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 stemming from the lower correlation exisiting between assets of different countries. The question that we raise in this paper is how to choose the best mix of countries to diversify internationally? We compare several methods of asset allocation from a Swiss perspective over the period 1988-2001. We simulate different investment policies and compare conditional and unconditional methods. We find that conditional methods, that explicitly assume time-variation in 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 in order 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 choose the best mix of countries to diversify. At the first sight, this question seems to be 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, Fama and French (1988, 1989) and Chen (1991) find that the dividend yield, the default or the term spread have some predictive power. Harvey (1991a) 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 an evidence that the main ingredients of mean-variance analysis are time-varying. This fact should be properly taken into account to improve the poor results obtained with the unconditional method.

This is exactly the way Solnik (1993) tackles this issue in an international setting. He assumes that expected returns are time-varying and he proposes a new asset allocation method, known as conditional allocation. Taking 16 national stock and bond market indices, he tries to predict the vector of expected returns with lagged variables such as the dividend yield or the one-month interest rate. Based on a mean-variance optimization, his analysis shows that the conditional allocation outperforms the unconditional one. Using a similar approach, Harvey

(1994) addresses the issue of including emerging markets into the analysis, whereas Klemkosky and Bharati (1995) explicitly consider the influence of transaction costs on the allocation results in the US market. Robertsson (2000) compares the results obtained with a weekly and a monthly rebalancing frequency on the Swedish market. Hamelink (2000) implements a conditional asset allocation by estimating the expected returns of 7 national stock markets with an international asset pricing model. Despite the diversity of situations examined in the above mentioned literature, the conclusions are remarkably similar. The results obtained with conditional allocations systematically outperform those obtained with unconditional strategies and various passive benchmark indices.

In the existing literature, only few papers have addressed the issue of international asset allocation from a Swiss perspective. Knight (1989) pursues an unconditional analysis and on a ex-post basis finds that a Swiss investor should hold Swedish and Japanese assets in order to improve his risk-return trade-off. Odier, Solnik and Zucchinetti (1995) try to find an appropriate investment policy for Swiss pension funds in an unconditional international setting. Unsurprisingly, they find that international diversification brings substantial gains. Hamelink (2000) investigates different asset allocation strategies using a QTARCH process for second moments and a conditional international asset pricing model (APM) to determine expected returns. His findings indicate that the conditional allocation yields less impressive results than those found in the previous studies analyzing conditional methods.

The main goal of our paper is to give a comprehensive view of the existing asset allocation methods available to an international investor today. Our study compares unconditional and conditional international asset allocations from a Swiss perspective in order to determine the most efficient method. This analysis is conducted in an 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 attempt to improve the unconditional approach in order to avoid its poor performance observed in previous studies due to a bad estimation of the parameters and too frequent reestimations. To this end, we use Bayes-Stein estimators that are less exposed to estimation risk. Then, two kinds of conditional allocation are implemented. The first is based on a direct and linear relation between returns of national market indices and predictive variables, whereas the second uses a conditional international APM with time-varying risk premia and betas. These two approaches are investigated because they present distinct features: the first method generally obtains very positive results and the second model is based on stronger theoretical foundations. We also allow the investor to protect his portfolio against currency risk with future contracts. This possibility contrasts with some of the previous studies, which adopted extreme positions: the hedge is either complete or inexistent. Finally, we 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 are used as input for determining expected returns for a subsequent period. The results of our empirical analysis, established on weekly data between January 1995 and January 2001, brings substantial credit to the conditional approach and confirm the superiority of the latter over the unconditional allocation.

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 mentioned above, one of our aims is to reproduce as much as possible the investment opportunity set that is available to an international investor located in Switzerland. We have therefore 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. These are very useful when implementing an international asset allocation, as MSCI's policy is to select liquid stocks in order to reach 60% of the total market capitalization of the market under consideration[1] (see MSCI (1998, 2001)). This remark is important, since the various allocations formulated in this study are based on index returns. To make this simplified approach realistic, we have to assume that it is possible to invest in such indices. It is therefore useful to work with MSCI indices which can be easily replicated with a subset of individual stocks that compose them. Returns of the

[1] Note that MSCI has recently decided to increase the market capitalization coverage target to 85%. This change of policy does not affect our study as it will take place in May 2002, which is of course out of our sample.

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: 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***
Phillipines	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 for weekly returns over the period January 1988-January 2001 (682 observations). Mean and standard deviation (Std Dev) are expressed in annual terms. Bold figures indicate that the first order autocorrelation coefficent (ρ1) is significant at 5% confidence level with a Bartlett test.

Table 1 shows that for developed markets the results in terms of mean and standard deviation are in line with previous studies. Japan is an exception with a very low mean return over that period. 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, we can reject the assumption of normality for all markets except for France. In order to test this feature, we compute Bera-Jarque (1980) statistics (not shown here to save space) and all of them reject normality at high significance level. More specifically one can notice the presence of fat tails and pronounced asymmetry for all the distributions. 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 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).

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

Harvey (1995a, 1995b)) and certainly weaken the diversification potential of emerging markets. For instance, Mexico has only 5 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 subperiods 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 subperiod, during which 3 major financial crises occured. 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 (1998)).

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 price of the future expressed in home currency is equal to :

$$F_0 = S_0 \frac{1+R_{Swiss}}{1+R_{Foreign}} \tag{1}$$

where F_0 is the price of the future 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 a foreign currency future, 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 :

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

where F_t is the price of the future 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 data from Datastream, it is possible to determine time-series of weekly returns for foreign currency futures. Because of lack of data, this procedure has only been applied to the 10 developed markets[2]. Finally, we only introduce currency futures contracts for hedging and not speculative purposes. Therefore, as Hamelink (2000), constraints are placed on the weights of these instruments :

$$0 \leq w_{it}^{Future} \leq w_{it}, \quad \forall i, \quad i = 1,...,10 \qquad (3)$$

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 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 on the efficient frontier. A criterion is to consider a rule whose application requires the knowledge of the vector of expected returns since, as Solnik (1993) and Harvey (1994) mention it, the better performance of conditional allocation surely stems from a more precise estimation of this vector. As Klemkosky and Bharati (1995) and Hamelink (2000), we have decided to 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.

[2] 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.

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 all the equities needed to replicate 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 apply 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 :

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

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

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

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 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 (subscript i=1,..,17 identify the indices of the 17 countries in our sample) and the second constraints indicates that short sales are not allowed in our context (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.

3.2. Unconditional asset allocation methodology

Several studies in international finance (see, for instance, Levy and Sarnat (1970), Knight (1989) or Odier and Solnik (1993)) applied the mean-variance algorithm to an entire historical data set. 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 in a forward looking perspective. This is why this method should be used in an ex-ante framework. Such an application necessitates 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). This problem is particularly acute for the vector of expectations and not so much for the covariance matrix as it has been advocated by Jorion (1985) and Michaud (1989). For this reason, we give a special attention to the vector of expected returns and 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 5 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 month from January 1995 to June 1995. Then, we repeat this procedure with the 5-year estimation window beginning six month later. We iterate this process until the end of our sample, i.e. in January 2001.

As mentioned earlier, the above method is subject to estimation error because of the use of historical means. This is why we try to improve the estimation of this vector with Bayes-Stein estimators. We do not detail the procedure here but the interested reader can find an extensive description in Jorion (1986). We will limit the presentation to an intuitive explanation. 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. Notice that, as Jorion (1985), we do not modify the historical covariance matrix.

3.3. Conditional asset allocation methodology

Conditional asset allocation is based on the presence of predictable time-varying components in returns that has been documented in several empirical papers. It has been found that stock returns are linearly associated with a set of lagged variables such as dividend yield, lagged stock returns, default and term spread. Two different versions of conditional asset allocation have been proposed in the literature. The first one has been initially implemented by Solnik (1993). He suggests to use ordinary least square regressions (OLS) of stock returns on lagged variables to determine expected returns. The second approach, proposed by Hamelink (2000), is based on a conditional asset pricing model with time-varying risk premia. In this case, the linear relation is used to model the evolution of the risk premia. In this paper we adopt an new orientation which consists in implementing and comparing both approaches.

3.3.1. OLS-based conditional allocation

This type of conditional allocation has been used by Harvey (1994), Robertsson (2000) and Solnik (1993) among others. It is based on the linear relationship[3] existing between stock index returns and a few lagged variables such as dividend yield, stock returns, a variable representing the spread for default and a variable representing the slope of the term structure. Although most of the empirical evidence has been obtained for the United States, Hawawini and Keim (1995) provide some evidence that this relationship also holds for other countries. Although the choice of these variables does not stem fom a theoretical model, one can easily see that these variables represent the link existing between general economic conditions and financial markets.

To implement our conditional asset allocation we have decided to use three conditioning variables. The first 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

[3] Harvey (1991b) compares various specifications of this relation and concludes that the linear relationship gives the best results.

maturity. We then select two local variables for each market. The first is the 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 governement bond and the yield on 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_{it} is the return on the index of country *i*, *DEFAULT* is the US default premium and *TERM* is the country *i* term premium. 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 6 months, they are used with the 3 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 proposed by Hamelink (2000) and can be theoretically justified by the work of Ferson and Harvey (1991). They show that the predictability of asset returns previously documented can be reconciled with the notion of market efficiency by assuming that these variables do not directly predict expected returns but the time-variation of risk premia. The model that we use to implement our conditional asset allocation is an adapted version of 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:

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

where $E\left(R_{it} \middle| I_{t-1}\right)$ 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 $E\left(R_{World,t} - R_{ft} \middle| I_{t-1}\right)$

and $E\left(R_{CHF,t} - R_{ft} \middle| I_{t-1}\right)$ 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 (1995) we weight every currency in this index by the amount of trade it does with Switzerland. The predictive variables that we use to model the time variation of betas and risk premia are similar to those used in the first conditional allocation method. For the World index factor we use the lagged World index return, the lagged US default premium, and the lagged US term premium. For the currency factor, we use the lagged currency factor and the lagged US term and default premia.

The implementation of this model follows the method of Ferson and Harvey (1991). It is a two-step methodology that first estimates betas by regressing the country returns on the returns of the two factors over a 2.5 years period. In a second step we regress cross-sectionally the country returns on the vector of betas to obtain the estimated risk premia for a week. Finally, the time series of risk premia are regressed on the predictive variables. The result of this estimation is used to determine expected returns for our optimization program. The rest of this procedure is the same as the one developed for the OLS-based conditional allocation.

3.3.3. Specification of the covariance matrix

In the light of the previous discussions it seems natural to use the conditioning variables to model the evolution through time of the covariance matrix. However, this approach raises several problems, one of the most important being that it does not ensure the positivity of the conditional variance matrix. Another approach would be 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. As Solnik (1993) and Klemkosky and Bharati (1995) we decide to continue to use our unconditional covariance matrix as it has been shown to be rather stable through time. This will also give us a fair comparison of the various methods we investigate as we only model the vector of expected returns.

3.4. Comparing the performance of the strategies

The issue of measuring the performance of the various strategies is crucial for our study where we try to compare the results of conditional and unconditional asset allocations. This task is rather complex as standard measures such as Jensen or Sharpe ratios are based on the assumption of independently and identically distributed returns. This is clearly not a good assumption for conditional methods as they are based on the idea that expected returns are time-varying. Dybvig and Ross (1985) and Solnik (1993) emphasize the problems raised by classical performance measures for conditional asset allocation as well as the choice of the relevant benchmark portfolio in an international context. In order to avoid these issues we use the Cornell (1979) performance mesure. 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. This measure boils down to computing a t-stat on the difference between the returns of the conditional and unconditional strategies, divided by the standard deviation computed with our unique estimate of the covariance matrix. 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: Returns on different 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 unexpected returns, the t-stat amounts to 2.3, which is significant at the 5 % confidence level. Keeping in mind the disappointing results of the APM-based conditional strategy, we have only calculated the Cornell measure for the two mentioned allocations.

Figure 1: Evolution of one Swiss Franc invested in 1995

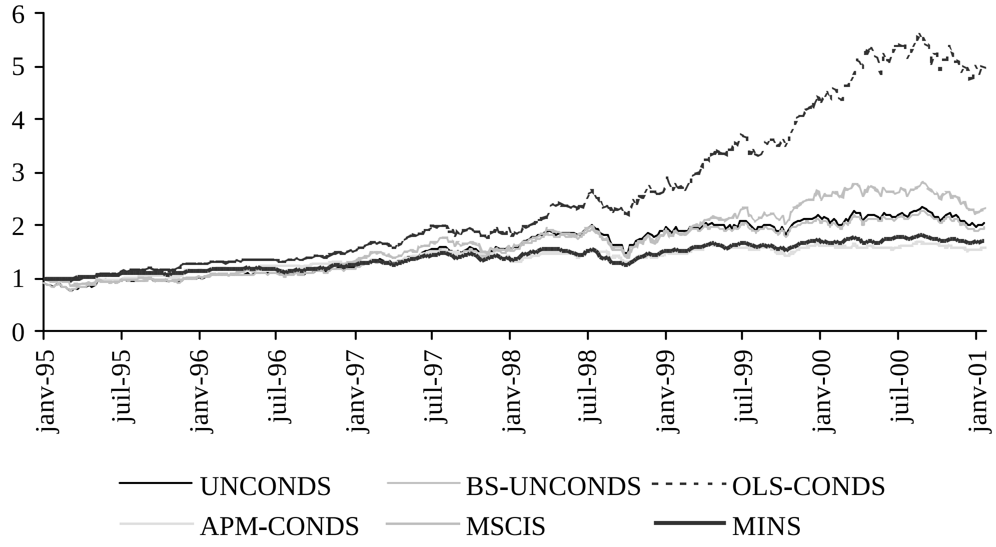
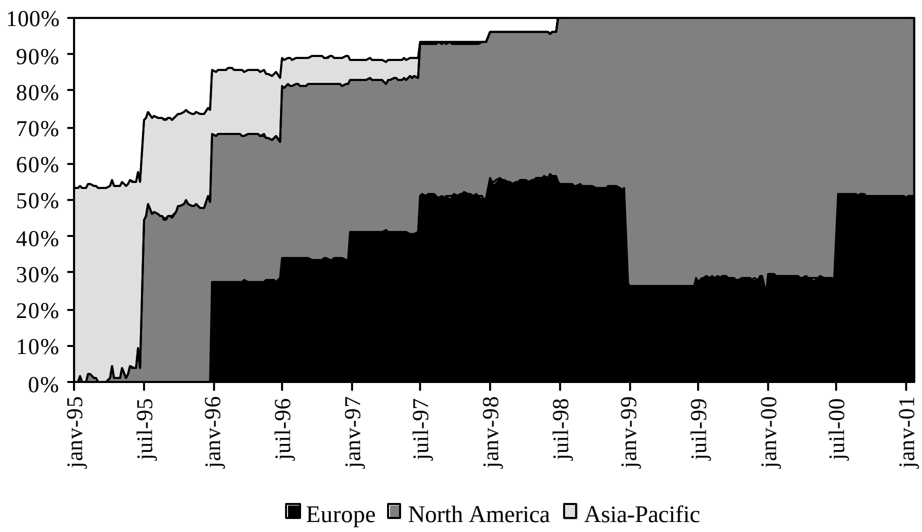


Figure 1 shows the evolution of one Swiss Franc invested in each strategy from the beginning of January 1995 until January 2001. It indicates that the performance of the OLS based conditional allocation is particularly strong during the bullish year of 1999 through investments in emerging and developed 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

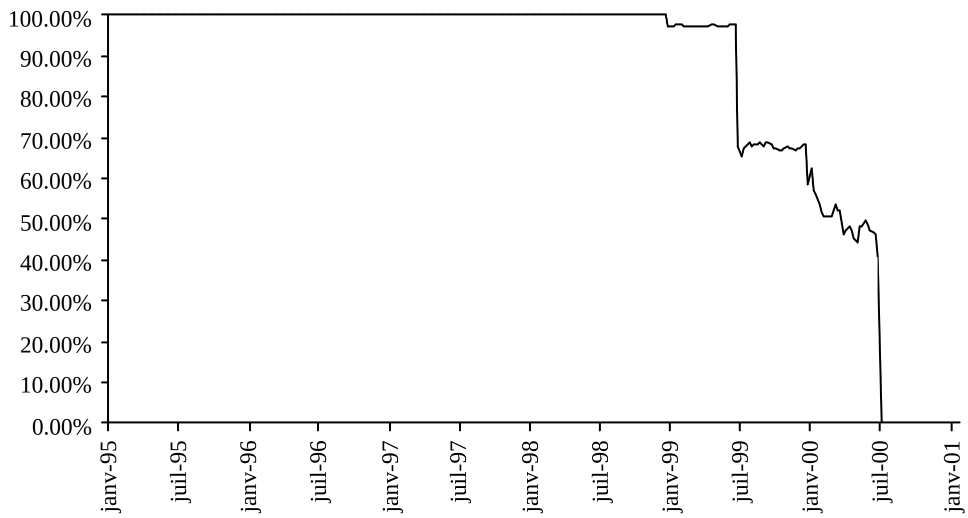
The classical unconditional asset allocation based on historical data reaches an annualized mean and standard deviation of 14.36% and 20.61% respectively. Figure 2 depicts the evolution of the allocation weights for the three developed regions, which are Europe, North America and the Asia-Pacific zone. 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 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 time hedged. As Hamelink (2000), these results confirm the interest to implement a currency hedging policy.

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



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 Jorion's paper (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.

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. 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

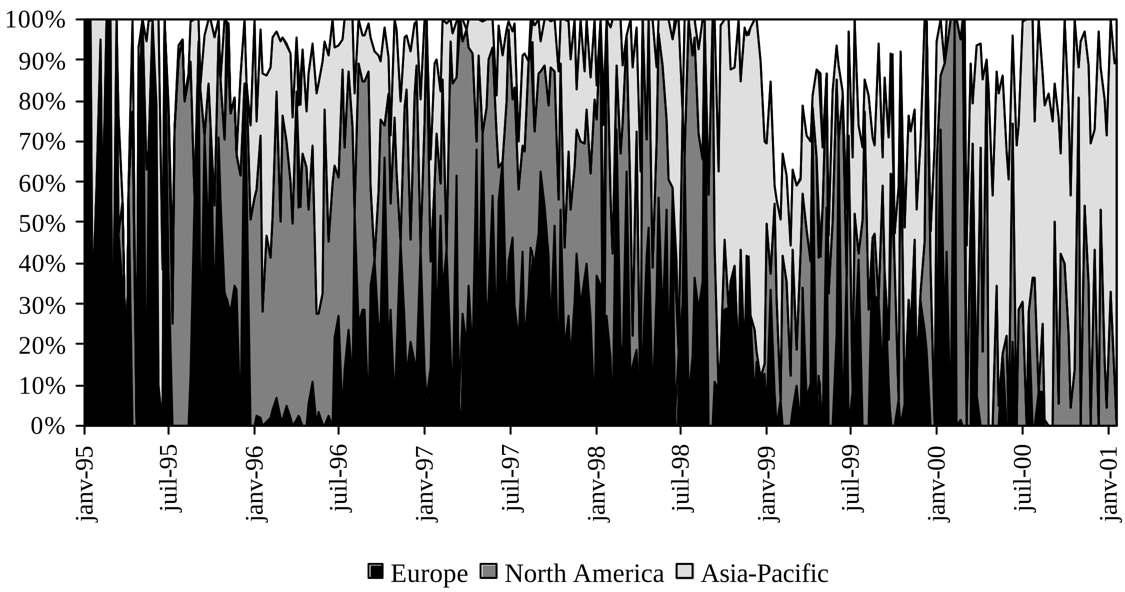
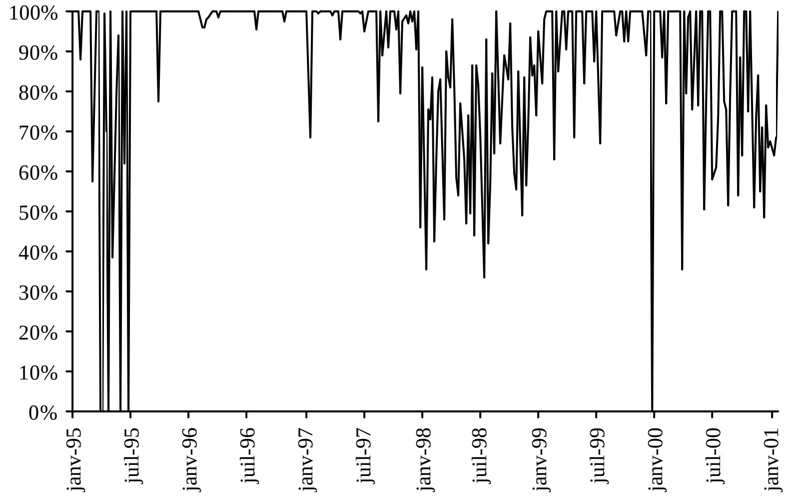


Figure 5 shows the evolution of the currency hedging ratio. Since it rarely falls under 50 %, this result confirms our assertion in favour of an active hedging policy.

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 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 weakness 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.

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 simulation 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.

This paper contributes to the existing literature in several ways. It is one of the first attempts to study all the investment strategies 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) we find that APM-based conditional allocation yields rather disappointing results. We also confirm that classical unconditional asset allocation provides a poor return even using Bayes-Stein estimators. All these results have been obtained under the most realistic conditions. We have tried to use a really international setting including most investable emerging markets. We also use currency hedging strategies and do not allow short sales on the indices. Finally, we use 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.

We would like to conclude on some topics for future research. Conditional asset allocation based on predictive regressions has outperformed all the other strategies by a large margin. However to keep the realistic framework in mind, there is one issue with this approach as it requires a lot of transactions. In fact the positions in the various assets change frequently and by large amounts. This raises the question of transaction costs associated with this strategy. An interesting line of research, that goes beyond the scope of this paper, would be to implement such a conditional strategy by putting constraints on the variation of weights and by taking account of the transactions costs. However, looking at the high returns earned by the conditional strategy we do not believe that its superiority would be put seriously into question as this strategy seems to be really able to take advantage of the effects of changing economic conditions on financial markets.

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