROE prediction models:

$$\frac{1}{n}\sum_{k=1}^{n}|FROE_{t+i}^{k} - RROE_{t+i}^{k}|$$

Where $FROE_{t+i}$ stands for the forecasted ROE for every individual firm *k* in year *t* for *i* years after the portfolio formation year and $RROE_{t+i}^{k}$ stands for the realized ROE for every individual firm *k* in portfolio formation year *t* for *i* years after the portfolio formation year.

In other words, the model computes the absolute average error between a prediction and a realized value. The lower (higher) the average error, the more (less) precise is the prediction model. To measure the model's performance, we propose using the Least Absolute Deviation method instead of the OLS that standard models employ. Also, Evans et al.'s (2012) regressions followed the Least Absolute Deviation method to avoid overweighting the outliers.

The above formula allows one to compare whether existing ROE prediction models, analysts' forecasts, or the adjusted analysts' forecast method is the most accurate approach to forecasting ROE. However, evaluating different ROE prediction models in terms of their accuracy has to be done in future research.

# 5 General Conclusions and Suggestions for Future Research

The thesis' main research question asked whether analysts forecast mean reversion in ROE. Our mean-reversion pattern of realized ROE was very similar to the one of von Arx (2015: 29). The results confirmed that the top (bottom) portfolios strictly decrease (increase) when reverting to the mean. Also, firms with initial high (low) profits remained more (less) profitable after the completion of the mean-reversion process. The most important difference was that the top and bottom portfolios had slightly more extreme values in the portfolio formation year.

Since we could not find any existing formulas for converting EPS to ROE and combining Worldscope with I/B/E/S data, we created a transformation technique to omit differences. The forecasts' graphical analysis answered our main research question and showed that analysts partially predicted a mean-reverting ROE. Further analysis revealed that analysts predict a stronger mean-reversion process one year after the portfolio formation year. However, the top and bottom portfolios saw a steep increase in $t_2$ and then remained above the other portfolios which contradicted previous studies of realized ROE values. Also, the results indicated a strong form of analyst optimism, particularly for two- to five-years-ahead forecasts.

The above findings were quite surprising and led to more questions. Therefore, we split the top and the bottom portfolio into 10 sub-portfolios. The analysts' optimism was clearly observable for the bottom portfolio. However, we found that analysts slightly undervalued the top portfolio in $t_1$.

Further, we observed that analysts rather release predictions for large firms (measured by their net income and common equity). Also, analysts publish drastically fewer predictions for past losers, and if they do, earnings predictions are positive. In contrast to previous literature, we then only selected firms for which a realized ROE and five-years-ahead predictions were available. Consequently, the sample significantly shrunk to 15'073 firms, most of which were larger and surprisingly more profitable. Therefore, we concluded that analysts have predictive power regarding future ROE.

After replotting the realized data, we still observed a mean-reverting ROE pattern but in a much weaker form. We confirmed the research question when only considering firms that analysts made predictions for: Analysts do predict a mean-reverting process in ROE. Furthermore, the analyst's optimism drastically declined to a few percentage points and forecast accuracy deeply improved. Therefore, the results indicated that analysts forecast ROE quite successfully for the firms they select. Nevertheless, a systematic bias was observable. Past losers, being part of the initial bottom portfolios, were overvalued, whereas past winners tended to be slightly undervalued.

The final sub-section proposed an approach to reducing the ROE forecast bias. Our ROE prediction model used analysts' forecasts, that include both, quantitative and qualitative information and adjusted them for the systemic bias our work observed. Additionally, we suggested a formula for evaluating the accuracy of various ROE prediction models.

We ensured comparability and validity by applying the same approach as von Arx (2015). The very similar mean-reversion graphs of von Arx's (2015) and this study approves the above statement. One of the limitations of our study is the sample structure. It is conducted for a considerable amount of firms in Europe but did not compare the results to other regions. Further, we compared analysts' predictions of realized ROE observations by using the median of portfolios. However, we did not compare the ROE of individual firms. The deviation of an individual firms' ROE from its forecast might be much higher as the portfolios suggested.

The results of this thesis could be helpful increasing analysts' forecast accuracy. Already the awareness of a systematic bias may be enough to improve future forecasts. Analysts' forecasts include both, quantitative and qualitative data. A model using analysts' forecasts and adjusting for the observed bias could possibly be superior in ROE forecast accuracy than existing models. Future research could also compare the accuracy of existing ROE predictions models by using the proposed absolute deviation model. This could result in more detailed knowledge about analysts' forecasts.

## Appendices

# Appendix 1

| | AT | BE | CH | DE | DK | ES | FI | FR | GB | GR | IR | IT | NL | NO | PT | SE | Tot. | Von A. |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **1982** | | | | | | | | | | | | | | | | | | |
| N | 16 | 42 | 28 | 186 | 36 | 35 | 47 | 139 | 280 | 0 | 13 | 48 | 56 | 33 | 0 | 73 | 1032 | 919 |
| Median | -0.07 | 0.07 | 0.07 | 0.05 | 0.12 | 0.03 | 0.05 | 0.09 | 0.10 | | 0.08 | 0.09 | 0.08 | 0.07 | | -0.01 | 0.07 | |
| Mean | -0.16 | 0.02 | 0.06 | 0.04 | 0.15 | -0.06 | 0.06 | 0.03 | 0.09 | | 0.07 | 0.03 | 0.08 | 0.06 | | -0.02 | 0.05 | |
| SD | 0.31 | 0.27 | 0.11 | 0.26 | 0.21 | 0.43 | 0.22 | 0.31 | 0.15 | | 0.08 | 0.42 | 0.14 | 0.47 | | 0.25 | 0.24 | |
| **1983** | | | | | | | | | | | | | | | | | | |
| N | 15 | 44 | 30 | 190 | 38 | 33 | 49 | 139 | 286 | 0 | 18 | 50 | 57 | 33 | 0 | 77 | 1059 | 938 |
| Median | -0.01 | 0.08 | 0.06 | 0.07 | 0.13 | 0.03 | 0.06 | 0.10 | 0.13 | | 0.13 | 0.08 | 0.10 | 0.11 | | -0.03 | 0.09 | |
| Mean | 0.01 | 0.07 | 0.05 | 0.04 | 0.17 | -0.07 | 0.09 | 0.06 | 0.11 | | 0.13 | -0.01 | 0.09 | 0.14 | | 0.00 | 0.07 | |
| SD | 0.16 | 0.21 | 0.10 | 0.20 | 0.18 | 0.30 | 0.15 | 0.24 | 0.16 | | 0.16 | 0.34 | 0.19 | 0.46 | | 0.17 | 0.20 | |
| **1984** | | | | | | | | | | | | | | | | | | |
| N | 20 | 43 | 32 | 207 | 40 | 35 | 53 | 152 | 301 | 0 | 21 | 51 | 63 | 34 | 0 | 80 | 1132 | 1005 |
| Median | 0.01 | 0.13 | 0.08 | 0.08 | 0.16 | 0.03 | 0.05 | 0.10 | 0.14 | | 0.09 | 0.12 | 0.13 | 0.11 | | -0.02 | 0.10 | |
| Mean | 0.02 | 0.10 | 0.10 | 0.07 | 0.18 | 0.03 | 0.12 | 0.05 | 0.12 | | 0.09 | 0.05 | 0.17 | 0.09 | | 0.01 | 0.09 | |
| SD | 0.22 | 0.37 | 0.10 | 0.22 | 0.20 | 0.41 | 0.18 | 0.30 | 0.16 | | 0.09 | 0.37 | 0.22 | 0.34 | | 0.18 | 0.23 | |
| **1985** | | | | | | | | | | | | | | | | | | |
| N | 23 | 45 | 47 | 219 | 47 | 41 | 53 | 160 | 387 | 2 | 23 | 62 | 66 | 42 | 2 | 80 | 1299 | 1161 |
| Median | -0.04 | 0.12 | 0.08 | 0.09 | 0.11 | 0.03 | 0.05 | 0.14 | 0.13 | 0.12 | 0.11 | 0.12 | 0.14 | 0.10 | -0.40 | -0.02 | 0.10 | |
| Mean | -0.02 | 0.12 | 0.11 | 0.10 | 0.13 | 0.03 | 0.11 | 0.11 | 0.13 | 0.12 | 0.09 | 0.11 | 0.15 | 0.16 | -0.40 | 0.02 | 0.11 | |
| SD | 0.51 | 0.19 | 0.14 | 0.20 | 0.24 | 0.23 | 0.23 | 0.21 | 0.23 | 0.07 | 0.17 | 0.29 | 0.11 | 0.40 | 0.58 | 0.21 | 0.22 | |
| **1986** | | | | | | | | | | | | | | | | | | |
| N | 28 | 45 | 57 | 229 | 47 | 42 | 55 | 165 | 438 | 7 | 26 | 66 | 65 | 41 | 10 | 84 | 1405 | 1275 |
| Median | 0.04 | 0.14 | 0.10 | 0.09 | 0.15 | 0.06 | 0.06 | 0.14 | 0.16 | 0.08 | 0.12 | 0.15 | 0.15 | 0.10 | 0.14 | -0.04 | 0.12 | |
| Mean | 0.05 | 0.13 | 0.12 | 0.10 | 0.12 | 0.13 | 0.14 | 0.11 | 0.17 | 0.22 | 0.13 | 0.18 | 0.13 | 0.05 | 0.17 | -0.02 | 0.12 | |
| SD | 0.23 | 0.24 | 0.11 | 0.23 | 0.28 | 0.33 | 0.27 | 0.25 | 0.26 | 0.33 | 0.16 | 0.22 | 0.15 | 0.52 | 0.22 | 0.25 | 0.25 | |
| **1987** | | | | | | | | | | | | | | | | | | |
| N | 35 | 54 | 74 | 235 | 45 | 45 | 56 | 170 | 458 | 19 | 30 | 82 | 64 | 43 | 28 | 84 | 1522 | 1418 |
| Median | 0.08 | 0.09 | 0.08 | 0.09 | 0.12 | 0.10 | 0.12 | 0.16 | 0.19 | 0.35 | 0.17 | 0.13 | 0.13 | 0.11 | 0.22 | 0.00 | 0.14 | |
| Mean | 0.08 | 0.08 | 0.10 | 0.11 | 0.11 | 0.12 | 0.11 | 0.13 | 0.19 | 0.39 | 0.19 | 0.14 | 0.10 | 0.20 | 0.24 | 0.03 | 0.14 | |
| SD | 0.21 | 0.23 | 0.09 | 0.21 | 0.23 | 0.17 | 0.32 | 0.24 | 0.23 | 0.36 | 0.21 | 0.17 | 0.23 | 0.51 | 0.23 | 0.24 | 0.23 | |
| **1988** | | | | | | | | | | | | | | | | | | |
| N | 42 | 86 | 118 | 300 | 60 | 80 | 63 | 324 | 825 | 20 | 33 | 156 | 104 | 71 | 33 | 97 | 2412 | 2249 |
| Median | 0.11 | 0.15 | 0.09 | 0.10 | 0.16 | 0.13 | 0.14 | 0.18 | 0.20 | 0.24 | 0.14 | 0.15 | 0.16 | 0.08 | 0.19 | -0.02 | 0.15 | |
| Mean | 0.13 | 0.15 | 0.10 | 0.12 | 0.19 | 0.17 | 0.20 | 0.20 | 0.21 | 0.27 | 0.20 | 0.16 | 0.19 | 0.11 | 0.23 | 0.03 | 0.17 | |
| SD | 0.41 | 0.25 | 0.18 | 0.16 | 0.18 | 0.18 | 0.25 | 0.28 | 0.26 | 0.24 | 0.22 | 0.16 | 0.23 | 0.41 | 0.23 | 0.27 | 0.24 | |
| **1989** | | | | | | | | | | | | | | | | | | |
| N | 44 | 85 | 128 | 378 | 98 | 95 | 83 | 402 | 1079 | 20 | 34 | 163 | 118 | 77 | 36 | 113 | 2953 | 2788 |
| Median | 0.14 | 0.15 | 0.10 | 0.11 | 0.12 | 0.14 | 0.06 | 0.18 | 0.17 | 0.26 | 0.18 | 0.13 | 0.16 | 0.14 | 0.13 | -0.02 | 0.14 | |
| Mean | 0.17 | 0.19 | 0.13 | 0.12 | 0.15 | 0.16 | 0.11 | 0.20 | 0.17 | 0.25 | 0.15 | 0.14 | 0.19 | 0.18 | 0.16 | 0.06 | 0.16 | |
| SD | 0.18 | 0.30 | 0.14 | 0.21 | 0.14 | 0.13 | 0.24 | 0.27 | 0.30 | 0.25 | 0.14 | 0.15 | 0.21 | 0.39 | 0.11 | 0.24 | 0.25 | |
| **1990** | | | | | | | | | | | | | | | | | | |
| N | 54 | 82 | 133 | 391 | 114 | 103 | 97 | 451 | 1158 | 21 | 44 | 168 | 124 | 81 | 40 | 137 | 3198 | 3018 |
| Median | 0.11 | 0.11 | 0.08 | 0.11 | 0.11 | 0.10 | 0.06 | 0.16 | 0.13 | 0.18 | 0.13 | 0.11 | 0.15 | 0.07 | 0.11 | 0.01 | 0.12 | |
| Mean | 0.14 | 0.10 | 0.11 | 0.12 | 0.14 | 0.10 | 0.07 | 0.14 | 0.13 | 0.27 | 0.07 | 0.11 | 0.18 | 0.10 | 0.13 | 0.06 | 0.12 | |
| SD | 0.11 | 0.28 | 0.18 | 0.17 | 0.17 | 0.14 | 0.15 | 0.28 | 0.29 | 0.47 | 0.30 | 0.13 | 0.21 | 0.40 | 0.11 | 0.24 | 0.24 | |
| **1991** | | | | | | | | | | | | | | | | | | |
| N | 54 | 84 | 135 | 412 | 118 | 111 | 91 | 469 | 1191 | 27 | 44 | 168 | 146 | 86 | 41 | 138 | 3315 | 3108 |
| Median | 0.09 | 0.08 | 0.08 | 0.09 | 0.08 | 0.08 | 0.03 | 0.12 | 0.08 | 0.14 | 0.13 | 0.08 | 0.15 | 0.06 | 0.07 | -0.01 | 0.09 | |
| Mean | 0.11 | 0.09 | 0.09 | 0.09 | 0.09 | 0.04 | 0.00 | 0.11 | 0.08 | 0.14 | 0.09 | 0.07 | 0.16 | 0.05 | 0.12 | 0.02 | 0.08 | |
| SD | 0.18 | 0.28 | 0.11 | 0.23 | 0.17 | 0.24 | 0.21 | 0.29 | 0.27 | 0.22 | 0.25 | 0.14 | 0.17 | 0.42 | 0.24 | 0.19 | 0.24 | |
| **1992** | | | | | | | | | | | | | | | | | | |
| N | 57 | 83 | 133 | 410 | 120 | 112 | 91 | 460 | 1175 | 44 | 44 | 166 | 154 | 89 | 41 | 137 | 3316 | 3116 |
| Median | 0.06 | 0.06 | 0.07 | 0.07 | 0.08 | 0.05 | 0.04 | 0.10 | 0.07 | 0.07 | 0.10 | 0.04 | 0.12 | 0.06 | 0.05 | -0.01 | 0.07 | |
| Mean | 0.05 | 0.04 | 0.06 | 0.03 | 0.08 | -0.08 | 0.00 | 0.08 | 0.07 | 0.14 | 0.04 | -0.02 | 0.12 | 0.06 | 0.05 | -0.02 | 0.05 | |
| SD | 0.25 | 0.29 | 0.19 | 0.29 | 0.24 | 0.35 | 0.33 | 0.25 | 0.29 | 0.28 | 0.26 | 0.25 | 0.23 | 0.57 | 0.17 | 0.16 | 0.28 | |
| **1993** | | | | | | | | | | | | | | | | | | |
| N | 56 | 81 | 132 | 424 | 119 | 110 | 86 | 467 | 1157 | 74 | 43 | 150 | 149 | 80 | 46 | 135 | 3309 | 3107 |
| Median | 0.05 | 0.06 | 0.08 | 0.07 | 0.08 | 0.05 | 0.10 | 0.08 | 0.07 | 0.10 | 0.13 | 0.05 | 0.12 | 0.09 | 0.02 | 0.00 | 0.07 | |
| Mean | 0.02 | 0.01 | 0.04 | 0.04 | 0.08 | -0.08 | 0.14 | 0.04 | 0.05 | 0.22 | 0.09 | -0.03 | 0.10 | 0.06 | -0.02 | 0.03 | 0.04 | |
| SD | 0.28 | 0.25 | 0.27 | 0.30 | 0.17 | 0.36 | 0.38 | 0.30 | 0.31 | 0.35 | 0.30 | 0.29 | 0.23 | 0.24 | 0.21 | 0.18 | 0.29 | |
| **1994** | | | | | | | | | | | | | | | | | | |
| N | 64 | 85 | 137 | 460 | 122 | 114 | 92 | 450 | 1164 | 91 | 43 | 145 | 152 | 91 | 45 | 137 | 3392 | 3169 |
| Median | 0.14 | 0.08 | 0.10 | 0.09 | 0.12 | 0.08 | 0.16 | 0.11 | 0.09 | 0.15 | 0.12 | 0.05 | 0.15 | 0.13 | 0.03 | 0.02 | 0.10 | |
| Mean | 0.11 | 0.09 | 0.10 | 0.08 | 0.12 | 0.04 | 0.21 | 0.10 | 0.08 | 0.18 | 0.10 | -0.01 | 0.17 | 0.13 | 0.00 | 0.07 | 0.09 | |
| SD | 0.36 | 0.24 | 0.22 | 0.33 | 0.20 | 0.35 | 0.33 | 0.23 | 0.32 | 0.33 | 0.17 | 0.28 | 0.21 | 0.24 | 0.24 | 0.20 | 0.28 | |

| | AT | BE | CH | DE | DK | ES | FI | FR | GB | GR | IR | IT | NL | NO | PT | SE | Tot. | Von A. |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **1995** | | | | | | | | | | | | | | | | | | |
| N | 61 | 81 | 139 | 458 | 120 | 113 | 92 | 433 | 1173 | 92 | 42 | 143 | 147 | 93 | 54 | 144 | 3385 | 3193 |
| Median | 0.15 | 0.09 | 0.09 | 0.10 | 0.13 | 0.10 | 0.16 | 0.09 | 0.11 | 0.14 | 0.13 | 0.08 | 0.18 | 0.15 | 0.06 | 0.00 | 0.10 | |
| Mean | 0.19 | 0.10 | 0.11 | 0.07 | 0.13 | 0.09 | 0.17 | 0.07 | 0.09 | 0.14 | 0.14 | 0.06 | 0.21 | 0.13 | 0.06 | 0.06 | 0.10 | |
| SD | 0.27 | 0.18 | 0.17 | 0.33 | 0.16 | 0.33 | 0.25 | 0.25 | 0.31 | 0.27 | 0.34 | 0.31 | 0.24 | 0.30 | 0.18 | 0.23 | 0.28 | |
| **1996** | | | | | | | | | | | | | | | | | | |
| N | 62 | 77 | 138 | 454 | 118 | 114 | 90 | 430 | 1169 | 92 | 41 | 141 | 152 | 87 | 56 | 142 | 3363 | 3164 |
| Median | 0.11 | 0.10 | 0.10 | 0.09 | 0.13 | 0.10 | 0.15 | 0.10 | 0.11 | 0.13 | 0.09 | 0.09 | 0.17 | 0.14 | 0.07 | 0.03 | 0.11 | |
| Mean | 0.13 | 0.09 | 0.11 | 0.03 | 0.12 | 0.12 | 0.15 | 0.09 | 0.09 | 0.15 | 0.11 | 0.09 | 0.21 | 0.16 | 0.10 | 0.06 | 0.09 | |
| SD | 0.20 | 0.19 | 0.21 | 0.37 | 0.24 | 0.22 | 0.14 | 0.26 | 0.32 | 0.21 | 0.22 | 0.27 | 0.25 | 0.19 | 0.26 | 0.18 | 0.28 | |
| **1997** | | | | | | | | | | | | | | | | | | |
| N | 81 | 90 | 169 | 581 | 151 | 137 | 113 | 617 | 1372 | 136 | 51 | 157 | 172 | 154 | 85 | 177 | 4243 | 3192 |
| Median | 0.12 | 0.15 | 0.13 | 0.13 | 0.14 | 0.12 | 0.20 | 0.14 | 0.11 | 0.14 | 0.11 | 0.11 | 0.19 | 0.16 | 0.07 | 0.02 | 0.13 | |
| Mean | 0.17 | 0.16 | 0.15 | 0.17 | 0.19 | 0.14 | 0.25 | 0.19 | 0.11 | 0.21 | 0.10 | 0.15 | 0.26 | 0.20 | 0.11 | 0.05 | 0.15 | |
| SD | 0.30 | 0.27 | 0.31 | 0.42 | 0.30 | 0.27 | 0.26 | 0.36 | 0.41 | 0.32 | 0.39 | 0.28 | 0.32 | 0.46 | 0.23 | 0.33 | 0.37 | |
| **1998** | | | | | | | | | | | | | | | | | | |
| N | 85 | 114 | 180 | 671 | 156 | 132 | 135 | 698 | 1401 | 146 | 53 | 179 | 191 | 165 | 72 | 198 | 4576 | 3327 |
| Median | 0.12 | 0.14 | 0.13 | 0.14 | 0.13 | 0.14 | 0.16 | 0.16 | 0.10 | 0.15 | 0.14 | 0.13 | 0.20 | 0.08 | 0.09 | 0.06 | 0.13 | |
| Mean | 0.12 | 0.16 | 0.16 | 0.18 | 0.15 | 0.18 | 0.22 | 0.24 | 0.07 | 0.17 | 0.12 | 0.18 | 0.28 | 0.06 | 0.10 | 0.09 | 0.15 | |
| SD | 0.45 | 0.37 | 0.28 | 0.47 | 0.28 | 0.18 | 0.39 | 0.46 | 0.47 | 0.26 | 0.42 | 0.28 | 0.47 | 0.40 | 0.16 | 0.35 | 0.41 | |
| **1999** | | | | | | | | | | | | | | | | | | |
| N | 87 | 112 | 175 | 701 | 147 | 129 | 134 | 744 | 1279 | 150 | 55 | 190 | 182 | 151 | 68 | 201 | 4505 | 3257 |
| Median | 0.09 | 0.15 | 0.13 | 0.13 | 0.12 | 0.14 | 0.16 | 0.17 | 0.07 | 0.17 | 0.15 | 0.13 | 0.19 | 0.06 | 0.10 | 0.03 | 0.12 | |
| Mean | 0.10 | 0.17 | 0.12 | 0.13 | 0.10 | 0.18 | 0.23 | 0.23 | 0.05 | 0.23 | 0.09 | 0.16 | 0.26 | 0.04 | 0.11 | 0.04 | 0.13 | |
| SD | 0.49 | 0.39 | 0.32 | 0.48 | 0.31 | 0.25 | 0.29 | 0.46 | 0.42 | 0.40 | 0.40 | 0.26 | 0.39 | 0.43 | 0.20 | 0.45 | 0.41 | |
| **2000** | | | | | | | | | | | | | | | | | | |
| N | 89 | 113 | 178 | 718 | 140 | 132 | 132 | 751 | 1206 | 211 | 59 | 210 | 160 | 136 | 64 | 226 | 4525 | 3646 |
| Median | 0.10 | 0.11 | 0.12 | 0.10 | 0.10 | 0.14 | 0.16 | 0.15 | 0.02 | 0.13 | 0.12 | 0.10 | 0.20 | 0.05 | 0.08 | 0.02 | 0.09 | |
| Mean | 0.10 | 0.03 | 0.12 | 0.04 | 0.08 | 0.14 | 0.19 | 0.16 | -0.01 | 0.18 | 0.04 | 0.11 | 0.18 | -0.04 | 0.11 | -0.01 | 0.07 | |
| SD | 0.35 | 0.46 | 0.33 | 0.47 | 0.33 | 0.26 | 0.36 | 0.47 | 0.44 | 0.29 | 0.43 | 0.34 | 0.35 | 0.48 | 0.25 | 0.52 | 0.42 | |
| **2001** | | | | | | | | | | | | | | | | | | |
| N | 83 | 106 | 196 | 753 | 134 | 133 | 137 | 739 | 1294 | 263 | 58 | 225 | 155 | 144 | 66 | 244 | 4730 | 3947 |
| Median | 0.07 | 0.08 | 0.08 | 0.05 | 0.07 | 0.11 | 0.10 | 0.11 | -0.02 | 0.07 | 0.03 | 0.06 | 0.14 | 0.02 | 0.05 | 0.00 | 0.05 | |
| Mean | 0.00 | 0.03 | 0.05 | -0.02 | 0.05 | 0.09 | 0.07 | 0.08 | -0.09 | 0.12 | -0.07 | -0.01 | 0.10 | -0.09 | 0.01 | -0.11 | -0.01 | |
| SD | 0.25 | 0.38 | 0.27 | 0.41 | 0.41 | 0.23 | 0.30 | 0.41 | 0.40 | 0.26 | 0.42 | 0.35 | 0.34 | 0.40 | 0.29 | 0.43 | 0.38 | |
| **2002** | | | | | | | | | | | | | | | | | | |
| N | 74 | 100 | 193 | 685 | 131 | 124 | 133 | 698 | 1361 | 274 | 59 | 215 | 143 | 152 | 58 | 282 | 4682 | 4436 |
| Median | 0.04 | 0.03 | 0.05 | 0.02 | 0.07 | 0.11 | 0.08 | 0.08 | -0.02 | 0.05 | 0.00 | 0.04 | 0.10 | 0.00 | 0.04 | -0.01 | 0.03 | |
| Mean | -0.03 | 0.02 | -0.01 | -0.09 | 0.06 | 0.09 | 0.03 | 0.03 | -0.10 | 0.07 | -0.06 | -0.03 | 0.03 | -0.12 | -0.01 | -0.11 | -0.04 | |
| SD | 0.34 | 0.37 | 0.25 | 0.40 | 0.34 | 0.25 | 0.25 | 0.40 | 0.43 | 0.28 | 0.29 | 0.31 | 0.32 | 0.42 | 0.28 | 0.37 | 0.37 | |
| **2003** | | | | | | | | | | | | | | | | | | |
| N | 68 | 104 | 190 | 678 | 125 | 123 | 129 | 684 | 1384 | 273 | 57 | 219 | 138 | 144 | 57 | 271 | 4644 | 4460 |
| Median | 0.06 | 0.07 | 0.07 | 0.04 | 0.06 | 0.12 | 0.08 | 0.08 | -0.01 | 0.05 | 0.04 | 0.04 | 0.08 | 0.09 | 0.04 | 0.00 | 0.04 | |
| Mean | 0.03 | 0.01 | 0.04 | -0.04 | 0.03 | 0.12 | 0.03 | 0.04 | -0.05 | 0.07 | -0.03 | -0.05 | 0.05 | 0.01 | 0.02 | -0.07 | -0.01 | |
| SD | 0.22 | 0.32 | 0.30 | 0.44 | 0.33 | 0.25 | 0.27 | 0.33 | 0.45 | 0.25 | 0.39 | 0.35 | 0.35 | 0.38 | 0.33 | 0.35 | 0.37 | |
| **2004** | | | | | | | | | | | | | | | | | | |
| N | 68 | 108 | 193 | 689 | 113 | 125 | 130 | 700 | 1443 | 274 | 54 | 226 | 133 | 153 | 52 | 272 | 4733 | 4471 |
| Median | 0.10 | 0.09 | 0.10 | 0.07 | 0.09 | 0.14 | 0.14 | 0.11 | 0.00 | 0.07 | 0.04 | 0.07 | 0.12 | 0.11 | 0.14 | 0.05 | 0.06 | |
| Mean | 0.10 | 0.12 | 0.07 | 0.03 | 0.03 | 0.13 | 0.13 | 0.08 | 0.00 | 0.08 | 0.02 | 0.04 | 0.10 | 0.09 | 0.14 | 0.02 | 0.05 | |
| SD | 0.32 | 0.37 | 0.27 | 0.45 | 0.42 | 0.28 | 0.33 | 0.42 | 0.44 | 0.32 | 0.45 | 0.33 | 0.38 | 0.41 | 0.47 | 0.33 | 0.40 | |
| **2005** | | | | | | | | | | | | | | | | | | |
| N | 66 | 121 | 191 | 696 | 110 | 123 | 127 | 686 | 1490 | 273 | 55 | 239 | 129 | 166 | 53 | 297 | 4822 | 4617 |
| Median | 0.14 | 0.12 | 0.11 | 0.10 | 0.11 | 0.17 | 0.16 | 0.14 | 0.00 | 0.05 | 0.06 | 0.11 | 0.16 | 0.16 | 0.09 | 0.09 | 0.08 | |
| Mean | 0.16 | 0.09 | 0.11 | 0.08 | 0.09 | 0.19 | 0.13 | 0.13 | -0.01 | 0.04 | 0.10 | 0.08 | 0.17 | 0.16 | 0.10 | 0.06 | 0.07 | |
| SD | 0.47 | 0.41 | 0.24 | 0.45 | 0.35 | 0.29 | 0.26 | 0.42 | 0.47 | 0.33 | 0.45 | 0.35 | 0.34 | 0.46 | 0.33 | 0.43 | 0.41 | |
| **2006** | | | | | | | | | | | | | | | | | | |
| N | 68 | 118 | 198 | 712 | 150 | 125 | 121 | 697 | 1534 | 262 | 55 | 247 | 127 | 184 | 52 | 366 | 5016 | 4855 |
| Median | 0.13 | 0.13 | 0.12 | 0.12 | 0.13 | 0.18 | 0.14 | 0.14 | -0.01 | 0.07 | 0.08 | 0.10 | 0.19 | 0.14 | 0.12 | 0.07 | 0.08 | |
| Mean | 0.11 | 0.10 | 0.13 | 0.07 | 0.14 | 0.19 | 0.13 | 0.16 | -0.03 | 0.07 | 0.06 | 0.08 | 0.17 | 0.09 | 0.12 | 0.03 | 0.06 | |
| SD | 0.38 | 0.34 | 0.27 | 0.43 | 0.32 | 0.35 | 0.26 | 0.40 | 0.46 | 0.33 | 0.47 | 0.30 | 0.31 | 0.47 | 0.25 | 0.46 | 0.40 | |
| **2007** | | | | | | | | | | | | | | | | | | |
| N | 70 | 117 | 195 | 724 | 156 | 127 | 118 | 687 | 1507 | 267 | 51 | 246 | 123 | 202 | 48 | 394 | 5032 | 4916 |
| Median | 0.12 | 0.12 | 0.14 | 0.11 | 0.08 | 0.17 | 0.18 | 0.14 | -0.02 | 0.08 | 0.13 | 0.10 | 0.18 | 0.05 | 0.17 | 0.06 | 0.07 | |
| Mean | 0.08 | 0.11 | 0.12 | 0.07 | 0.07 | 0.17 | 0.11 | 0.14 | -0.05 | 0.09 | 0.10 | 0.10 | 0.14 | -0.02 | 0.16 | 0.03 | 0.05 | |
| SD | 0.39 | 0.36 | 0.31 | 0.41 | 0.44 | 0.34 | 0.33 | 0.34 | 0.44 | 0.32 | 0.31 | 0.40 | 0.33 | 0.51 | 0.27 | 0.45 | 0.40 | |
| **2008** | | | | | | | | | | | | | | | | | | |
| N | 68 | 109 | 192 | 720 | 155 | 128 | 118 | 688 | 1392 | 251 | 49 | 234 | 111 | 195 | 50 | 418 | 4878 | 4720 |
| Median | 0.08 | 0.08 | 0.09 | 0.07 | 0.02 | 0.09 | 0.10 | 0.08 | -0.02 | 0.04 | -0.02 | 0.05 | 0.11 | 0.00 | 0.05 | 0.02 | 0.04 | |
| Mean | 0.10 | 0.06 | 0.05 | 0.04 | -0.06 | 0.07 | 0.05 | 0.03 | -0.05 | 0.00 | -0.06 | -0.01 | 0.04 | -0.10 | 0.05 | -0.03 | 0.00 | |
| SD | 0.36 | 0.26 | 0.31 | 0.37 | 0.36 | 0.32 | 0.33 | 0.34 | 0.42 | 0.31 | 0.36 | 0.36 | 0.33 | 0.43 | 0.40 | 0.43 | 0.37 | |

| | AT | BE | CH | DE | DK | ES | FI | FR | GB | GR | IR | IT | NL | NO | PT | SE | Tot. | Von A. |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **2009** | | | | | | | | | | | | | | | | | | |
| N | 68 | 107 | 183 | 700 | 148 | 127 | 113 | 677 | 1316 | 250 | 46 | 231 | 102 | 180 | 47 | 415 | 4710 | 4441 |
| Median | 0.07 | 0.08 | 0.08 | 0.04 | 0.01 | 0.04 | 0.02 | 0.05 | -0.01 | 0.01 | -0.05 | 0.02 | 0.06 | 0.02 | 0.08 | 0.00 | 0.02 | |
| Mean | 0.00 | 0.04 | 0.02 | 0.01 | -0.08 | 0.05 | -0.01 | 0.00 | -0.05 | 0.02 | -0.09 | -0.03 | 0.06 | -0.05 | 0.05 | -0.04 | -0.02 | |
| SD | 0.27 | 0.27 | 0.30 | 0.37 | 0.39 | 0.33 | 0.34 | 0.34 | 0.39 | 0.29 | 0.44 | 0.35 | 0.26 | 0.48 | 0.38 | 0.43 | 0.37 | |
| **2010** | | | | | | | | | | | | | | | | | | |
| N | 63 | 101 | 183 | 660 | 147 | 125 | 115 | 653 | 1209 | 237 | 45 | 231 | 101 | 176 | 49 | 409 | 4504 | 3883 |
| Median | 0.07 | 0.10 | 0.10 | 0.10 | 0.04 | 0.07 | 0.09 | 0.09 | -0.01 | -0.03 | 0.06 | 0.04 | 0.12 | 0.01 | 0.10 | 0.03 | 0.05 | |
| Mean | -0.01 | 0.07 | 0.08 | 0.08 | -0.06 | 0.03 | 0.03 | 0.06 | -0.03 | -0.10 | -0.01 | -0.03 | 0.10 | -0.05 | 0.19 | -0.03 | 0.01 | |
| SD | 0.37 | 0.28 | 0.26 | 0.33 | 0.44 | 0.38 | 0.32 | 0.31 | 0.39 | 0.36 | 0.33 | 0.34 | 0.26 | 0.41 | 0.44 | 0.45 | 0.36 | |
| **2011** | | | | | | | | | | | | | | | | | | |
| N | 63 | 94 | 176 | 637 | 124 | 122 | 113 | 635 | 1173 | 221 | 41 | 222 | 100 | 183 | 48 | 402 | 4354 | |
| Median | 0.08 | 0.08 | 0.10 | 0.10 | 0.04 | 0.07 | 0.07 | 0.09 | -0.01 | -0.06 | 0.05 | 0.05 | 0.10 | 0.00 | 0.03 | 0.05 | 0.04 | |
| Mean | 0.01 | 0.02 | 0.08 | 0.05 | -0.06 | 0.06 | 0.03 | 0.05 | -0.01 | -0.15 | -0.07 | -0.03 | 0.03 | -0.07 | 0.05 | -0.05 | 0.00 | |
| SD | 0.34 | 0.28 | 0.29 | 0.34 | 0.40 | 0.28 | 0.29 | 0.33 | 0.38 | 0.39 | 0.46 | 0.36 | 0.37 | 0.36 | 0.32 | 0.43 | 0.36 | |
| **2012** | | | | | | | | | | | | | | | | | | |
| N | 61 | 86 | 175 | 599 | 116 | 125 | 117 | 590 | 1143 | 203 | 38 | 218 | 95 | 176 | 47 | 406 | 4195 | |
| Median | 0.09 | 0.06 | 0.08 | 0.07 | 0.05 | 0.05 | 0.06 | 0.08 | -0.01 | -0.06 | 0.09 | 0.04 | 0.08 | 0.06 | 0.05 | 0.02 | 0.04 | |
| Mean | 0.03 | -0.01 | 0.07 | 0.02 | 0.00 | -0.04 | 0.03 | 0.03 | -0.04 | -0.14 | 0.09 | 0.00 | 0.05 | -0.02 | 0.04 | -0.08 | -0.01 | |
| SD | 0.31 | 0.32 | 0.24 | 0.32 | 0.34 | 0.42 | 0.34 | 0.33 | 0.36 | 0.47 | 0.39 | 0.35 | 0.33 | 0.51 | 0.41 | 0.43 | 0.36 | |
| **2013** | | | | | | | | | | | | | | | | | | |
| N | 58 | 91 | 167 | 568 | 111 | 122 | 117 | 592 | 1148 | 193 | 38 | 223 | 92 | 160 | 48 | 412 | 4140 | |
| Median | 0.09 | 0.05 | 0.09 | 0.07 | 0.06 | 0.07 | 0.08 | 0.06 | -0.01 | -0.02 | 0.06 | 0.03 | 0.10 | 0.06 | 0.04 | 0.04 | 0.04 | |
| Mean | 0.03 | 0.00 | 0.06 | 0.01 | 0.04 | 0.05 | 0.03 | 0.00 | -0.03 | -0.05 | 0.07 | 0.02 | 0.09 | 0.01 | -0.01 | -0.09 | -0.01 | |
| SD | 0.23 | 0.33 | 0.27 | 0.38 | 0.28 | 0.38 | 0.30 | 0.39 | 0.39 | 0.45 | 0.31 | 0.37 | 0.34 | 0.33 | 0.39 | 0.44 | 0.38 | |
| **2014** | | | | | | | | | | | | | | | | | | |
| N | 56 | 86 | 164 | 532 | 110 | 127 | 117 | 592 | 1093 | 191 | 37 | 214 | 88 | 154 | 47 | 400 | 4008 | |
| Median | 0.10 | 0.05 | 0.10 | 0.08 | 0.07 | 0.09 | 0.08 | 0.07 | -0.01 | 0.01 | 0.11 | 0.06 | 0.11 | 0.04 | 0.05 | 0.08 | 0.05 | |
| Mean | 0.07 | 0.02 | 0.07 | 0.05 | 0.01 | 0.10 | 0.04 | 0.01 | -0.01 | 0.02 | 0.08 | 0.03 | -0.01 | -0.01 | 0.01 | 0.00 | 0.02 | |
| SD | 0.19 | 0.29 | 0.24 | 0.37 | 0.41 | 0.45 | 0.29 | 0.38 | 0.39 | 0.42 | 0.29 | 0.35 | 0.39 | 0.46 | 0.24 | 0.42 | 0.38 | |
| **2015** | | | | | | | | | | | | | | | | | | |
| N | 31 | 58 | 114 | 239 | 76 | 95 | 114 | 280 | 839 | 133 | 21 | 131 | 59 | 138 | 32 | 381 | 2741 | |
| Median | 0.11 | 0.11 | 0.11 | 0.11 | 0.08 | 0.08 | 0.10 | 0.06 | -0.01 | 0.02 | 0.17 | 0.08 | 0.11 | 0.00 | 0.09 | 0.08 | 0.05 | |
| Mean | 0.13 | 0.07 | 0.07 | 0.10 | 0.04 | 0.04 | 0.07 | 0.01 | -0.02 | 0.00 | 0.14 | 0.06 | 0.06 | -0.10 | 0.07 | -0.05 | 0.01 | |
| SD | 0.13 | 0.41 | 0.23 | 0.26 | 0.37 | 0.34 | 0.32 | 0.28 | 0.29 | 0.25 | 0.26 | 0.26 | 0.24 | 0.43 | 0.28 | 0.52 | 0.32 | |
| **Grand Total N** | | | | | | | | | | | | | | | | | **121130** | **91796** |

# Appendix 2

| | EPS | EPS1NE | EPS1MD | EPS2NE | EPS2MD | EPS3NE | EPS3MD | EPS4NE | EPS4MD | EPS5NE | EPS5MD | LTNE | LTMN |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **1986** | | | | | | | | | | | | | |
| N | 1501 | 1248 | 1248 | 1023 | 1023 | 387 | 387 | 25 | 25 | 0 | 0 | 63 | 63 |
| Median | 0.3 | 3.0 | 5.4 | 3.0 | 7.2 | 1.0 | 6.3 | 1.0 | 1.9 | | | 1.0 | 10.6 |
| Mean | -16.4 | 4.6 | 15.3 | 4.4 | 17.8 | 2.1 | 20.0 | 1.2 | 4.8 | | | 1.8 | 11.1 |
| SD | 1972.7 | 4.2 | 69.0 | 3.8 | 76.9 | 1.8 | 115.7 | 0.6 | 8.2 | | | 2.9 | 6.0 |
| **1987** | | | | | | | | | | | | | |
| N | 2427 | 1641 | 1641 | 1444 | 1444 | 574 | 574 | 41 | 41 | 0 | 0 | 246 | 246 |
| Median | 0.3 | 3.0 | 4.7 | 3.0 | 6.4 | 1.0 | 6.6 | 1.0 | 4.7 | | | 1.0 | 10.0 |
| Mean | 118.2 | 5.2 | 152.8 | 4.7 | 264.5 | 2.3 | 22.6 | 1.2 | 12.8 | | | 1.3 | 12.1 |
| SD | 4987.8 | 5.1 | 5554.3 | 4.6 | 9315.6 | 2.2 | 109.4 | 0.5 | 21.5 | | | 1.2 | 13.0 |
| **1988** | | | | | | | | | | | | | |
| N | 2969 | 1869 | 1869 | 1635 | 1635 | 436 | 436 | 40 | 40 | 6 | 6 | 298 | 298 |
| Median | 0.4 | 3.0 | 5.2 | 3.0 | 7.3 | 1.0 | 10.8 | 1.0 | 1.8 | 1.0 | 2.7 | 1.0 | 10.0 |
| Mean | 110.3 | 5.6 | 218.1 | 5.2 | 31.5 | 2.5 | 34.1 | 1.0 | 8.7 | 1.0 | 2.7 | 2.1 | 9.9 |
| SD | 4768.8 | 5.3 | 8331.8 | 5.0 | 356.8 | 2.3 | 164.1 | 0.2 | 19.1 | 0.0 | 2.1 | 3.5 | 4.8 |
| **1989** | | | | | | | | | | | | | |
| N | 3233 | 1887 | 1887 | 1691 | 1691 | 333 | 333 | 26 | 26 | 3 | 3 | 300 | 300 |
| Median | 0.4 | 4.0 | 5.3 | 4.0 | 7.0 | 1.0 | 8.0 | 1.0 | 1.3 | 1.0 | 12.0 | 1.0 | 10.0 |
| Mean | 210.3 | 6.2 | 25.7 | 5.7 | 31.3 | 2.4 | 31.7 | 1.0 | 4.1 | 1.0 | 16.9 | 1.8 | 10.8 |
| SD | 10166.0 | 5.6 | 329.2 | 5.2 | 388.9 | 2.7 | 170.2 | 0.2 | 6.9 | 0.0 | 18.3 | 1.6 | 4.6 |
| **1990** | | | | | | | | | | | | | |
| N | 3365 | 1922 | 1922 | 1764 | 1764 | 417 | 417 | 30 | 30 | 7 | 7 | 516 | 516 |
| Median | 0.3 | 4.0 | 3.8 | 4.0 | 4.8 | 1.0 | 4.1 | 1.0 | 1.2 | 1.0 | 3.3 | 1.0 | 10.0 |
| Mean | 230.4 | 6.3 | 19.1 | 5.6 | 23.8 | 2.6 | 19.4 | 1.1 | 7.8 | 1.0 | 23.7 | 1.6 | 10.3 |
| SD | 11747.2 | 5.7 | 201.0 | 5.0 | 218.9 | 2.8 | 75.1 | 0.3 | 22.7 | 0.0 | 50.3 | 1.7 | 8.6 |
| **1991** | | | | | | | | | | | | | |
| N | 3420 | 2261 | 2261 | 2109 | 2109 | 642 | 644 | 38 | 38 | 5 | 5 | 494 | 494 |
| Median | 0.2 | 4.0 | 2.6 | 4.0 | 3.5 | 2.0 | 2.1 | 1.0 | 2.9 | 1.0 | 5.5 | 1.0 | 11.0 |
| Mean | 179.5 | 7.1 | 12.2 | 6.3 | 16.6 | 2.5 | 10.6 | 1.1 | 16.1 | 1.0 | 18.1 | 1.5 | 11.7 |
| SD | 9416.2 | 7.2 | 110.0 | 6.2 | 137.8 | 2.1 | 32.7 | 0.3 | 29.4 | 0.0 | 28.3 | 1.2 | 9.5 |
| **1992** | | | | | | | | | | | | | |
| N | 3434 | 2347 | 2347 | 2167 | 2167 | 878 | 879 | 45 | 45 | 5 | 5 | 557 | 557 |
| Median | 0.1 | 4.0 | 1.6 | 4.0 | 2.6 | 2.0 | 2.4 | 1.0 | 1.9 | 1.0 | 0.7 | 1.0 | 10.5 |
| Mean | 41.7 | 7.7 | 7.6 | 6.8 | 11.6 | 2.8 | 10.4 | 1.1 | 6.9 | 1.2 | 14.7 | 1.6 | 11.3 |
| SD | 1804.0 | 8.2 | 97.8 | 7.1 | 89.9 | 2.6 | 24.8 | 0.3 | 15.0 | 0.4 | 28.8 | 2.0 | 9.0 |
| **1993** | | | | | | | | | | | | | |
| N | 3515 | 2353 | 2353 | 2141 | 2141 | 1034 | 1035 | 156 | 157 | 17 | 18 | 450 | 450 |
| Median | 0.1 | 5.0 | 1.8 | 4.0 | 2.9 | 2.0 | 2.2 | 1.0 | 1.4 | 1.0 | 48.7 | 1.0 | 11.0 |
| Mean | -58.9 | 8.2 | 7.6 | 7.0 | 11.6 | 3.2 | 7.9 | 1.2 | 15.2 | 1.0 | 48.9 | 2.1 | 11.7 |
| SD | 4359.5 | 8.6 | 66.0 | 7.0 | 83.8 | 3.5 | 114.7 | 0.5 | 43.8 | 0.0 | 49.5 | 3.9 | 7.9 |
| **1994** | | | | | | | | | | | | | |
| N | 3539 | 2523 | 2523 | 2420 | 2420 | 1387 | 1387 | 182 | 182 | 30 | 30 | 495 | 495 |
| Median | 0.2 | 5.0 | 2.5 | 4.0 | 3.2 | 2.0 | 3.2 | 1.0 | 2.7 | 1.0 | 8.2 | 2.0 | 11.0 |
| Mean | 56.4 | 8.5 | 10.1 | 7.4 | 12.7 | 4.2 | 11.3 | 1.5 | 16.1 | 1.0 | 37.9 | 2.7 | 12.7 |
| SD | 2644.1 | 8.9 | 73.9 | 7.8 | 94.9 | 5.1 | 91.4 | 0.8 | 38.3 | 0.2 | 51.9 | 10.7 | 11.0 |
| **1995** | | | | | | | | | | | | | |
| N | 3536 | 2655 | 2655 | 2557 | 2557 | 1461 | 1461 | 126 | 126 | 14 | 14 | 596 | 596 |
| Median | 0.2 | 5.0 | 2.4 | 5.0 | 3.0 | 2.0 | 2.9 | 1.0 | 2.6 | 1.0 | 55.2 | 2.0 | 10.0 |
| Mean | 213.0 | 8.4 | 8.0 | 7.6 | 13.6 | 3.9 | 14.2 | 1.2 | 20.1 | 1.0 | 63.1 | 2.1 | 11.7 |
| SD | 9248.5 | 8.3 | 78.7 | 7.5 | 97.6 | 4.6 | 98.4 | 0.5 | 41.5 | 0.0 | 54.2 | 2.2 | 11.1 |
| **1996** | | | | | | | | | | | | | |
| N | 4439 | 2878 | 2878 | 2765 | 2765 | 1615 | 1615 | 307 | 308 | 30 | 30 | 855 | 855 |
| Median | 0.2 | 5.0 | 2.6 | 4.0 | 3.3 | 2.0 | 4.2 | 1.0 | 2.1 | 1.0 | 1.4 | 1.0 | 10.2 |
| Mean | 87.6 | 8.1 | -10106.0 | 7.3 | 34891.9 | 4.1 | 18.5 | 1.4 | 10.7 | 1.2 | 2.9 | 2.0 | 12.0 |
| SD | 3552.6 | 8.4 | 542700 | 7.5 | 1834059 | 4.9 | 132.9 | 0.8 | 28.4 | 0.6 | 4.6 | 2.9 | 19.9 |
| **1997** | | | | | | | | | | | | | |
| N | 4844 | 3044 | 3044 | 2889 | 2889 | 1824 | 1826 | 256 | 257 | 41 | 41 | 976 | 976 |
| Median | 0.3 | 4.0 | 2.6 | 4.0 | 3.4 | 2.0 | 4.1 | 1.0 | 2.7 | 1.0 | 5.6 | 1.0 | 11.0 |
| Mean | 95.3 | 7.3 | -1648.5 | 6.4 | 15414.8 | 3.3 | 33.6 | 1.2 | 140.6 | 1.0 | 28.8 | 2.1 | 12.5 |
| SD | 7344.9 | 7.7 | 180498 | 6.7 | 693568 | 3.7 | 787.2 | 0.6 | 2011.7 | 0.0 | 91.4 | 2.9 | 18.8 |
| **1998** | | | | | | | | | | | | | |
| N | 4946 | 3176 | 3174 | 3041 | 3041 | 2084 | 2084 | 571 | 571 | 194 | 194 | 1080 | 1080 |
| Median | 0.2 | 4.0 | 2.3 | 4.0 | 3.0 | 2.0 | 3.3 | 1.0 | 2.3 | 1.0 | 2.3 | 1.0 | 10.2 |
| Mean | 240.1 | 7.3 | 5180.1 | 6.5 | 8430.4 | 3.6 | 66.4 | 1.5 | 9.8 | 1.1 | 10.7 | 2.3 | 13.0 |
| SD | 12948.2 | 7.3 | 290686 | 6.4 | 461962 | 3.7 | 2471.3 | 0.9 | 67.3 | 0.4 | 42.7 | 4.0 | 20.5 |

| | EPS | EPS1NE | EPS1MD | EPS2NE | EPS2MD | EPS3NE | EPS3MD | EPS4NE | EPS4MD | EPS5NE | EPS5MD | LTNE | LTMN |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **1999** | | | | | | | | | | | | | |
| N | 5009 | 3180 | 3180 | 2977 | 2977 | 2156 | 2157 | 1001 | 1001 | 473 | 474 | 948 | 948 |
| Median | 0.2 | 4.0 | 1.8 | 4.0 | 2.5 | 2.0 | 3.3 | 1.0 | 3.0 | 1.0 | 3.9 | 1.0 | 11.0 |
| Mean | 131.2 | 6.8 | 4859.4 | 6.2 | 12516.6 | 3.5 | -33.0 | 1.7 | 33.3 | 1.3 | 100.3 | 1.7 | 15.7 |
| SD | 9775.6 | 7.0 | 274283 | 6.3 | 683678 | 3.6 | 2644.1 | 1.2 | 551.1 | 0.6 | 1753.3 | 2.2 | 22.8 |
| **2000** | | | | | | | | | | | | | |
| N | 5238 | 3109 | 3109 | 2955 | 2955 | 2271 | 2271 | 1223 | 1223 | 592 | 592 | 845 | 845 |
| Median | 0.2 | 3.0 | 1.4 | 3.0 | 2.0 | 2.0 | 2.3 | 1.0 | 3.0 | 1.0 | 4.1 | 1.0 | 12.0 |
| Mean | 107.5 | 4.8 | 18299.5 | 4.6 | 25359.4 | 3.1 | 444.7 | 1.8 | 13.3 | 1.3 | 14.1 | 2.0 | 15.7 |
| SD | 14227.8 | 5.0 | 1040335 | 4.4 | 1379719 | 2.8 | 21979.7 | 1.2 | 53.0 | 0.7 | 52.0 | 4.3 | 31.3 |
| **2001** | | | | | | | | | | | | | |
| N | 5196 | 2808 | 2808 | 2682 | 2682 | 2111 | 2111 | 1139 | 1139 | 560 | 560 | 1002 | 1002 |
| Median | 0.1 | 3.0 | 1.0 | 3.0 | 1.5 | 2.0 | 1.8 | 1.0 | 2.3 | 1.0 | 2.6 | 2.0 | 10.0 |
| Mean | 202.2 | 4.8 | 9.0 | 4.6 | 27.8 | 3.0 | 49.6 | 1.6 | 10.8 | 1.2 | 11.8 | 2.6 | 11.7 |
| SD | 14081.4 | 4.8 | 423.1 | 4.5 | 825.2 | 2.6 | 1564.2 | 1.0 | 45.7 | 0.5 | 26.0 | 3.4 | 31.1 |
| **2002** | | | | | | | | | | | | | |
| N | 5116 | 2557 | 2557 | 2392 | 2392 | 1819 | 1819 | 985 | 985 | 365 | 365 | 1153 | 1153 |
| Median | 0.0 | 3.0 | 1.0 | 3.0 | 1.5 | 2.0 | 1.9 | 1.0 | 2.0 | 1.0 | 2.2 | 2.0 | 8.0 |
| Mean | 248.6 | 5.3 | -14085.5 | 5.1 | -15037.3 | 3.1 | -13726.5 | 1.6 | 22.8 | 1.1 | 11.0 | 2.3 | 10.9 |
| SD | 17687.4 | 6.0 | 711930 | 5.6 | 736075 | 3.0 | 586171 | 1.1 | 341.7 | 0.4 | 29.0 | 5.7 | 21.6 |
| **2003** | | | | | | | | | | | | | |
| N | 5079 | 2262 | 2262 | 2188 | 2188 | 1689 | 1689 | 903 | 903 | 428 | 428 | 1104 | 1104 |
| Median | 0.1 | 3.0 | 1.2 | 3.0 | 1.7 | 2.0 | 2.3 | 1.0 | 2.4 | 1.0 | 2.7 | 2.0 | 8.3 |
| Mean | 201.8 | 5.9 | 21.8 | 5.8 | 21.9 | 3.5 | 29.1 | 1.7 | 15.5 | 1.3 | 18.6 | 2.9 | 10.5 |
| SD | 13949.8 | 6.4 | 452.2 | 6.2 | 346.5 | 3.3 | 509.9 | 1.3 | 63.3 | 0.8 | 89.0 | 3.2 | 17.9 |
| **2004** | | | | | | | | | | | | | |
| N | 5157 | 2349 | 2349 | 2306 | 2306 | 1831 | 1831 | 949 | 949 | 512 | 512 | 999 | 999 |
| Median | 0.1 | 3.0 | 1.6 | 3.0 | 2.1 | 2.0 | 2.5 | 1.0 | 2.8 | 1.0 | 2.9 | 2.0 | 7.2 |
| Mean | 184.0 | 6.2 | 14.5 | 5.9 | 17.1 | 3.7 | 21.0 | 1.8 | 21.7 | 1.3 | 24.0 | 2.2 | 9.8 |
| SD | 11787.2 | 6.8 | 228.4 | 6.2 | 222.6 | 3.6 | 248.7 | 1.3 | 123.6 | 0.8 | 145.8 | 3.1 | 19.8 |
| **2005** | | | | | | | | | | | | | |
| N | 5351 | 2720 | 2719 | 2622 | 2621 | 2001 | 2001 | 782 | 782 | 411 | 411 | 1011 | 1011 |
| Median | 0.1 | 3.0 | 1.5 | 3.0 | 2.1 | 2.0 | 2.5 | 1.0 | 2.5 | 1.0 | 2.8 | 1.0 | 6.9 |
| Mean | 342.7 | 5.6 | 30.4 | 5.4 | 29.1 | 3.6 | 21.4 | 1.7 | 19.3 | 1.5 | 16.9 | 1.9 | 9.8 |
| SD | 20752.1 | 6.3 | 527.9 | 6.0 | 488.6 | 3.5 | 276.3 | 1.3 | 148.1 | 1.0 | 39.5 | 2.0 | 13.3 |
| **2006** | | | | | | | | | | | | | |
| N | 5463 | 2797 | 2796 | 2696 | 2696 | 2127 | 2127 | 891 | 891 | 340 | 340 | 999 | 999 |
| Median | 0.1 | 3.0 | 1.6 | 3.0 | 2.1 | 2.0 | 2.6 | 1.0 | 2.6 | 1.0 | 3.0 | 1.0 | 7.6 |
| Mean | 353.6 | 6.1 | 20.8 | 5.9 | 39.0 | 3.8 | 31.4 | 1.8 | 16.8 | 1.2 | 20.0 | 3.2 | 10.2 |
| SD | 21460.5 | 6.7 | 473.1 | 6.5 | 623.9 | 3.8 | 428.7 | 1.4 | 76.0 | 0.7 | 122.7 | 28.4 | 13.6 |
| **2007** | | | | | | | | | | | | | |
| N | 5476 | 2969 | 2968 | 2873 | 2872 | 2230 | 2229 | 733 | 733 | 386 | 386 | 1099 | 1099 |
| Median | 0.1 | 3.0 | 1.5 | 3.0 | 2.0 | 2.0 | 2.5 | 1.0 | 2.7 | 1.0 | 4.0 | 1.0 | 6.8 |
| Mean | 350.7 | 6.1 | 23.8 | 6.0 | 32.3 | 4.1 | 34.1 | 1.5 | 23.3 | 1.2 | 27.4 | 3.5 | 9.5 |
| SD | 20128.8 | 6.7 | 513.7 | 6.4 | 638.9 | 4.1 | 590.1 | 0.9 | 143.2 | 0.5 | 132.0 | 11.6 | 13.8 |
| **2008** | | | | | | | | | | | | | |
| N | 5229 | 2783 | 2783 | 2743 | 2743 | 2287 | 2287 | 1196 | 1196 | 720 | 720 | 882 | 882 |
| Median | 0.1 | 3.0 | 0.9 | 3.0 | 1.2 | 2.0 | 1.6 | 1.0 | 2.1 | 1.0 | 3.1 | 1.0 | 5.0 |
| Mean | 56.3 | 6.4 | 14.6 | 6.1 | 20.1 | 4.4 | 50.2 | 2.0 | 46.1 | 1.5 | 17.5 | 3.3 | 6.5 |
| SD | 2856.8 | 7.1 | 413.6 | 6.8 | 471.9 | 4.6 | 1043.9 | 1.7 | 823.2 | 1.0 | 68.2 | 10.5 | 18.1 |
| **2009** | | | | | | | | | | | | | |
| N | 4999 | 2784 | 2784 | 2739 | 2739 | 2342 | 2342 | 1221 | 1221 | 767 | 767 | 958 | 958 |
| Median | 0.0 | 3.0 | 1.0 | 3.0 | 1.4 | 2.0 | 1.9 | 1.0 | 2.4 | 1.0 | 3.5 | 2.0 | 7.6 |
| Mean | 14.1 | 6.6 | 9.8 | 6.5 | 15.3 | 4.9 | 21.7 | 2.1 | 25.7 | 1.7 | 17.6 | 4.7 | 11.8 |
| SD | 1171.2 | 7.6 | 201.9 | 7.5 | 237.4 | 5.4 | 314.5 | 2.0 | 423.4 | 1.5 | 36.8 | 9.7 | 21.0 |
| **2010** | | | | | | | | | | | | | |
| N | 4870 | 2743 | 2742 | 2675 | 2674 | 2241 | 2240 | 938 | 938 | 484 | 484 | 1150 | 1150 |
| Median | 0.1 | 3.0 | 1.2 | 3.0 | 1.7 | 3.0 | 2.2 | 1.0 | 2.5 | 1.0 | 3.4 | 2.0 | 10.8 |
| Mean | 39.3 | 7.2 | 9.9 | 7.1 | 12.2 | 5.3 | 20.6 | 2.3 | 27.0 | 2.0 | 44.7 | 4.4 | 15.2 |
| SD | 3554.8 | 8.3 | 182.7 | 8.0 | 141.1 | 5.6 | 323.6 | 2.3 | 432.8 | 1.8 | 607.9 | 8.9 | 25.6 |
| **2011** | | | | | | | | | | | | | |
| N | 4814 | 2649 | 2648 | 2586 | 2585 | 2142 | 2141 | 870 | 870 | 386 | 386 | 1067 | 1067 |
| Median | 0.1 | 3.0 | 1.2 | 3.0 | 1.6 | 3.0 | 2.0 | 1.0 | 2.6 | 1.0 | 4.0 | 2.0 | 8.0 |
| Mean | -71.8 | 7.0 | 2.1 | 6.9 | 11.1 | 5.3 | 13.4 | 2.3 | 21.4 | 1.7 | 18.3 | 4.4 | 11.9 |
| SD | 4483.3 | 8.0 | 141.8 | 7.8 | 128.5 | 5.6 | 142.6 | 2.2 | 241.6 | 1.4 | 43.7 | 10.4 | 24.2 |
| **2012** | | | | | | | | | | | | | |
| N | 4667 | 2561 | 2561 | 2492 | 2492 | 2068 | 2068 | 753 | 753 | 368 | 368 | 987 | 987 |
| Median | 0.1 | 3.0 | 1.1 | 3.0 | 1.5 | 3.0 | 2.1 | 1.0 | 2.9 | 1.0 | 3.9 | 2.0 | 7.8 |
| Mean | 36.2 | 6.9 | 5.4 | 6.7 | 9.1 | 5.5 | 13.3 | 2.1 | 18.7 | 1.7 | 18.8 | 3.6 | 10.9 |
| SD | 2632.3 | 7.9 | 55.1 | 7.6 | 48.7 | 5.8 | 58.5 | 1.9 | 65.9 | 1.3 | 43.2 | 8.2 | 30.0 |

| | EPS | EPS1NE | EPS1MD | EPS2NE | EPS2MD | EPS3NE | EPS3MD | EPS4NE | EPS4MD | EPS5NE | EPS5MD | LTNE | LTMN |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **2013** | | | | | | | | | | | | | |
| N | 4564 | 2493 | 2492 | 2418 | 2417 | 2035 | 2034 | 862 | 862 | 404 | 404 | 926 | 926 |
| Median | 0.1 | 3.0 | 1.2 | 3.0 | 1.6 | 3.0 | 2.1 | 1.0 | 2.3 | 1.0 | 3.8 | 2.0 | 8.8 |
| Mean | 51.2 | 6.7 | 8.0 | 6.7 | 9.3 | 5.3 | 11.9 | 1.9 | 14.7 | 1.6 | 19.8 | 4.1 | 12.2 |
| SD | 3439.7 | 7.6 | 26.0 | 7.5 | 35.2 | 5.5 | 30.7 | 1.6 | 39.5 | 1.1 | 49.5 | 8.4 | 23.1 |
| **2014** | | | | | | | | | | | | | |
| N | 4355 | 2533 | 2533 | 2471 | 2471 | 2099 | 2099 | 904 | 904 | 425 | 425 | 644 | 905 |
| Median | 0.1 | 3.0 | 1.1 | 3.0 | 1.6 | 3.0 | 2.2 | 1.0 | 2.4 | 1.0 | 3.4 | 2.0 | 9.8 |
| Mean | 70.3 | 6.6 | 8.3 | 6.5 | 9.7 | 5.2 | 12.4 | 2.1 | 15.7 | 1.6 | 20.3 | 3.9 | 15.7 |
| SD | 4578.1 | 7.5 | 27.2 | 7.4 | 31.6 | 5.5 | 36.5 | 1.9 | 43.3 | 1.3 | 55.2 | 8.7 | 31.9 |
| **2015** | | | | | | | | | | | | | |
| N | 2797 | 2516 | 2516 | 2469 | 2469 | 2051 | 2051 | 877 | 877 | 459 | 459 | 664 | 905 |
| Median | 0.1 | 3.0 | 1.2 | 3.0 | 1.5 | 3.0 | 2.2 | 1.0 | 2.4 | 1.0 | 3.9 | 2.0 | 8.6 |
| Mean | 6.7 | 6.4 | 8.2 | 6.5 | 9.8 | 5.3 | 12.5 | 2.1 | 15.8 | 1.8 | 21.7 | 3.6 | 12.5 |
| SD | 163.8 | 7.4 | 32.9 | 7.3 | 34.9 | 5.5 | 34.1 | 1.9 | 44.2 | 1.5 | 52.5 | 9.4 | 25.1 |
| **Grand Total N** | **128548** | | **75609** | | **71925** | | **48575** | | **18073** | | **8434** | | **23866** |

Where EPS is the downloaded realized EPS from Thomson Reuters' Worldscope, EPS**i**NE is the number of analysts' estimates a EPS prediction consists of *i* years ahead and EPS**i**MD is the median of the analysts' predictions for *i* years ahead.

# Appendix 3

## Balance Sheet Items

Operating Assets

| **Components** | **Worldscope item** |
|---|---|
| Receivables (Net) | WC02051 |
| Inventories | WC02101 |
| Prepaid Expenses | WC02140 |
| Other Current Assets | WC02149 |
| Property, Plant and Equipment | WC02501 |
| Other Assets – Total | WC02652 |
| Investment in Associated Companies | WC0256 |

Operating Liabilities

| **Components** | **Worldscope item** |
|---|---|
| Accounts Payable | WC03040 |
| Accrued Payroll | WC03054 |
| Income Taxes Payable | WC03063 |
| Deferred Taxes | WC03263 |
| Deferred Income | WC03262 |
| Other Liabilities | WC03273 |
| Provision for Risks and Charges | WC03260 |

Financial Assets

| **Components** | **Worldscope item** |
|---|---|
| Cash & Short Term Investments | WC02001 |
| Long-term Receivables | WC02258 |

| | |
|---|---|
| Other Investments | WC02250 |

Financial Obligations

| **Components** | **Worldscope item** |
|---|---|
| Short Term Debt & Current Portion of Long-term Debt | WC03051 |
| Other Current Liabilities | WC03066 |
| Long-term Debt | WC03251 |
| Preferred Stock | WC03451 |

Common Shareholder Equity

| **Components** | **Worldscope item** |
|---|---|
| Common Equity | WC03501 |
| Preferred Stock | WC03451 |

Current Assets

| **Components** | **Worldscope item** |
|---|---|
| Cash & Short Term Investments | WC02001 |
| Receivables (Net) | WC02051 |
| Inventories | WC02101 |
| Prepaid Expenses | WC02140 |
| Other Current Assets | WC02149 |

Current Liabilities

| **Components** | **Worldscope item** |
|---|---|
| Accounts Payable | WC03040 |

| | |
|---|---|
| Short Term Debt & Current Portion of Long-term Debt | WC03051 |
| Accrued Payroll | WC03054 |
| Income Taxes Payable | WC03063 |
| Dividends Payable | WC03061 |
| Other Current Liabilities | WC03066 |

**Income Statement Items**

Operating Revenue

| **Components** | **Worldscope item** |
|---|---|
| Net Sales or Revenues | WC01001 |

Operating Expenses

| **Components** | **Worldscope item** |
|---|---|
| Cost of Goods Sold | WC01051 |
| Depreciation, Depletion & Amortization | WC01151 |
| Selling, General & Administrative Expenses | WC01101 |
| Other Operating Expenses | WC01230 |
| Operating Expenses – Total | WC01249 |
| Other Income/Expense (Net) | WC01262 |
| After Tax Other Income/Expense | WC01504 |
| Minority Interest – Income Statement | WC01501 |

Net Financial Expenses

| **Components** | **Worldscope item** |
|---|---|
| Extraordinary Credit – Pretax | WC01253 |

| | |
|---|---|
| Extraordinary Charge – Pretax | WC01254 |
| Non-Operating Interest Income | WC01266 |
| Interest Expense on Debt | WC01251 |
| Interest Capitalized | WC01255 |
| Preferred Dividend Requirements | WC01701 |
| Foreign Currency Translation Gain/Loss | WC01351 |

Earnings / Net Income

| **Components** | **Worldscope item** |
|---|---|
| Pretax Income | WC01401 |
| -Income Tax | WC01451 |

General Items

| **Components** | **Worldscope item** |
|---|---|
| Total Assets | WC02999 |
| Total Liabilities | WC03351 |
| Total Liabilities & Shareholders' Equity | WC03999 |
| Nation Code | WC06027 |
| Company Name | WC06001 |
| Industry Group | WC06011 |
| Net Cash Flow – Financing | WC04890 |
| Net Cash Flow – Investing | WC04870 |
| Net Cash Flow – Operating Activities | WC04860 |
| Accounting Standards Followed | WC07536 |
| Fiscal Year End Exchange Rate (US$) | WC06102 |
| Total Debt | WC03255 |

| | |
|---|---|
| Earnings Before Interest & Taxes (EBIT) | WC18191 |
| Earnings Before Interest, Taxes & Depreciation (EBITDA) | WC18198 |
| Minority Interest – Balance Sheet | WC03426 |
| Common Shares Outstanding | WC05301 |
| Market Capitalization | WC08001 |
| Net Income After Preferred Dividends | WC01706 |
| Common Dividends (Cash) | WC05376 |
| Dividends per Share | WC05101 |
| Price/Book Value Ratio – Close | WC09304 |
| Price/Earnings Ratio – Close | WC09104 |
| Beta | WC09802 |

## References

Abarbanell, J. S. (1991): Do Analysts' Earnings Forecasts Incorporate Information in Prior Stock Price Changes?, in: *Journal of Accounting and Economics*, Vol. 14, p. 147–165.

Albrecht, S. W./Lookabill, L. L./McKeown, J. C. (1977): The Time-Series Properties of Annual Earnings, in: *Journal of Accounting Research*, Vol. 15, p. 226–244.

Ali, A./Klein, A./Rosenfeld, J. (1992): Analysts' Use of Information and Transitory in Permanent Earnings Components Annual EPS Forecasting, in: *The Accounting Review*, Vol. 67, p. 183–198.

Allen, D. E./ Salim, H. M. (2005): Forecasting Profitability and Earnings: A Study of the UK Market (1982–2000), in: *Applied Economics*, Vol. 37, p. 2009–2018.

Altunbas¸S. Y./Karagiannis, A./Liu, M.-H./Tourani-Rad, A. (2008): Mean Reversion of Profitability: Evidence from the European-Listed Firms, in: *Managerial Finance*, Vol. 34, p. 799–815.

Archibald, T. R. (1967): The Return to Straight-Line Depreciation: An Analysis of a Change in Accounting Method, in: *Journal of Accounting Research*, Vol. 5, p. 164–180.

Ashton, D./Wang, P. (2013): Terminal Valuations, Growth Rates and the Implied Cost of Capital, in: *Review of Accounting Studies*, Vol. 18, p. 261–290.

Ball, R./Brown, P. (1968): An Empirical Evaluation of Accounting Income Numbers, in: *Journal of Accounting Research*, Vol. 6, p. 159–178.

Ball, R./Watts, R. L. (1972): Some Time Series Properties of Accounting Income, in: *The Journal of Finance*, Vol. 27, p. 663–681.

Barber, B./Lehavy, R./McNichols, M./Trueman, B. (2001): Can Investors Profit from the Prophets? Security Analyst Recommendations and Stock Returns, in: *The Journal of Finance*, Vol. 56, p. 531–563.

Basu, S. (1997): The Conservatism Principle and the Asymmetric Timeliness of Earnings, in: *Journal of Accounting and Economics*, Vol. 24, p. 3–37.

Beaver, W. H. (1970): The Time Series Behavior of Earnings, in: *Journal of Accounting Research*, Vol. 8, p. 62–99.

Boulding, K. E. (1936): Time and Investment, in: *Economica*, Vol. 3, p. 196–220.

Bradshaw, M. T./Drake, M. S./Myers, J. N./Myers, L. A. (2012): A Re-Examination of Analysts' Superiority over Time-Series Forecasts of Annual Earnings, in: *Review of Accounting Studies*, Vol. 17, p. 944–968.

Brooks, L. D./Buckmaster, D. A. (1976): Further Evidence of the Time-Series Properties of Accounting Income, in: *The Journal of Finance*, Vol. 31, p. 1359–1373.

Brown, L. D. (1993). Earnings Forecasting Research: Its Implications for Capital Markets Research, in: *International Journal of Forecasting*, Vol. 9, p. 295–320.

Brown, L. D./Hagerman, L./Griffin, P. A./Zmijewski, M. E. (1987a): An Evaluation of Alternative Proxies for the Market's Assessment of Unexpected Earnings, in: *Journal of Accounting and Economics*, Vol. 9, p. 159–193.

Brown, L. D./Richardson, G. D./Schwager, S. J. (1987b): An Information Interpretation of Financial Analyst Superiority in Forecasting Earnings, in: *Journal of Accounting Research*, Vol. 25, p. 49–67.

Brown, L. D./Rozeff, M. S. (1978): The Superiority of Analyst Forecasts as Measures of Expectations: Evidence from Earnings, in: *The Journal of Finance*, Vol. 33, p. 1–16.

Bryan, D. M./Tiras, S. L. (2007): The Influence of Forecast Dispersion on the Incremental Explanatory Power of Earnings, Book Value, and Analyst Forecasts on Market Prices, in: *The Accounting Review*, Vol. 82, p. 651–677.

Burgstahler, D./Eames, M. (2006): Management of earnings and analysts' forecasts to achieve zero and small positive earnings surprises, in: *Journal of Business Finance and Accounting*, Vol. 33, p. 633–652.

Butler, K. C./Lang, L. H. P. (1991): The Forecast Accuracy of Individual Analysts: Evidence of Systematic Optimism and Pessimism, in: *Journal of Accounting Research*, Vol. 29, p. 150–156.

Canarella, G./Miller, S. M./Nourayi, M. M. (2013): Firm Profitability: Mean-Reverting or Random-Walk Behavior?, in: *Journal of Economics and Business*, Vol. 66, p. 76–97.

Collins, W. A./Hopwood, W. S. (1980): A Multivariate Analysis of Annual Earnings Forecasts Generated from Quarterly Forecasts of Financial Analysts and Univariate Time-Series Models, in: *Journal of Accounting Research*, Vol. 18, p. 390–406.

Copeland, T./Dolgoff, A./Moel, A. (2004): The Role of Expectations in Explaining the Cross-Section of Stock Returns, in: *Review of Accounting Studies*, Vol. 9, p. 149–188.

Da, Z./Warachka, M. (2011): The Disparity between Long-Term and Short-Term Forecasted Earnings Growth, in: *Journal of Financial Economics*, Vol. 100, p. 424–442.

Das, S./Levine, C. B./Sivaramakrishnan, K. (1998): Earnings Predictability and Bias in Analysts' Earnings Forecasts, in: *Accounting Review*, Vol. 73, p. 277–294.

Dechow, P. M./Sloan, R. G. (1997). Returns to Contrarian Investment Strategies: Tests of Naive Expectations Hypotheses, in: *Journal of Financial Economics*, Vol. 43, p. 3–27.

Diether, K. B./Malloy, C. J./Scherbina, A. (2002): Differences of Opinion and the Cross Section of Stock Returns, in: *The Journal of Finance*, Vol. 57, p. 2113–2141.

Easton, P. D./Sommers, G. A. (2007): Effect of Analysts' Optimism on Estimates of the Expected Rate of Return Implied by Earnings Forecasts, in: *Journal of Accounting Research*, Vol. 45, p. 983–1015.

Easton, P./Taylor, G./Shroff, P./Sougiannis, T. (2002): Using Forecasts of Earnings to Simultaneously Estimate Growth and the Rate of Return on Equity Investment, in: *Journal of Accounting Research*, Vol. 40, p. 657–676.

Elgers, P. T./Lo, M. H. (1994): Reductions in Analysts' Annual Earnings Forecast Errors Using Information in Prior Earnings and Security Returns, in: *Journal of Accounting Research*, Vol. 32, p. 290–303.

Evans, M. E./Njoroge, K./Yong, K. O. (2012): An Examination of the Statistical Significance and Economic Implications of Model-Based and Analyst Earnings Forecasts: An Examination of the Statistical Significance and Economic Implications of Model-Based and Analyst Earnings Forecasts, in: *Working Paper*, p. 1–52.

Fairfield, P. M./Sweeney, R. J./Yohn, T. L. (1996): Accounting Classification and the Predictive Content of Earnings, in: *The Accounting Review*, Vol. 71, p. 337–355.

Fairfield, P. M./Yohn, T. L. (2001): Using Asset Turnover and Profit Margin to Forecast Changes in Profitability, in: *Review of Accounting Studies*, Vol. 6, p. 371–385.

Fama, E. F./French, K. R. (2006): Profitability, Investment and Average Returns, in: *Journal of Financial Economics*, Vol. 82, p. 491–518.

Fama, E. F./French, K. R. (2000): Forecasting Profitability and Earnings, in: *The Journal of Business*, Vol. 73, p. 161–175.

Fisher, I. (1907): The Rate of Interest: Its Nature, Determination and Relation to Economic Phenomena, Macmillan, New York.

Francis, J./Chen, Q./Willis, R. H./Philbrick, D. (2004): Security Analyst Independence, in: *The Research Foundation of CFA Institute*.

Francis, J./Philbrick, D. (1993): Analysts' Decisions as Products of a Multi-Task Environment, in: *Journal of Accounting Research*, Vol. 31, p. 216–230.

Frankel, R./Lee, C. M. C. (1998): Accounting Valuation, Market Expectation, and Cross-Sectional Stock Returns, in: *Journal of Accounting and Economics*, Vol. *25*, p. 283–319.

Freeman, R. N./Ohlson, J. A./Penman, S. H. (1982): Book Rate-of-Return and Prediction of Earnings Changes: An Empirical Investigation, in: *Journal of Accounting Research*, Vol. 20, p. 639–653.

Gebhardt, W. R./Lee, C. M. C./Swaminathan, B. (2001): Toward an Implied Cost of Capital, in: *Journal of Accounting Research*, Vol. 39, p. 135–176.

Gleason, C./Lee, C. M. C. (2003): Analyst Forecast Revisions and Market Price Discovery, in: *The Accounting Review*, Vol. 78, p. 193–225.

Gonedes, N. J. (1973): Properties of Accounting Numbers: Models and Tests, in: *Journal of Accounting Research*, Vol. 11, p. 212–237.

Green, J./Hand, J. R. M./Zhang, X. F. (2016): Errors and questionable judgments in analysts' DCF models, in: *Review of Accounting Studies*, Vol. 21, p. 597–632.

Han, B. H./Manry, D./Shaw, W. (2001): Improving the Precision of Analysts' Earnings Forecasts by Adjusting for Predictable Bias, in: *Review of Quantitative Finance and Accounting*, Vol. 17, p. 81–98.

Harris, R. D. F./Wang, P. (2013): An Improved Earnings Forecasting Model, in: *University of Exeter Business School*, p. 1-34.

Harris, T./Nissim, D. (2004): Convergence Trends for Profitability and Payout, *Working Paper*, p. 1-40.

Hong, H./Lim, T./Stein, J. C. (2000): Bad News Travels Slowly: Size, Analyst Coverage, and the Profitability of Momentum Strategies, in: *The Journal of Finance*, Vol. 55, p. 265–295.

Hou, K./van Dijk, M. A./Zhang, Y. (2012): The Implied Cost of Capital: A New Approach, in: *Journal of Accounting and Economics*, Vol. 53, p. 504–526.

Hui, K./Wei, J./You, H. (2013): Analyst Incentives, Forecast Biases, and Stock Returns, in: *Working Paper*, p. 1-53.

I/B/E/S International Inc. (2000): The I/B/E/S Glossary: A Guide to Understanding I/B/E/S Terms and Conventions, in: *I/B/E/S International Inc.*, p. 1-55.

Jagannathan, R./Ma, T. (2005): Does Analyst Bias Drive Stock Return Anomalies? An Empirical Investigation, in: *Working Paper*, p. 1-44.

Jegadeesh, N./Kim, J./Krische, S. D./Lee, C. M. C. (2004): Analyzing the Analysts: When Do Recommendations Add Value?, in: *The Journal of Finance*, Vol. 59, p. 1083–1124.

Jung, B./Shane, P. B./Yang, S. (2008): The Existence and Value-Relevance of Financial Analysts' Long-term Growth Forecasts, in: *McCombs Research Paper Series*, Vol. ACC-04-09, p. 1-48.

Kross, W./Ro, B./Schroeder, D. (1990): Earnings Expectations: The Analysts' Information Advantage, in: *The Accounting Review*, Vol. 65, p. 461–476.

La Porta, R./Lakonishok, J./Shleifer, A./Vishny, R. W. (1997): Good News for Value Stocks: Further Evidence on Market Efficiency, in: *The Journal of Finance*, Vol. 52, p. 859–874.

Little, I. M. D. (1962): Higgledy Piggledy Growth, in: *Bulletin of the Oxford University Institute of Economics & Statistics*, Vol. 24, p. 387–412.

Lookabill, L. L. (1976): Some Additional Evidence on the Time Series Properties of Accounting Earnings, in: *The Accounting Review*, Vol. 51, p. 724–738.

Mueller, D. C. (1977): The Persistence of Profits above the Norm, in: *Economica*, Vol. 44, p. 369–380.

Nissim, D./Penman, S. (2001): Ratio Analysis and Equity Valuation: From Research to Practice, in: *Review of Accounting Studies*, Vol. 6, p. 109–154.

Nordal, K. B./Næs, R. (2012). Mean Reversion in Profitability for Non-Listed Firms, in: *European Financial Management*, Vol. 18, p. 929–949.

O'Brien, P. C. (1987): Analysts' Forecasts as Earnings Expectations, *Journal of Accounting and Economics*, Vol. 10, p. 53-83.

Palepu, K. G./Healy, P. M./Bernard, V. L./Peek, E. (2010): Business Analysis & Valuation: IFRS Edition: Text and Cases, South-Western Andover, 2nd Edition.

Penman, S. H. (1991): An Evaluation of Accounting Rate-of-return, in: *Journal of Accounting, Auditing & Finance*, Vol. 6, p. 233–255.

Penman, S. H. (2013): Financial Statement Analysis and Security Valuation, New York: McGraw-Hill, 5th Edition.

Scherbina, A. (2004): Analyst Disagreement, Forecast Bias and Stock Returns, *Working Paper*.

Schumpeter, J. A. (1934): Theorie der wirtschaftlichen Entwicklung: eine Untersuchung über Unternehmergewinn, Kapital, Kredit, Zins und den Konjunkturzyklus, 6th Edition, Berlin.

Soliman, M. T. (2004): Using Industry-Adjusted DuPont Analysis to Using Industry-Adjusted DuPont Analysis to Predict Future Profitability, *Working Paper*.

Stigler, G. J. (1963): *The Rate of Return*, Princeton University Press.

Thomson Reuters (2010): I/B/E/S ON DATASTREAM, in: *Thomson Reuters*, p. 1-142.

Thomson Financial (2007): Worldscope Database Datatype Definitions Guide, in: *Thomson Financial*, p. 1–492.

von Arx, L. (2015): Using Long-Term Tendencies of ROE in Equity Valuation: Analysis and Investment Strategies for the European Market, p. 1-238.

Watts, R. L./Leftwich, R. W. (1977): The Time-Series of Annual Accounting Earnings, in: *Journal of Accounting Research*, Vol. 15, p. 253–271.

Webb, S. (1888): The Rate of Interest and the Laws of Distribution, in: *The Quarterly Journal of Economics*, Vol. 2, p. 188–208.