How to diversify internationally?

A comparison of conditional and unconditional asset allocation methods*

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Abstract:
To obtain the maximum benefits from diversification, financial theory suggests that investors should invest internationally because of the larger potential for risk reduction. The question that we raise in this paper is how to select the optimal portfolio of countries? This article synthesizes the major international asset allocation methods based on mean-variance analysis that have been proposed so far in the literature. In particular it compares two types of conditional asset allocation with unconditional methods. The different policies are simulated in a truly ex-ante framework that reflects exactly the uncertainty faced by the portfolio manager at the moment he has to decide upon his future investments. The asset allocation methods are implemented from a Swiss perspective over the period 1988-2001. We find that conditional methods based on direct predictability of expected returns outperform all other asset allocation methods.

Keywords: portfolio management, international diversification, asset pricing models, conditioning information.

JEL Classification: G11, G12, G15

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1. Introduction

Since the birth of financial theory, it is well-known that investors should diversify their risks. Moreover, to get the maximum benefits from diversification, they should invest internationally because of the larger potential for risk reduction stemming from lower correlation between assets. The question that we raise in this paper is how to select the optimal portfolio of countries? At the first sight, this question seems irrelevant because financial theory has the answer. Since Markowitz (1952), the theory proposes a normative framework to determine investors optimal choices. According to this model, they make their decisions regarding the mean and the variance of their portfolio's returns. Usually, these parameters are obtained by calculating the vector of expected returns and the covariance matrix with historical data. Thus, this unconditional approach supposes a certain stability of the parameters through time. However, the poor results obtained with this method call for more efficient approaches. One reasonable alternative to this unconditional empirical procedure would be to assume that the moments characterizing the multivariate distribution of asset returns change through time. This argument finds its origin in a series of papers that have shown that stock returns can be partly predicted with a number of lagged variables. For instance, Keim and Stambaugh (1986), Fama and French (1989) and Chen (1991) find that the dividend yield, the default or the term spread have some predictive power. Harvey (1991) also documents that lagged returns of national stock market indices help to forecast their respective evolution during the following time period. These results can be interpreted as evidence that the main inputs of mean-variance analysis are time-varying and emphasize the need to use a conditional approach.

There are two ways to incorporate this predictability in an asset allocation framework. The first method uses lagged variables in linear regression models to forecast directly expected returns. Solnik (1993) is the first to implement this approach in an international setting. His results show that the conditional allocation outperforms the unconditional one. Using a similar methodology, Harvey (1994) and Cavaglia et al. (1997) address the issue of including emerging markets into the analysis, whereas Klemkosky and Bharati (1995) and Robertsson

(2000) provide an analysis of conditional asset allocation in a domestic framework. These studies unanimously show that this conditional approach yields a superior performance compared to a strategy based on unconditional moments. The second method has sounder theoretical foundations as it involves using the predictive variables to forecast time-varying risk premia of an international asset pricing model (APM). Hamelink (2000) and Fletcher and Hillier (2003) are examples of this approach. However, both studies are not able to document that these types of conditional allocations provide a significant improvement over the unconditional method.

This study assesses unconditional and conditional international asset allocations from a Swiss perspective[1]. The main contribution of the paper is to synthesize the major international asset allocation methods based on mean-variance analysis that have been proposed so far in the literature. It is also the first time that the two conditional asset allocation methods are compared. For all the considered strategies, we focus our attention on the estimation of expected returns (and not of the covariance matrix of returns) as it has been shown to be the main source of estimation error in mean-variance analysis. Moreover, the ambition of the paper is to provide a general assessment of the various strategies without explicitly entering into the precise practical implementation such as the replication of a stock market index or the inclusion of transaction costs.

The analysis is conducted in the original framework outlined below. First of all, we formulate a truly international allocation, since we select 17 markets (including 6 emerging markets) that represent the major part of the World market capitalization. We also adopt a truly out-of-sample approach to investigate our investment strategies. This means that we estimate the parameters of the various models over a period, and these estimates are used as input for determining expected returns for a subsequent period. An additional feature of this study is to attempt to improve the results obtained with the unconditional approach by using Bayes-Stein estimators that are less exposed to estimation risk. Then, two kinds of conditional allocation are implemented. The first one is based on direct predictability of expected returns, whereas the second one uses a conditional international APM with time-varying risk premia and betas. Finally, we allow the investor to protect his portfolio against currency risk with futures contracts. This possibility contrasts with some of the previous studies, which adopt extreme

[1] In the existing literature, only few papers have addressed the issue of international asset allocation from a Swiss perspective. Examples are Knight (1989), Odier, Solnik and Zucchinetti (1995) and Hamelink (2000).

positions: the hedge is either complete or inexistent. The results of the empirical analysis, established on weekly data between January 1995 and January 2001, bring substantial credit to the conditional approach based on direct predictability and confirm the superiority of the latter over the unconditional allocation. Furthermore, we document that the conditional allocation based on APM yields rather unconvincing results and that Bayes-Stein estimators do not improve significantly the performance of unconditional strategies.

The rest of the paper is structured as follows: the next section describes the data. The implementation of the unconditional and conditional allocations is detailed in Section 3. Section 4 presents the results of the various strategies and the last section concludes our work.

2. Data

As the aim of the paper is to reproduce as much as possible the investment opportunity set that is available to an international investor located in Switzerland, we have selected developed and emerging markets according to their market capitalization and liquidity. The developed markets are France, Germany, United Kingdom, Italy, Switzerland, Canada, United States, Japan, Hong Kong, Singapore and Australia. The emerging markets are: Argentina, Brazil, Mexico, South Korea, Philippines and Thailand. We use national market price indices from Morgan Stanley Capital International (MSCI), which have been extracted from Datastream International. Returns of the 17 MSCI national stock markets indices are measured in Swiss Francs on a weekly basis. Table 1 gives descriptive statistics for the 17 series of returns.

Table 1 shows that for developed markets the results in terms of mean and standard deviation are in line with previous studies on similar periods. Looking at emerging markets the results for South American countries display the usual features of such markets: high returns associated with high risks. However, Asian emerging markets display unusually low mean returns which can be attributed to severe corrections that began in 1997. Regarding the statistical properties of these series, one can notice the presence of fat tails and asymmetry for almost all the distributions. We formally test the assumption of normality by computing Bera-Jarque (1980) statistics (not shown here to save space) and all of them reject normality at high significance level[2]. The strong and significant first order autocorrelation of some markets confirms that returns cannot be considered as being totally independent. This result also justifies to some extent the use of the lagged stock market return as a predictive variable.

Table 1: Descriptive Statistics for Returns on National MSCI Indexes (1988-2001)

	Mean	Std Dev.	Skewness	Kurtosis	ρ1
Developed markets					
Germany	15.81%	24.19%	-0.35	4.65	-0.008
France	17.49%	23.84%	0.07	3.43	0.012
U.K.	12.09%	20.43%	-0.11	3.50	-0.056
Italy	11.79%	28.44%	0.06	3.81	0.043
Switzerland	17.69%	18.94%	-0.33	5.69	0.062
Canada	13.25%	24.64%	-0.18	4.34	-0.008
U.S.A.	18.50%	23.40%	-0.09	3.54	***-0.082***
Hong Kong	20.08%	36.07%	-0.31	4.83	0.066
Japan	3.46%	25.68%	0.14	3.97	***-0.076***
Singapore	13.66%	29.23%	-0.13	7.41	0.028
Australia	9.60%	23.10%	-0.05	3.54	-0.010
Emerging markets					
Argentina	54.27%	115.74%	2.44	29.64	***-0.124***
Brazil	40.84%	81.47%	-0.55	7.98	***0.116***
Mexico	33.60%	52.85%	0.21	8.40	***0.083***
S. Korea	10.05%	45.89%	-0.03	11.81	***-0.093***
Philippines	11.83%	38.30%	-0.09	5.89	0.068
Thailand	8.58%	47.26%	0.36	6.49	0.019

Note: These statistics are computed from weekly returns in CHF over the period January 1988-January 2001 (682 observations). Means and standard deviations (Std Dev) are expressed in annual terms. Bold figures indicate that the first order autocorrelation coefficient (ρ1) is significant at 5% confidence level with a Bartlett test.

The correlation matrix reproduced in Table 2 deserves some comments. Panel A shows the correlations between developed markets. We observe some potential for diversification but it is limited as they are rather high (the lowest correlation is 0.32). Panel B shows that correlations between emerging markets are quite low. Panel C indicates that the links between developed and emerging markets have notably increased compared to previous studies (see

[2] It might be argued that using mean-variance analysis with non-normal distributions is inappropriate. However, financial theory does not provide so far a convincing and tractable model of asset allocation considering higher moments of return distributions.

Harvey (1995a, 1995b)) and certainly weaken the diversification potential of emerging markets.

Table 2: International Correlations (1988-2001)

Panel A: Correlations between developed markets

	Ger.	Fra.	U.K.	Ita.	Swi.	Can.	U.S.A.	H.K.	Jap.	Sin.	Aus.
Germany	1.00										
France	0.74	1.00									
U.K.	0.59	0.64	1.00								
Italy	0.56	0.57	0.50	1.00							
Switzerland	0.65	0.60	0.55	0.44	1.00						
Canada	0.50	0.58	0.57	0.43	0.48	1.00					
U.S.A.	0.53	0.60	0.62	0.47	0.50	0.79	1.00				
Hong Kong	0.45	0.45	0.51	0.36	0.37	0.45	0.47	1.00			
Japan	0.37	0.41	0.43	0.32	0.38	0.35	0.36	0.36	1.00		
Singapore	0.45	0.45	0.50	0.39	0.41	0.46	0.49	0.66	0.43	1.00	
Australia	0.44	0.47	0.56	0.39	0.41	0.56	0.54	0.51	0.39	0.49	1.00

Panel B: Correlations between emerging markets

	Arg.	Bra.	Mex.	Kor.	Phi.	Tha.
Argentina	1.00					
Brazil	0.20	1.00				
Mexico	0.32	0.35	1.00			
S. Korea	0.16	0.18	0.27	1.00		
Phillipines	0.17	0.24	0.33	0.31	1.00	
Thailand	0.23	0.24	0.31	0.45	0.52	1.00

Panel C: Correlations between developed and emerging markets

	Ger.	Fra.	U.K.	Ita.	Swi.	Can.	U.S.A.	H.K.	Jap.	Sin.	Aus.
Argentina	0.16	0.22	0.17	0.17	0.17	0.22	0.25	0.23	0.10	0.23	0.25
Brazil	0.24	0.29	0.26	0.21	0.24	0.31	0.36	0.26	0.24	0.26	0.30
Mexico	0.42	0.41	0.41	0.34	0.34	0.45	0.52	0.36	0.31	0.38	0.42
S. Korea	0.27	0.30	0.32	0.27	0.22	0.34	0.36	0.37	0.33	0.43	0.37
Phillipines	0.37	0.37	0.38	0.29	0.31	0.41	0.42	0.48	0.28	0.56	0.43
Thailand	0.39	0.36	0.37	0.35	0.31	0.37	0.38	0.48	0.33	0.66	0.40

Note: The correlations are computed with weekly returns expressed in Swiss Franc over the period January 1988-January 2001 (682 observations).

For instance, Mexico has only five correlations below 40%. It is difficult to interpret these results. A first possible cause is the modification of the economic structures of emerging markets. Nevertheless, we have calculated the correlation matrix during two sub-periods from 1988 to 1993 and from 1994 to 2001 (we do not show them here to save space) and we have found that this rise is solely due to the second sub-period, during which three major financial crises occurred. This observation brings a second interpretation: correlation between bearish markets may increase because of the predominance of global information over local one (see for instance Erb, Harvey and Viskanta (1994) and Solnik (1999)).

3. Methodology

3.1. General methodology

3.1.1. Currency hedging

Currency risk is an important factor for every investor who is willing to invest abroad. To be more realistic, an international asset allocation should integrate this risk and consider, if needed, hedging instruments. Contrary to some of the previous studies, we let the investor choose his optimal currency hedge by means of short positions on foreign currency futures. Since we consider a Markowitz framework, we need to define the mean and variance of these instruments. In the absence of arbitrage**,** the futures price expressed in home currency is equal to:

$$F_0 = S_0 \frac{1+R_{Swiss}}{1+R_{Foreign}} \qquad (1)$$

where F_0 is the futures price at time 0 (expressed in foreign currency per Swiss Franc), S_0 is the spot exchange rate at time 0 (expressed in foreign currency per Swiss Franc), R_{Swiss} is the Swiss interest rate and $R_{Foreign}$ is the foreign interest rate. Looking at the weekly return of a short position on foreign currency futures, we simply assume that the contract expires at the end of the week This assumption allows us to eliminate basis risk and to write the equality: $F_t = S_t$. Considering equation (1), the return on this short position can be written in the following way :

$$\frac{F_0 - F_t}{S_0} = \frac{F_0 - S_t}{S_0} = \frac{S_0 \frac{1+R_{Swiss}}{1+R_{Foreign}} - S_0 - S_t + S_0}{S_0} = \frac{R_{Swiss} - R_{Foreign}}{1+R_{Foreign}} - \frac{S_t - S_0}{S_0} \qquad (2)$$

where F_t is the futures price at time *t* and S_t is the spot exchange rate at the end of the week, i.e. at time *t*. With this equation and one-week Euro-market interest rates obtained from Datastream, it is possible to determine time-series of weekly returns for foreign currency futures. Because of lack of data for emerging markets, this procedure is only applied to the 10 developed markets[3]. Finally, we only introduce currency futures contracts for hedging and not speculative purposes. Therefore, constraints are placed on the weights of these instruments:

$$0 \leq w_{it}^{Future} \leq w_{it}, \quad i = 1, \ldots, 10 \tag{3}$$

where w_{it}^{Future} is the weight of the portfolio invested in a short position in the future for country *i* between *t-1* and *t* and w_{it} is the weight invested in country (index) *i* between *t-1* and *t*. Equation (3) indicates that, at best, only the initial amount invested at the beginning of each week can be hedged against currency variations. It also means that capital gains cannot be protected, which is a minor problem regarding the weekly rebalancing frequency considered in our study.

3.1.2. Investment rule for portfolio selection

In the mean-variance framework, an investment rule is needed to determine a precise portfolio among the infinite number of efficient portfolios. As Klemkosky and Bharati (1995) and Hamelink (2000), we select, at the beginning of each week, the portfolio that maximizes the ex-ante Sharpe ratio, where the riskless asset is the one-week Swiss interest rate on the Euro-market. When the latter is superior to the maximized Sharpe ratio, the total wealth is invested in the Euro-market.

In the optimization program, we do not allow short sales, for it is unrealistic to short the various MSCI market indices. Moreover, we ignore, for simplicity, initial deposits and margin calls of the currency futures contracts. Therefore, the classical constraint implying that the weights sum up to one only applies to the weights invested in the MSCI indices and not to those concerning futures. The optimization program, including 17 indices and 10 currency futures, can be summarized as follows:

[3] For these markets, an alternative is to use cross-hedging. i.e. use currencies strongly correlated to the one that do not have markets/data. We do not investigate this issue here.

$$\max_{w_{it}} \quad \frac{E\left(R_{pt}\right)-R_{ft}}{s\left(R_{pt}\right)}$$

$$s.t. \ \sum_{i=1}^{17} w_{it} = 1$$

$$w_{it} \geq 0 \quad i = 1,...,27 \qquad (4)$$

where $E\left(R_{pt}\right)=\sum_{i=1}^{27} w_{it} E\left(R_{it}\right)$ and $s\left(R_{pt}\right)=\sqrt{\sum_{i=1}^{27}\sum_{j=1}^{27} w_{it} w_{jt} s\left(R_{it}, R_{jt}\right)}$. $E\left(R_{pt}\right)$ is the expected return of the portfolio *p* at time *t*, $E\left(R_{it}\right)$ is the expected return of the index or the future *i* at time *t*, $s\left(R_{it}, R_{jt}\right)$ is the covariance between the returns of assets *i* and *j*. $s\left(R_{pt}\right)$ is the standard deviation of the returns of portfolio *p* at time t, w_{it} is the fraction of the portfolio devoted to asset *i* at time *t*. The first constraint in the program (4) reflects the fact that the wealth should be fully invested in all the indices (subscripts i=1,..,17 identify the indices of the 17 countries in our sample) and the second type of constraint indicates that short sales are not allowed (except for futures which are short by definition). The constraint in equation (3) that the position in currency futures should not exceed the cash position is also integrated in the optimization program.

3.1.3. Specification of the covariance matrix

A closer look at the program in equation (4) indicates that, besides expected returns, the elements of the covariance matrix of returns need to be estimated as well. One possibility is to condition the covariance matrix on the predictive variables used for forecasting expected returns. However this procedure raises two issues. First, the dynamics of covariances does not seem to be related to these variables (see Cochrane (2001), p. 26) and second their use does not ensure the positivity of the conditional covariance matrix. An alternative is to model the evolution of the covariance matrix as a GARCH process. But this approach is only well-suited for small dimension problems. A 27x27 covariance matrix is clearly impossible to estimate because of the explosion of the number of parameters. Moreover, some researchers (e.g. Chopra and Ziemba (1993)) show that errors in the covariance matrix have a much smaller impact on optimal weights than errors in expected returns. Finally, other authors (e.g. Dahlquist and Harvey (2001) and Solnik (1993)) argue that this matrix is rather stable through time. For all these reasons we use the unconditional covariance matrix for all the strategies we consider and focus our attention on the estimation of expected returns. More precisely, in our simulations, the covariance matrix is computed over a five-year window and readjusted every six month.

3.2. Unconditional asset allocation methodology

Several studies in international finance (see, for instance, Levy and Sarnat (1970) or Odier and Solnik (1993)) apply the mean-variance algorithm to an entire historical dataset. These papers only give an idea of the ex-post performance of such investment choices. However, portfolio managers would like to know if these methods perform well from a forward looking perspective. This is why this method should be used in an ex-ante framework. Such an application requires as input estimates of expected returns, covariances and variances. The natural solution is to compute these parameters with historical data. Unfortunately, estimators based on historical data are not very accurate and contain estimation errors. Through quadratic optimization, these errors have a large impact on the optimal weights and often create unintuitive and undiversified portfolios. This fact has been emphasized among others by Jobson and Korkie (1981), Jorion (1985, 1986) and more recently by Drobetz (2001). Since this problem is particularly acute for the vector of expectations (see Michaud (1989), Jorion (1985) and Chopra and Ziemba (1993)), we use two alternative techniques to estimate this vector: historical data and Bayes-Stein estimators precisely examined in an asset allocation context by Jorion (1986).

In order to implement the unconditional allocation we face a choice between leaving the weights constant throughout the whole period or adjusting them more or less frequently to reflect changing economic conditions. We think that a periodical reallocation is more realistic especially for emerging markets. We first estimate the historical mean vector and covariance matrix over a period of five years, from January 1990 to December 1994. We then use these parameters as inputs to estimate the optimal weights when maximizing the program in equation (4). The weights obtained from this procedure are used to form optimal portfolios in the next six months from January 1995 to June 1995. Then, we repeat this procedure with the five-year estimation window beginning six months later. We iterate this process until the end of our sample, i.e. January 2001.

The second type of unconditional allocation is implemented with Bayes-Stein estimators of expected returns. We limit the presentation of these estimators to an intuitive explanation but an extensive description can be found in Jorion (1986). The idea is to reduce the noise in estimates of historical means and to weight the original estimates with a correction factor. This technique avoids having extreme values in expected returns that involve unrealistic weights. Apart from the expected return vector the rest of the procedure is exactly the same as above.

3.3. Conditional asset allocation methodology

3.3.1. OLS-based conditional allocation

This type of conditional allocation is based on the linear relationship[4] existing between stock index returns and a few lagged variables, generally related to interest rates or to the level of assets prices. Although most of the empirical evidence has been obtained for the United States, a survey by Hawawini and Keim (1995) provide some evidence that such results also hold for many other countries. Although the choice of these variables does not stem from a theoretical model, one can see that this linear relationship represents the link existing between general economic conditions and financial markets as argued by Dahlquist and Harvey (2001).

To implement our conditional asset allocation we use three conditioning variables: the default spread, the term spread and the lagged stock returns. The motivation for using these variables is given among others by Chen (1991) who shows that the default and term spreads are closely linked to the evolution of the business cycle and by Harvey (1991) who finds that there is some predictive power in past returns. The first instrument is a global variable that is used for all 17 countries. It is a global default spread measured on the US market. More precisely, it is the difference between the yield on 10-year Baa rated corporate bonds and the yield on a government bond index of the same maturity. We use a US variable to represent the default spread because such data is unavailable for other countries of our sample. However, this approximation seems reasonable as US credit conditions have an important influence on World credit markets. We then select two local variables for each market. The first is the

[4] Harvey (2001) compares various specifications of this relation and concludes that the linear relationship gives the best results.

lagged return on the local stock index and the second is a variable representing the slope of the term structure. It is the lagged difference between the yield on a 10-year government bond and the one-week Euro-market interest rate. For every market we estimate the following equation:

$$R_{it} = a_0 + a_1 DEFAULT_{t-1} + a_2 R_{it-1} + a_3 TERM_{it-1} + e_{it} \qquad with\ \ t=1,..,T \tag{5}$$

Here R_i is the return on the market index of country *i* expressed in Swiss Francs, *DEFAULT* is the US default spread and *TERM* is the country *i* term spread. The parameters (a_0, a_1, a_2, a_3) of this equation are estimated by OLS for every market on a five-year period. Over the next six months, they are used with the three conditioning variables to predict the one-week ahead expected returns. These expected returns are used with the unconditional covariance matrix as inputs to obtain optimal weights for the program in equation (4). We finally obtain the returns on the optimal portfolio. The procedure is then repeated with an estimation window beginning 6 months later.

3.3.2. APM-based conditional allocation

In this second type of asset allocation, expected returns are obtained from a theoretical asset pricing model. This specific approach has been recently implemented by Hamelink (2000) and Fletcher and Hillier (2003) and can be theoretically justified by the work of Ferson and Harvey (1991). They argue that the predictability of asset returns previously documented can be reconciled with the notion of market efficiency by showing that these variables are predictors of risk premia of an APM. The model we use to implement the conditional asset allocation is the international capital asset pricing model proposed by Sercu (1980). This model has two factors, a market factor represented by a World market index and an exchange rate factor. This conditional international asset pricing model can be written as:

$$E\left(R_{it}\left|I_{t-1}\right.\right) = R_{ft} + b_{it,World} E\left(R_{World,t} - R_{ft}\left|I_{t-1}\right.\right) + b_{it,CHF} E\left(R_{CHF,t} - R_{ft}\left|I_{t-1}\right.\right) \tag{6}$$

where $E\left(R_{it}\left|I_{t-1}\right.\right)$ is the expected return on asset *i* conditional on the information set I_{t-1}. R_{ft} is the Swiss risk-free rate, $b_{it,World}$ and $b_{it,CHF}$ are the conditional betas and $E\left(R_{World,t} - R_{ft}\left|I_{t-1}\right.\right)$

and $E\left(R_{CHF,t} - R_{ft} \left| I_{t-1}\right.\right)$ are the conditional risk premia on the two factors. $R_{World,t}$ is the World market index computed by MSCI and $R_{CHF,t}$ is the return on an index representing the evolution of the Swiss Franc with respect to the other countries that are used in our study. Following Harvey (1995a), we weigh every currency in this index by the amount of trade between Switzerland and each country of the sample. The predictive variables chosen to model the time variation of risk premia are similar to those used in the first conditional allocation method. The World index factor risk premium is predicted by the lagged World index return, the lagged US default and term spreads. The currency factor risk premium is estimated with the lagged currency factor and the lagged US term and default spreads. As one can see, the predictive variables are all global. The justification of this choice can be found in Harvey (1995b) who argues that if markets are integrated as assumed by the international capital asset pricing model, then only global variables have an impact on risk premia.

The implementation of this model follows Ferson and Harvey (1991). To obtain the risk premia we use a two-step methodology. It first estimates betas by regressing the country returns on the returns of the two factors over a two year and a half period. In a second step, we regress cross-sectionally the country returns on the vector of betas to obtain the estimated risk premia. These cross-sectional regressions are re-estimated every week with a new return vector and the same vector of betas for the next six month. This procedure is repeated by using data starting six months later. It is iterated until the end of the sample to finally get two times series of risk premia over the whole sample period. In a second phase, we regress each risk premium on lagged predictive variables over a five-year window in a similar spirit to equation (5) to obtain coefficients of the linear regression. Over the next six months, the coefficients are used with the three conditioning variables to predict the one-week ahead risk premium. Finally, the two risk premia are introduced in equation (6) and used in conjunction with the betas estimated initially to get an estimate of the conditional expected return for country *i*. The rest of this procedure is the same as the one developed for the OLS-based conditional allocation, where conditional expected returns are introduced in the mean-variance optimization described in (4) to obtain the weights of the portfolio maximizing the Sharpe ratio.

3.4. Comparing the performance of the strategies

Measuring the performance of the various strategies is a crucial issue to compare the results of conditional and unconditional asset allocations. This task is rather complex as standard measures such as Sharpe ratios or the Jensen measure can lead to wrong conclusions in case the investors dynamically modify the weights of the assets in their portfolio. More precisely, these measures may induce a negative bias for the conditional approach if the investor has a utility function different from the quadratic one (see Dybvig and Ross (1985)) or if the investor has some timing ability (see Grinblatt and Titman (1989)). An additional issue comes from the fact that in an international setting the weights of the efficient portfolio are not observable (see Solnik (1993)): as a result, it is impossible to define a clear benchmark from which systematic risk measures can be computed. In order to avoid these issues, we use the Cornell (1979) performance measure. This measure typically does not use a benchmark and is intended to compare the performance of an uninformed (unconditional strategy) investor and informed (conditional strategy) investor. It is written as follows:

$$C = E\left[\sum_{i=1}^{N} w_{it}\left(R_{it} - E\left(R_{it}\right)\right)\right] = \sum_{i=1}^{N} \mathrm{cov}\left(w_{it}, R_{it}\right) \tag{7}$$

where w_{it} are the weights of the investment in asset i at time t, R_{it} is the return of asset i at time t and $E(R_{it})$ is the unconditional expectation on asset i at time t. Typically, the Cornell measure is the sum of N covariances between the weights w_{it} and the return on asset i at time t. Writing $R_{it} = E(R_{it}) + e_{it}$ allows us to describe the intuition behind this measure. If the investor has a superior information, he is able to predict the term e_{it} [5]. Therefore, he will modify the weights according to this information, thus inducing a positive covariance between the weights and the returns. Conversely, we can check that a passive investment (without valuable information) obtains a Cornell measure of zero. For computational purposes, this measure boils down to calculating the empirical counterpart of equation (7), which is equal to:

$$\frac{1}{T}\sum_{t=1}^{T}\left(R_{pt} - \sum_{i=1}^{N} w_{it} E\left(R_{it}\right)\right) \tag{8}$$

where R_{pt} is the return of portfolio following a conditional strategy and $E(R_{it})$ is the unconditional expected return of asset i that is estimated with historical means. Standard t-tests are used to determine if the Cornell measure is significantly different from zero. We also compute the Sharpe ratios of the various investment policies in order to have comparable figures with other studies.

4. Empirical results

4.1. Summary of the results

Table 3 summarizes the main characteristics of the returns on 6 strategies tested on a weekly basis between January 1995 and January 2001. We have added two strategies to those discussed so far. The first is the MSCI World index that is a frequent benchmark used in international portfolio management. The second is the minimum variance portfolio that is a strategy found to outperform frequently standard asset allocations (see for instance Haugen and Baker (1991)).

Table 3: Descriptive Statistics of Asset Allocation Methods

	Mean	Std. Deviation	Sharpe ratio
Unconditional	14.37%	20.62%	0.605
Bayes-Stein-unconditional	13.58%	20.18%	0.579
OLS-based conditional	32.31%	24.18%	1.257
APM-based conditional	8.45%	11.46%	0.573
MSCI World	16.95%	21.65%	0.695
Minimum variance	10.09%	13.09%	0.626

The unconditional allocations are dominated by all other strategies in terms of Sharpe ratio, except for the APM-based conditional allocation. Consistently with the previous studies, the OLS-based conditional allocation obtains by far the best Sharpe ratio. Moreover, we can emphasize the good performance of the MSCI World index, which is only beaten by the first conditional strategy. Besides the comparison of Sharpe ratios, the more suitable performance measure proposed by Cornell (1979) also gives credit to the superiority of the OLS-based conditional allocation over the classical unconditional one. Under the assumption of nullity of Cornell measure, its t-stat amounts to 2.3, which is significant at the 5 % confidence level. We are therefore confident to claim that the conditional allocation based on direct predictability

[5] This prediction may be due to some stock picking or factor timing ability. Even though we are not able to separate these two sources of predictability, Grinblatt and Titman (1989) show that the Cornell measure is the sum of the timing and selection components.

yields a superior performance. We have not computed the Cornell measure for the APM-based conditional strategy as it is obvious that it does not beat the unconditional method.

Figure 1: Evolution of one Swiss Franc invested in 1995

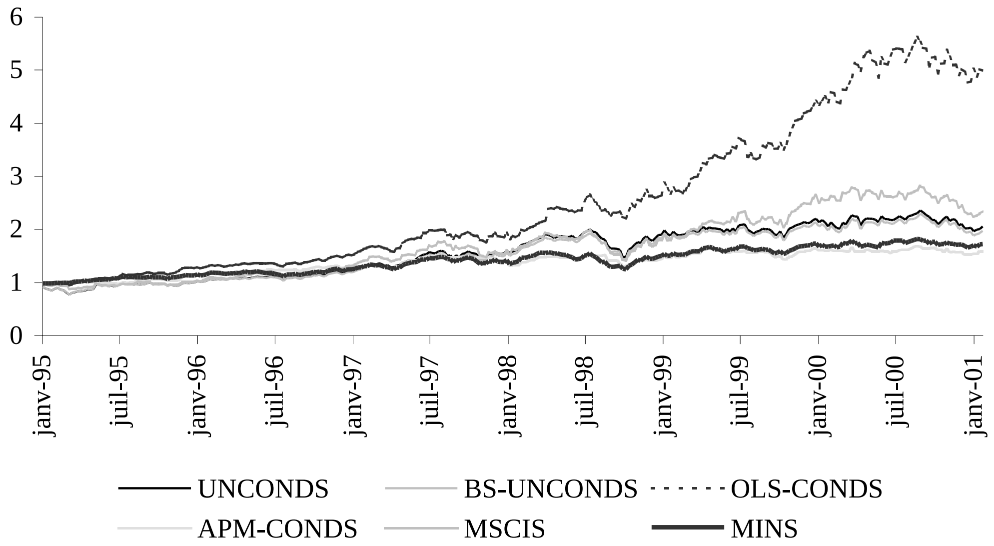
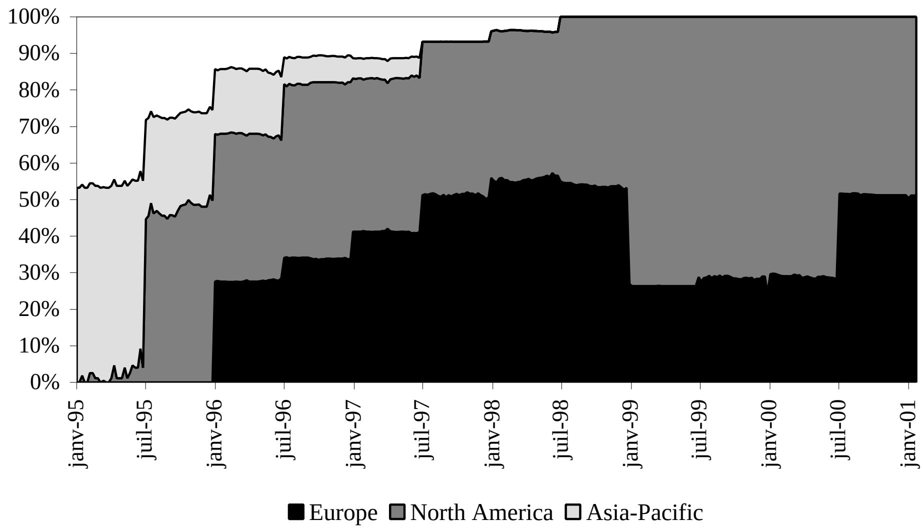


Figure 1 shows the evolution of one Swiss Franc invested in each strategy from the beginning of January 1995 until January 2001. It indicates that the performance of the OLS based conditional allocation is particularly strong during the bullish year of 1999 through investments in emerging and developed Asian markets. This is also the case for the MSCI World index, which contains a significant exposure to the Japanese stock market. In short, this graph illustrates the domination of the OLS-based conditional allocation that appears in Table 3.

4.2. Unconditional allocations

The classical unconditional asset allocation based on historical data reaches an annualized mean and standard deviation of 14.36% and 20.61% respectively. Figure 2 depicts the evolution of the allocation weights for the three developed regions, which are Europe, North America and the Asia-Pacific zone. In order to be readable, this graph does not consider the six emerging countries. Nevertheless, these weights can be determined by the white area between the 100%-line and the cumulative percentage of the three developed regions. Europe and North America obtain the major part of the invested wealth: most of the time, Switzerland and the United-States are targeted by this strategy. Surprisingly, the percentage invested in emerging markets is quite low compared to the one found by Harvey (1994). This is probably due to increasing correlations between developed and emerging countries documented in Table 2 and to weak average returns for the Asia emerging zone.

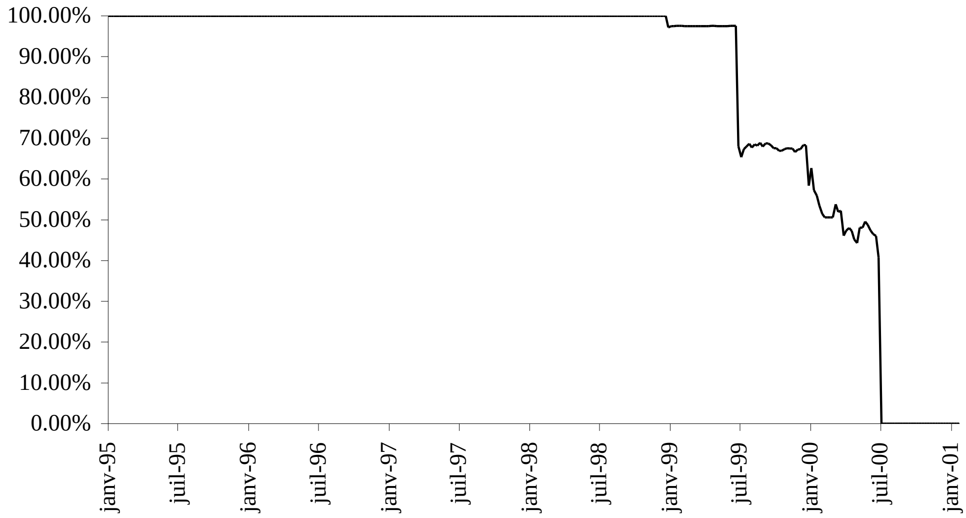
Figure 2: Evolution of the weights for the unconditional allocation



The next figure shows the evolution of the currency hedge ratio. This latter is defined as the percentage of investment that is hedged against currency variation. Of course we only consider developed markets, for which short positions on futures contracts have been implemented. It is interesting to see that foreign investments are most of the time hedged. These results confirm the interest to implement a currency hedging policy.

The results of the Bayes-Stein allocation are very close to the classical unconditional strategy, since the annualized return-risk couple is equal to 13.57% and 20.17%. Moreover, the correlation between the two series of returns amounts to 99.7%. Therefore, the Bayes-Stein allocation leads to the same optimal choices. Considering the fact that Jorion (1985) gives a lot of credit to Bayes-Stein estimators, these results are disappointing. An explanation can be found by comparing our implementation with the one proposed by Jorion (1985). He uses 60 observations to determine the vector of expected returns whereas 260 data points are considered in our study. But Jobson and Korkie (1985) explain that 200 observations are enough to give a reasonable approximation of this vector. Considering this assertion, it is not surprising that the vector that we calculate is not made up of extreme values and is not significantly influenced by the correction factor induced by the Bayes-Stein methodology.

Figure 3: Evolution of the currency hedge ratio for the unconditional allocation



4.3. Conditional allocations

The first conditional allocation based on a linear relation between market returns and lagged variables produces the best results: the annualized mean and standard deviation are equal to 32.31% and 24.18%. Figure 4 shows the evolution of the fraction of the wealth invested in the three developed areas. When compared to Figure 2, one notices that the optimal weights obtained with this asset allocation method are very volatile. This is inherent to this strategy as it explicitly assumes that expected returns are time-varying. A closer look at the weights shows that between January 1995 and July 1998, this strategy prioritizes Europe and North America, since the cumulated percentage often fluctuates between 60 and 80%. Then, developed and emerging Asian markets take an increasing importance. Once again, let us stress that the percentage allocated to emerging markets throughout the whole period is quite weak compared to Harvey's results (1994).

Figure 4: Evolution of the weights for the conditional allocation

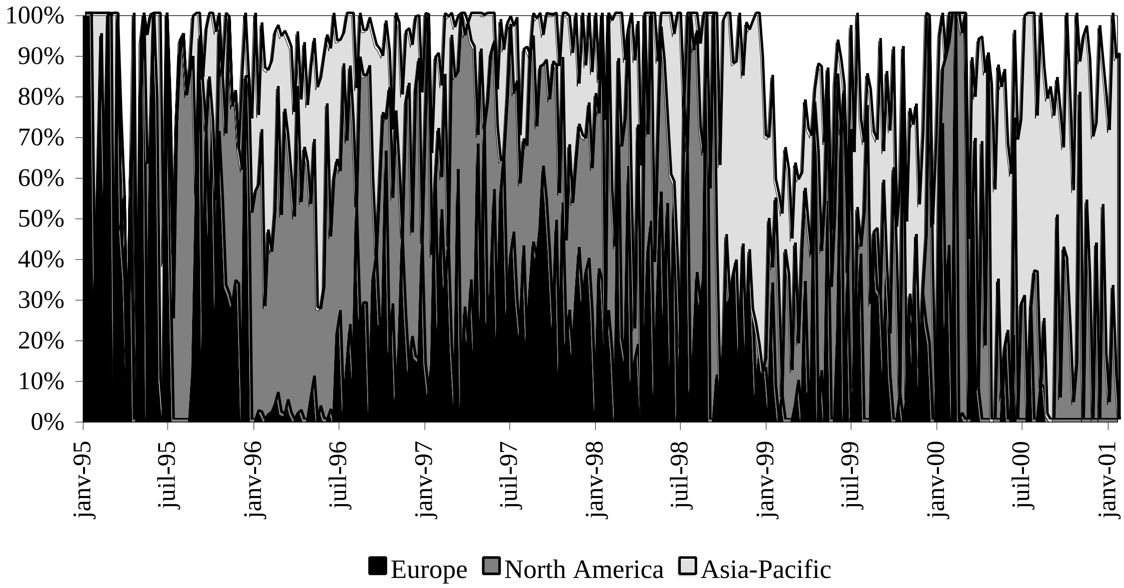
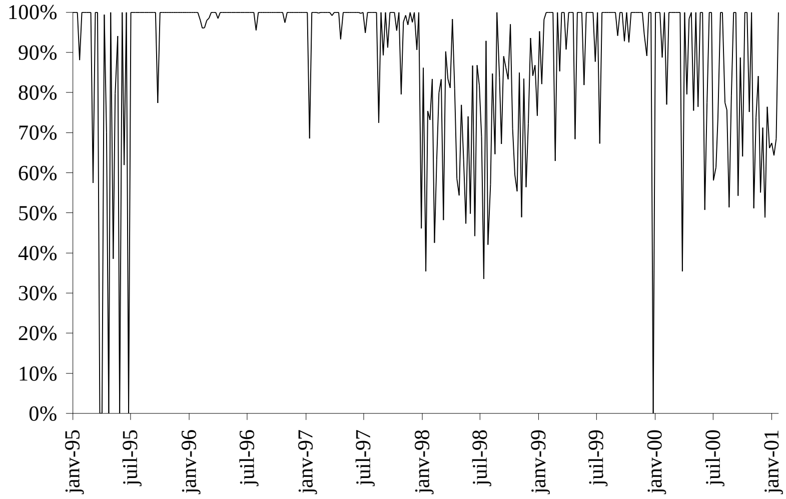


Figure 5 shows the evolution of the currency hedging ratio. Since it rarely falls under 50 %, this result confirms our assertion in favour of an active hedging policy.

Looking at the second type of conditional asset allocation, which uses a dynamic international APM, the performance is very disappointing. With an annualized mean and standard deviation of 8.45% and 11.45%, this strategy is the less attractive one. During the allocation period, North America and the Asia-Pacific region capture the major part of the invested funds. But the total investor's wealth is also frequently invested in the Euro-market when the optimized Sharpe ratio is inferior to the one-week Swiss interest rate.

Figure 5: Evolution of the currency hedge ratio for the conditional allocation



Since the implementation of the two distinct conditional allocations is one of the original developments of our study, the direct comparison of both strategies deserves some comments. Two reasons come to our minds to explain the poor results obtained by the APM-based conditional allocation. First of all, the econometric specification, inspired by Ferson and Harvey (1991), certainly contains some estimation problems, such as cross-sectional heteroscedasticity, that are liable to misestimate expected risk premia. But the main issue comes from the observation that all expected market returns are mainly determined by the expected World market risk premium: most of the time, they are all positive or negative following the sign of this premium. This close link associated with the volatility of the premium introduces a binary investment policy, which consists in either buying international stock when the expected World market premium is positive or being fully invested in the Euro-market when the latter is inferior to zero. Unfortunately, the bad informational signals transmitted by this model are very costly in terms of performance because of the low level of the Swiss interest rate. The econometric specification, the violation of the international capital asset pricing model assumptions, a bad choice of the lagged variables used to predict the premia are the most likely reasons to explain the failure of our APM-based allocation.

4.4. Other allocations

In addition to the previous allocations, we propose two other strategies for comparison purposes. The first one supposes that the MSCI World index is held during the whole allocation period. Its annualized mean and standard deviation are equal to 16.94% and 21.64%. We also implement a minimum variance portfolio based on the historical covariance matrix. This second allocation with an annualized mean and standard deviation of 10.09 % and 13.08 % gets mainly focused on the United States, Canada, Australia and Japan. It is interesting to notice that its currency hedging ratio never falls under 100 %, which is not surprising regarding the objective of this strategy. The results of this strategy are rather disappointing as it usually yielded superior results (see Haugen and Baker (1991)).

5. Conclusions

This paper compares the different asset allocation methods available to the Swiss investor wishing to diversify internationally. To answer the question addressed in the title of this paper, we strongly recommend to use a conditional asset allocation method based on direct estimation of expected returns. Based on our simulations we find that such an investment strategy would have produced an impressive average annual return of 32.31% compared to an annual return of 14.37% obtained with the classical unconditional method. It also outperforms the unconditional strategy in terms of Cornell measure and Sharpe ratios. These results confirm that although the out-of-sample predictive power of conditioning variables is low, their use in a conditional asset allocation framework adds value to the investment process[6].

This paper contributes to the existing literature in several ways. It is one of the first attempts to study the main investment strategies based on a mean-variance framework available to the international investor. It is also the first time that the two conditional asset allocation methods are compared. The outcome of our paper confirms several results obtained earlier in the academic literature. We find that the OLS-based conditional asset allocation outperforms the other methods as Solnik (1993) initially documented. As Hamelink (2000) and Fletcher and Hillier (2003) we find that APM-based conditional allocation yields rather disappointing results. We also confirm that classical unconditional asset allocation achieves a poor risk/return performance even with Bayes-Stein estimators. Let us also emphasize that all these

[6] Several authors, (e.g. Bossaerts and Hillion (1999)) criticized the use of such variables because of their low explanatory power in regression such as equation (5). Nevertheless, Kandel and Stambaugh (1996) show that even if the predictive power is low, it still significantly affects the portfolio choices of a risk-averse investor and increases his expected utility.

results have been obtained in a truly ex-ante framework that reflects exactly the uncertainty faced by the portfolio manager at the moment he has to decide upon his future investments.

The results obtained in this paper raise numerous questions that deserve additional research. The major task is to get more precise insights into the origin of the performance achieved with conditional strategies. One explanation could be that this strategy is able to take advantage of the effects of changing economic conditions on financial markets. Moreover, there are other important questions such as the optimal choice of predictive variables and the type of markets and market situations in which this strategy is most likely to be effective. The practical implementation of such strategies should be of particular interest to practitioners. This notably raises the question of replicating the indexes, integrating transaction costs or putting constraints on the variation of weights during the allocation process. All these issues will be addressed in future research.

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