International TAA Strategies and Currencies

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Abstract

We model time-varying returns on international stock and bond markets from the perspective of a Swiss investor using two alternative models. Both a conditional version of the international APT (Oertmann 1997) and direct regressions of asset returns on instrumental variables yield significant out-of-sample predictions (Solnik 1993). Due to the workings of the cross-sectional constraints, the factor model works better for stocks than for bonds. We form portfolios based on Black-Litterman expectations and find that the way currency decisions are integrated in the investment process matters more than the potential of enhancing performance by TAA.

JEL classification: G11, G12, G15

Keywords: International Portfolio Choice, Currency-Hedging, Conditional Asset Pricing, Black-Litterman Model

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1 Introduction

Asset managers face the question whether and how their performance can be enhanced by dynamic portfolio strategies[1]. In addition, international portfolio managers need to approach the role of currencies, specifically whether to hedge and how much, in their asset allocation. From a more general point of view, the first problem is about tactical asset allocation (TAA), the second is by and large a matter of strategic asset allocation (SAA)[2]. Looking at the performance of 91 U.S. pension plans over the period from 1974 – 1983 Brinson, Hood, and Beebower (1986) conclude that the implications of strategic decisions outweigh tactical (or active) decisions. This theme is reiterated by a sequel to their study (Brinson, Singer, and Beebower 1991) and is now regarded as common sense in the asset management industry. However it remains to be seen, whether the general claim that "compared against SAA, TAA is of second order importance" holds also in the case of currency decisions in international portfolios.

In this paper we compare the quantitative importance of typical currency policies with a TAA based on macroeconomic conditioning variables. Using a common set of instrumental variables we estimate two different models of time-varying expected returns. With rolling out-of-sample return estimates we form alternative portfolios for either bonds and stocks where we vary the way currencies are integrated in the asset allocation process. The contributions of our paper are: an out-of-sample comparison of two forecasting methods over two broad asset classes (stocks and bonds) and the subsequent application of the Black-Litterman method as a mean of restricting portfolio weights. These particular results can then be interpreted from the perspective of

[1]We use the terms "TAA" and "dynamic portfolio strategies interchangeably in this article. See Lee (2000) for a proper definition of TAA and Dahlquist and Harvey (2001) for the relation between benchmarking, strategic and tactical asset allocation

[2]Of course, once an investor has settled for a particular kind of currency allocation he might want to consider to deviate tactically from that decision. In this paper, we will focus on the strategic aspect of the currency decision.

SAA vs. TAA.

Both topics, the timing of returns and international portfolio theory, have *separately* each been widely discussed in the literature, theoretically as well as empirically. The main findings on time-variation are that expected returns vary with the state of the economy and that fundamental macroeconomic variables like market-wide PE ratios or interest rate spreads can partly capture this variation. International finance theory extends (conditional) asset pricing to include currency risks in the spirit of the IAPM of Solnik (1974), Sercu (1980) and Adler and Dumas (1983)[3]. Among others, the empirical results of Dumas and Solnik (1995) showed that currency risks are priced. Hence, bearing the PPP risks associated with currency positions gets rewarded. The implication for asset managers is to treat currencies as a separate asset class which has the potential to widen the investment horizon in order to achieve a better risk-return trade-off. The latter assertion has been contended by the "free-lunch hypothesis of currency hedging" of Perold and Schulman (1988) which advocates a one-to-one hedging of foreign investments.

In order to gauge the potential of TAA, we have chosen a set of five instrumental variables and estimate two different types of return models: Firstly, we estimate a conditional factor pricing model following Oertmann (1997) which is similar to the latent variables model of Ferson (1990). The factor model imposes a cross-sectional constraint the time-variation in expected returns. Expected returns are the product of exposure to systematic risk factors and their (time-varying) premia. Specifically, we estimate a three factor model with a market factor and two currency factors (Euro and U$) as our concern are international TAA strategies. Secondly, we use a simple OLS regression of returns on instruments like Solnik (1993) does. This way we

[3] Actually, it is the other way round: The (one-period) IAPM can be extended to a conditional model. An easily accessible review of international portfolio theory is given by Jorion and Khoury (1996). Please see also Stulz (1995) for a comprehensive survey of international asset pricing theory.

can maximize the statistical information[4] per asset without regard for cross-sectional consistency.

Our major finding on the out-of-sample predictability of returns is that only a small part of time-variation can be explained, especially out-of-sample. Even though out-of-sample correlations between realized and expected returns of around 0.25 are tiny[5], they are significant for some asset classes. By and large our numbers are in line with other research (Solnik 1993; Oertmann 1997; De Santis, Gerard, and Hillion 1999). A comparison of the predictability in the two return models yields an ambiguous picture which can be related to the mechanics of the models. It remains to be seen in the second part of our study whether this level of predictability can be transformed into economically relevant portfolio returns.

Brinson, Hood, and Beebower (1986) compare the contribution of strategic and tactical decisions by looking at neutral policy weights of pension plans so that they are able to decompose realized investment returns into active and passive components. Their method looks at the data on particular funds' returns and their strategic weights[6]. Our approach of combining a model of time-varying expected returns with different currency allocations in dynamic portfolio strategies is more similar to De Santis, Gerard, and Hillion (1999) who model expected returns in DEM on six countries[7] as a GARCH-in-the-mean process along the lines of De Santis and Gerard (1997). Using similar instrumental variables[8] but a different model of expected return and a finer set of asset classes, their major finding is that the inclusion of currencies in a simultane-

[4]To be precise, we maximize the statistical information within a *linear* framework.

[5]A correlation of 0.25 implies that only about 6% of realized return variation can be explained by variation in expected returns.

[6]For the implementation of the Black-Litterman method we had to settle on some neutral or "policy" weights of our *hypothetical* strategies. By comparing benchmark performance and Black-Litterman portfolios we eventually come close to the method of Brinson, Hood, and Beebower (1986) but without explicitly decomposing investment returns. Still, our approach is conceptually very different from theirs.

[7]France, Germany, Japan, Netherlands, UK, U.S.

[8]A major difference is that they use the local term spread between short and long bond interest rates as a local instrument.

ous optimization outperforms both a full hedging and a currency overlay management. This contrasts with our main result: We find only a small under-performance of the overlay management while especially our unitary hedging strategy exhibits a markedly worse trade-off between risk and return.

Comparing the relative importance of incorporating conditioning information and the choice of currency allocation, our results suggest that decisions on currency hedging matter more than the implementation of a macroeconomic TAA strategy. But once the hedging decision has been taken, a TAA based on anticipating business conditions can add some incremental value. Overall, this is not surprising, as currency hedging is a determinant of strategic asset allocation. Viewed from this angle, our results extend the theme of Brinson, Hood, and Beebower (1986)[9] to the case of international investments while using a completely different methodology.

We have organized this paper as follows: In the next section (2) we describe our data set. Section 3 describes the two models of expected returns (3.1), the statistical methodology of gauging out-of-sample predictability (3.2) and our empirical results on predictability in both models (3.3). Then we apply this predictability in section 4 to mean-variance efficient portfolios which are formed dynamically based on current out-of-sample predictions. We describe portfolio formation under typical currency treatments (4.1) and the Black-Litterman method used to obtain "well-behaved" portfolio (4.2) before presenting our results on the economic importance of TAA based on macroeconomic variables vis-a-vis strategic currency allocation (4.3). Our results are summarized in section 5.

[9]Brinson, Hood, and Beebower (1986) and Brinson, Singer, and Beebower (1991) do not regard currencies but the relative impact of asset allocation policy, timing and selection. The treatment of currencies corresponds to the strategic policy decision and our TAA corresponds to timing. As we are working with broad indices there is no selection component in our study.

2 Data

All raw data times series were obtained from Thomson Financial (formerly Datastream). Our sample stretches from February 1986 until July 2001. Out-of-sample estimates of expected returns are computed from rolling windows with 143 observations each. So the first return estimation uses data from February 1986 until January 1998. We obtain a history of 42 out-of-sample estimates from February 1998 until July 2001. In the remainder of this section we will shortly describe the construction of returns, instrumental variables and factors. Some instrumental variables and factors were constructed as G7-basket variables. Appendix A describes the construction of the basket weights in more detail. Descriptive statistics of the asset returns can be found in table 1. Descriptive statistics for the factors and instruments are presented in table 2, their correlations with the assets in table 3.

2.1 Returns

Monthly simple returns are calculated from the perspective of a Swiss franc investor. In addition it should be noted that the sole inputs for all calculations are the returns in excess of the Swiss franc's one-month Euromarket rate. In particular this implies that the first two moments of the return distributions used for the mean-variance portfolios are computed from excess returns. This is consistent with the notion that taking nominal asset returns in excess of the nominal riskfree[10] rate proxies for real excess returns – in excess of the real and conditionally riskfree interest rate (Campbell 1991; Merton 1980)[11].

[10]Please note that the riskfree rate is not constant over time. It is riskfree in the sense that the rate of return is known for sure at the beginning of the investment horizon (here: one month).

[11]As noted by Campbell, Lo, and MacKinlay (1997, p. 182) it is standard in empirical work to estimate moments of return distributions from excess returns without citing any reason for this. Campbell (1991) makes this case only for *log*-returns where the price deflator (CPI) cancels out. The notion that taking excess returns is a (crude) matter of conditioning in general can be found in Merton (1980).

We looked at the stock, bond and money markets of Switzerland, the U.S. and today's EMU-zone. Our returns were calculated from stock indices of MSCI, bond indices from Thomson Financial and money market rates from the London Euromarket as well as currency rates quoted by WM/Reuters.

2.2 Instrumental variables

The link between time-variation in expected returns and business cycles is widely reported. Fama and French (1989) explored statistically the relation between interest rate spreads and U.S. stock returns. A concise survey of typical instrumental variables has recently been given by Campbell (2000, Section I.A.4). These economic state variables can be built into formal pricing models as successfully shown by Jagannathan and Wang (1996) and Harvey (1991) who has also demonstrated their usefulness in an international setting. We have constructed five typical instrument variables with the potential to anticipate global business cycles. It should be noted that we have tested several combinations of the five instruments below, also with respect to taking first differences. By and large our results are robust to these variations. In addition to the five business cycle indicators presented below, two more variables have been commonly used in prior research: a dummy variable for the month of January and the lagged return on a market wide portfolio of stocks (Harvey 1991; Hawawini and Keim 1995). While other common variables such as the dividend price ratio (equally omitted by us) can be easily related to the price-earnings ratio included in our list, the story behind these two might be of a different nature. We disregarded both. Most of all, we had to limit the number of instruments in order to ensure numerical tractability, especially for the IAPT (section 3.1.1). In addition, the January dummy did not yield significant slope coefficients in univariate regressions on returns conducted in-sample (results not reported here). Similar regressions showed some (in-sample) validity for the lagged market return. Given the highly persistent nature of our business cycle indicators, this variable did not seem to add much value in a multivariate context.

We constructed the following instrumental variables:

DEF Spread between U.S. corporate bond interest rates with a Moody's rating of AAA and Baa respectively.

TED The spread between the one-month interest rate on U.S. Treasury Bills and the corresponding Euromarket one-month rate for deposits in U.S. Dollar.

dPE Log-changes of the Thomson Financial stock market indices's price-earnings ratios for the G7 countries weighted by their GDP (see appendix A for the construction of G7 baskets).

TRM GDP weighted basket of term spreads in the G7 countries. The term spread is defined as the difference between long bond rates and short term money market instruments. The short rates used are the one-month rates from the London Euromarket, long rates are the redemption yields of the Thomson Financial government bond indices[12].

dVol Log-change in the implied volatility index of the Chicago Board of Options Exchange (CBOE).

CONST Constant instrument.

2.3 Factors

For the IAPT model described in section 3.1.1 we need to specify a set of common return factors plus a set of currency (in general: PPP) hedge factors. In the setting of

[12]For Italy, the yield on treasury bonds traded in the secondary market is used due to lacking history of the corresponding index.

the Intertemporal Capital Asset Pricing Model (Merton 1973) a similar pricing formula is derived where the factors are interpreted as state variable hedges and the where market must be included, too. Our focus is on the effects of currencies and given the conditional nature of our estimates we need to keep a check on the number of factors in order to keep the model numerically tractable. Hence we have chosen to construct the following factors for estimating the IAPT. Please note that we estimate the IAPT separately for bond and stock markets (see section 3.1.1) where we have chosen to use two different market factors for each case:

rMS The stock market factor is constructed as the monthly simple return in Swiss franc of the MSCI World index (including dividends) measured in excess of the one-month Euromarket rate on Swiss franc deposits. Please note that the MSCI world index is a value-weighted index.

rMB For the "bonds-model" we use a GDP weighted portfolio of returns on G7 government bond market indices (Thomson Financial). The Italian index is only included as of April 1991 owing to lack of data. Again, the returns are monthly simple excess returns.

dEUR Simple net change in Swiss franc per Euro exchange rate. For months prior to the introduction of the Euro in 1999 the Swiss franc / Deutschmark rate is used.

dUSD Simple net change in Swiss franc per U.S. Dollar exchange rate.

	Stock Markets			Forex Forwards		Bond Markets		
	EMU	U.S.	CH	EUR	USD	EMU	U.S.	CH
Avg.	0.69%	0.92%	0.80%	0.05%	0.16%	0.18%	0.36%	0.08%
Vol.	5.71%	6.22%	5.41%	1.18%	3.54%	1.89%	3.69%	1.23%
$t(\text{Avg.} > 0)$	1.64	2.02	2.00	0.62	0.61	1.33	1.32	0.92
Max	14.97%	14.22%	14.38%	2.94%	11.39%	4.11%	11.96%	4.06%
Min	-22.58%	-26.91%	-23.57%	-3.03%	-9.11%	-6.72%	-9.00%	-3.32%
	Correlations							
Stocks EMU	1.00							
Stocks U.S.	0.71	1.00						
Stocks CH	0.75	0.66	1.00					
FX EUR	0.46	0.35	0.18	1.00				
FX USD	0.48	0.72	0.36	0.38	1.00			
Bonds EMU	0.46	0.29	0.24	0.70	0.23	1.00		
Bonds U.S.	0.47	0.73	0.39	0.36	0.88	0.41	1.00	
Bonds CH	0.13	0.10	0.26	0.04	0.08	0.45	0.24	1.00

Descriptive statistics and correlation coefficients were computed from the monthly excess returns in Swiss Franc over the entire data sample from March 1986 until July 2001.

Table 1: Descriptive statistics of test assets

	Factors				Lagged Instruments				
	dEUR	dUSD	rMB	rMS	DEF	TED	dPE	TRM	dVol
Avg.	-0.04%	0.01%	0.36%	0.64%	0.86%	0.58%	0.20%	0.81%	0.05%
Vol.	1.17%	3.49%	2.59%	5.40%	0.24%	0.42%	4.32%	0.77%	17.78%
$t(\text{Avg.} > 0)$	-0.50	0.05	1.87	1.62	48.63	18.91	0.62	14.29	0.04
Max	2.84%	11.68%	7.88%	14.56%	1.58%	2.56%	11.37%	248.23%	1.01%
Min	-2.98%	-9.27%	-5.68%	-22.94%	0.53%	0.11%	-21.92%	-109.49%	-0.46%
	Correlations								
dEUR	1.00								
dUSD	0.37	1.00							
rMB	0.44	0.78	1.00						
rMS	0.33	0.60	0.68	1.00					
DEF	0.10	-0.02	-0.00	0.07	1.00				
TED	0.07	-0.02	0.06	0.05	0.52	1.00			
dPE	-0.01	0.20	0.07	0.12	0.08	-0.20	1.00		
TRM	-0.06	0.02	0.04	0.02	-0.40	-0.29	-0.07	1.00	
dVol	0.05	-0.03	-0.02	-0.09	-0.05	0.03	-0.50	-0.00	1.00

Descriptive statistics and correlation coefficients were computed for monthly data over the entire data sample from March 1986 until July 2001 (respectively February 1986 until June 2001 for the lagged instruments).

Table 2: Descriptive statistics of factors and instruments

	Factors				Lagged Instruments				
Assets	dEUR	dUSD	rMB	rMS	DEF	TED	dPE	TRM	dVol
Stocks EMU	0.46	0.47	0.54	0.82	-0.00	0.02	0.13	-0.02	-0.09
Stocks U.S.	0.35	0.72	0.71	0.89	0.01	0.02	0.10	0.01	-0.08
Stocks CH	0.17	0.36	0.42	0.72	-0.05	-0.04	0.13	0.01	-0.16
FX EUR	1.00	0.38	0.46	0.35	0.07	0.04	-0.01	-0.03	0.05
FX USD	0.37	1.00	0.78	0.61	-0.02	0.01	0.19	0.02	-0.03
Bonds EMU	0.68	0.23	0.59	0.33	-0.01	0.04	-0.05	0.04	-0.01
Bonds U.S.	0.35	0.88	0.90	0.59	-0.05	0.03	0.09	0.01	-0.04
Bonds CH	0.02	0.08	0.32	0.13	-0.11	-0.03	-0.10	0.13	-0.00

Correlation coefficients were computed for monthly data over the entire data sample from March 1986 until July 2001 (respectively February 1986 until June 2001 for the lagged instruments). The numbers are rounded, hence the seemingly perfect correlation between Forex Forwards and the corresponding currency factors.

Table 3: Correlations between test assets and factors as well as lagged instruments

3 Estimates of time-varying expected returns and their evaluation

In this section we explore the statistical predictability of world stock and bond markets using two different model of expected returns conditioned on one set of macroeconomic instruments. We will first present our two models of time-varying expected returns (3.1). One is a conditional version of the IAPT which has been used by Oertmann (1997). This model puts a cross-sectional constraint on returns *and their predictability*. As an alternative, we follow Solnik (1993) and model the conditionally expected returns from a time-series regression of returns on the (lagged) instruments. Then we describe our measure of gauging the predictive value of out-of-sample estimates which we obtain from univariate regressions of realized returns on their forecasts. The empirical results are reported at the end of this section.

3.1 Two alternative models using the same indicator variables

In this study, we limit ourselves to model predictability using macroeconomic instrumental variables. The economic intuition behind this approach is to associate time-variation in expected returns with business cycles and corresponding variation in the risk taking of representative investors. We did not explore the potential of any technical strategies[13] or other alternative models of time-varying expected returns. With an eye on our empirical setup using excess returns, we will present all models in terms of excess returns.

[13] See Lofthouse (2001, Chapter 20) or Solnik (1999) concerning currencies, Lo, Mamaysky, and Wang (2000) for equities.

3.1.1 A conditional version of the International APT

An economic model of expected returns is an asset pricing model. The workhorse in international finance is to use the IAPM surveyed and generalized by Adler and Dumas (1983). Oertmann (1997) estimates a conditional version of this model using GMM in a formulation which is similar to the latent variable model of Ferson (1990). In this model, the (excess) returns r_i are decomposed into their exposure to a set of common risk factors and an orthogonal component

$$r_{i,t} = \sum_f \beta_{i,f} f_{f,t} + \varepsilon_{i,t} \tag{1}$$

and the risk factors are further decomposed into an expected and an unexpected component

$$f_{f,t} = \lambda_{f,t} + \delta_{f,t} \tag{2}$$

This leads to expected asset (excess) returns being the product of their exposure to risk factors and the expected risk premium per factor:

$$\mu_{i,t} = \sum_f \beta_{i,f} \lambda_{f,t} \tag{3}$$

Hence expected returns are cross-sectionally constrained by the common factor risk premia.

Time variation is introduced by modelling the expected factor risk premia $\lambda_{i,t}$ as a linear function of conditioning information $Z_{z,t-1}$ (known at the beginning of period t):

$$\lambda_{i,t} = \sum_z \omega_{i,z} Z_{z,t-1} \tag{4}$$

The model is estimated with GMM as a system of N equations (N being the number of assets) of the form

$$r_{i,t} = \mu_{i,t} + \sum_f \beta_{i,f}\delta_{f,t} + \varepsilon_{i,t} = \sum_f \beta_{i,f}\left(\lambda_{f,t} + \delta_{f,t}\right) + \varepsilon_{i,t} \tag{5}$$

where the unexpected component of factor changes $\delta_{f,t}$ has previously been estimated from a VAR system:

$$\delta_{i,t} = f_{i,t} - \sum_f c_{i,f} f_{f,t-1} - \sum_z d_{i,z} Z_{z,t-1} \tag{6}$$

Please note that the set of instruments includes also a constant, hence the VAR above is estimated with intercept.

3.1.2 Remarkably similar risk premia for both stocks and bonds

A prime concern for the empirical implementation of the conditional IAPT model stems from the specification and the non-linearity of the moment conditions. Violation of the economic or econometric assumptions (especially ergodicity of the time series) could be compounded here with ill-behaved numerical "solutions" of the GMM estimation. We estimated the model separately for our two sets of test assets: Stocks plus money markets and bonds plus money markets. We found that the estimated currency risk premia were remarkably similar – as predicted for integrated world markets where factor risks are awarded identically across markets. And the covariation in the market premium for stocks and bonds is also remarkably high. These results are illustrated in figure 1 for the USD premium, figure 2 for the EUR premium and figure 3 for the market premium.

Please note that both the bonds-model and the stocks-model are estimated with the same currency factors, only the market factors are different[14]. Hence it is very logical

[14]The MSCI world stock index return respectively a GDP weighted basket of G7 government bond

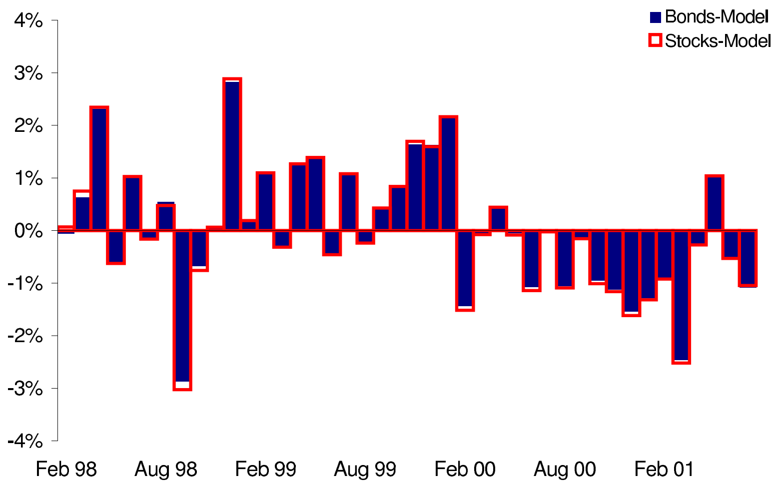

Figure 1: Estimated out-of-sample USD risk premia of the IAPT

in theory but still surprising in practice to see such a close fit in predicted out-of-sample risk premia which were estimated using different "left-hand side" assets.

3.1.3 Direct regressions of asset returns on instruments

The model described in the previous section imposes an economic structure on the way that the conditioning variables induce time-variation into expected returns. In addition, its implementation requires the estimation of a highly non-linear system with 33 parameters. So it might be prone to errors which may both arise from the economic assumptions as well as the numerical properties of the system. For the purpose of our paper, we are interested in *some* model of time-varying returns whose estimates can be plugged into dynamic portfolio strategies. So we have chosen to contrast the IAPT estimations with direct asset-by-asset time-series regressions of excess returns

indices from Thomson Financial (Datastream), see section 2 for further details.

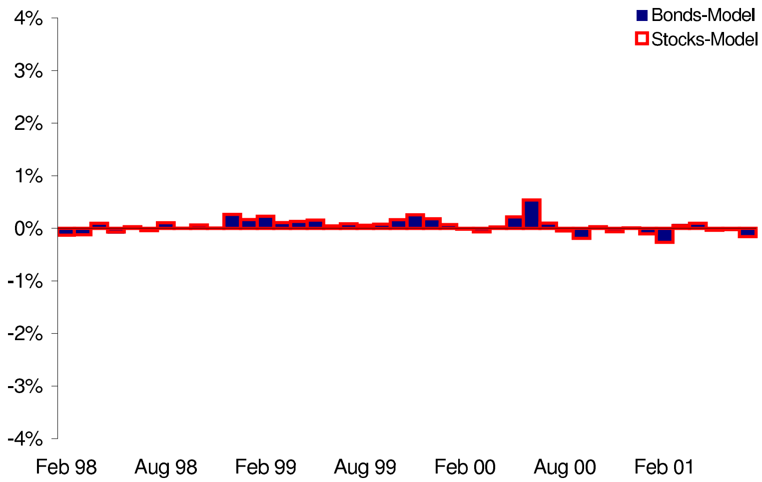

Figure 2: Estimated out-of-sample DEM risk premia of the IAPT

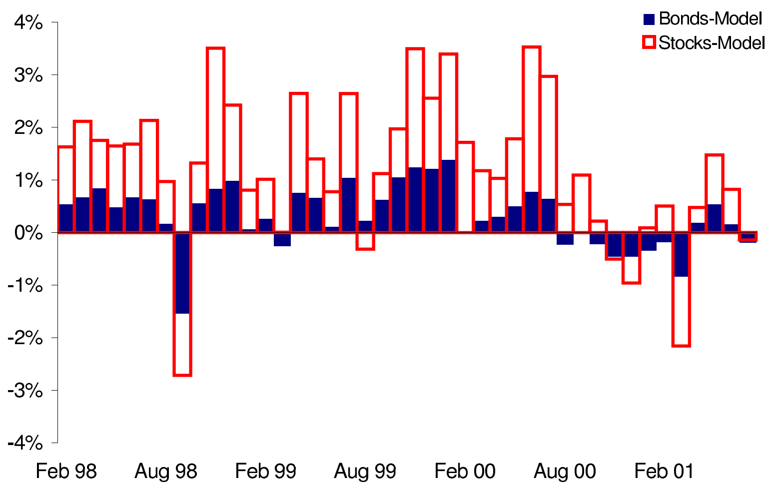

Figure 3: Estimated out-of-sample market risk premia of the IAPT

on (lagged) instruments. In a similar context, this setup has been employed by Solnik (1993). For obvious reasons we will call this model the *Z-Regression*:

$$r_{i,t} = \sum_{z} \beta_{i,z} Z_{z,t} + \varepsilon_{i,t} \tag{7}$$

This way we lose additional insights about risk premia and the (economic) sources of expected return as the regression model is of a purely statistical nature. Still, the choice of variables is economically motivated[15].

3.2 Methods to gauge out-of-sample predictability

The two models described in the previous sections yield estimates of expected returns conditional on information $\boldsymbol{Z}_{t-1}$. Computed over rolling windows they yield a history of out-of-sample estimates. Still at need is a measure of their predictive content *out-of-sample*. We have chosen to gauge the viability of out-of-sample estimates with a regression of realizations on forecasts. To be precise, we regress realized excess returns, $r_{i,t}$, on the conditionally expected returns by the respective model, $E^{\text{Model}}\left(r_{i,t}|\boldsymbol{Z}_{t-1}\right)$:

$$r_{i,t} = \gamma_{0,i} + \gamma_{1,i} \cdot E^{\text{Model}}\left(r_{i,t}|\boldsymbol{Z}_{t-1}\right) + \xi_{i,t} \tag{8}$$

This way we are looking at the *linear* relationship between realizations and forecasts. Please note that these *predictability regressions* are estimated asset-by-asset and independently from the type of forecasting model. Bossaerts and Hillion (1999) use a similar approach to compare a wide array of forecasting methods[16]. Perfect foresight of the forecasts would imply $\gamma_{0,i} = 0$ and $\gamma_{1,i} = 1$. The intercept (γ_0) of the regres-

[15] Again, it is the story of returns varying with business cycles which can be anticipated with the conditioning variables

[16] They estimate a SUR system in order to correct t-statistics, though.

sion could be interpreted as the bias of the forecasts while the slope (γ_1) measures the predictability. The regression's R^2 equals the squared correlation coefficient between realizations and forecasts. Hence this setup is amenable to common intuitions about measuring the interrelation between two variables. Again, it should be stressed that this limits our comparison to linear relationships between r and $E(r|\cdot)$, but not necessarily to a linear relation between conditioning variables Z_{t-1} and returns. As an additional measure of "goodness-of-fit" we will look at the root mean square error (RMSE):

$$\mathrm{RMSE}\left(r_i\right) = \sum_{t=1}^{T} \frac{\left(r_{i,t} - E^{\mathrm{Model}}\left(r_{i,t}|\cdot\right)\right)^2}{T+1} \tag{9}$$

We will also calculate in-sample RMSE's for use in the Black-Litterman updating of expected values described in more detail below. The Black-Litterman method is based on the method of mixed estimation (Theil 1973, pp. 349ff). Grinold and Kahn (2000) propose a regression similar to ours described above which they use to make tactical shifts in portfolios based on the values of some predictor. In a separate paper, we will explore these links further. For the time being it should be noted, that the "predictability regression" is not only very simple but also amenable to common intuitions about evaluating forecasts. What is more, it has the potential to be embedded in a wider framework of tactical portfolio methods.

3.3 Out-of-sample predictability is limited but significant

In this section we present the results of the predictability regressions described in the previous sections for our two sets of assets and our two models. Hence we get a 2×2 matrix of results which we present in two tables (Table 4 and 5) having two panels each. Please note that for the Z-Regressions, there are no cross-sectional constraints on the estimates. Hence the estimates are identical for assets included in both sets,

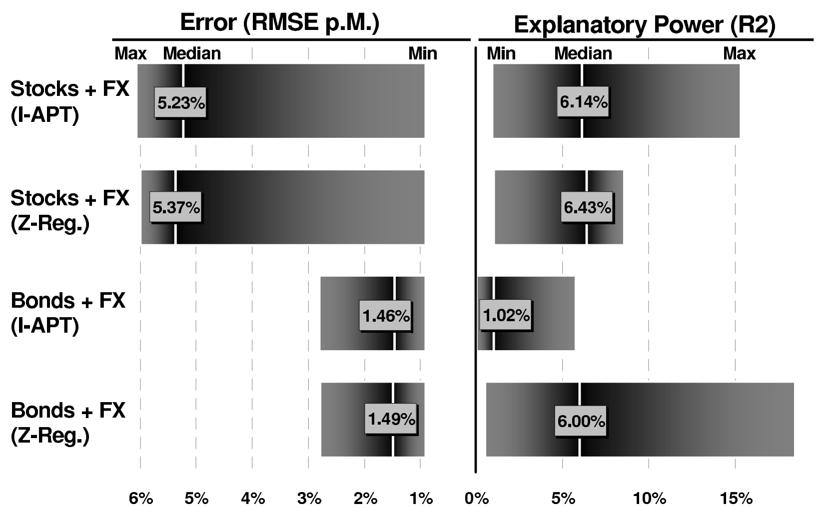

Figure 4: Range of RMSE and R^2 in predictability regressions

which pertains to the currency forwards here. In order to preserve symmetry in our presentation of both forecasting models we have decided to structure our report by the sets of test assets which means that the results of the Z-Regressions for the currency forwards are reported twice. Figure 4 graphically summarizes the results by comparing the ranges of values for R^2 and RMSE obtained in each model over the cross-section of test assets.

Table 4 presents the results of running the predictability regression described in the previous section on out-of-sample estimates for the three stock markets (EMU, U.S. and Switzerland) and currency forwards over our out-of-sample period from February 1988 to July 2001. The upper Panel (A) shows results for expectations from the IAPT, the lower Panel (B) for the Z-Regressions. The average estimation errors (RMSE) are

Assets	RMSE	α $t(\alpha)$	β $t(\beta)$	R^2
		PANEL A: IAPT		
Stocks EMU	5.75%	-0.014	2.015	14.54%
		(-1.104)	(2.608)	
Stocks U.S.	6.07%	0.003	0.787	4.40%
		(0.234)	(1.357)	
Stocks CH	5.23%	-0.020	2.084	15.33%
		(-1.746)	(2.691)	
FX Fwd. EUR	0.90%	0.001	-0.595	0.96%
		(0.468)	(-0.621)	
FX Fwd. USD	2.80%	0.007	0.545	6.14%
		(1.635)	(1.618)	
		PANEL B: Z-REGRESSIONS		
Stocks EMU	5.83%	-0.005	1.323	8.59%
		(-0.432)	(1.939)	
Stocks U.S.	6.00%	0.000	1.093	6.43%
		(-0.005)	(1.658)	
Stocks CH	5.37%	-0.014	1.240	8.46%
		(-1.190)	(1.923)	
FX Fwd. EUR	0.91%	0.001	-0.626	1.05%
		(0.472)	(-0.651)	
FX Fwd. USD	2.79%	0.007	0.549	6.00%
		(1.634)	(1.598)	

Regression results and RMSE for a regression of realized excess returns, $r_{i,t}$, on models' forecasts $E^{\text{Model}}\left(r_{i,t}|\boldsymbol{Z}_{t-1}\right)$:

$$r_{i,t} = \gamma_{0,i} + \gamma_{1,i} \cdot E^{\text{Model}}\left(r_{i,t}|\boldsymbol{Z}_{t-1}\right) + \xi_{i,t}$$

for the 42 out-of-sample estimates obtained for the sample from February 1998 to July 2001.

Table 4: Out-of-sample predictability of stocks-model

fairly similar in both panels. Especially the stock markets exhibit wide margins of error of about 5-6% per month. The regressions slopes of the stock markets are all significant[17] in the Z-Regressions with R^2 between 6% and 8.5%. The cross-sectionally restricted IAPT achieves even higher R^2 for EMU (14.54%) and Swiss (15.33%) stocks while giving up explanatory power for U.S. stocks. Intriguingly, both models find also a modest predictability for U.S. currency forwards but not for the Euro (DEM).

Comparing these results with the corresponding Table 5 for the bonds, we find broadly similar degrees of predictability for bond markets in the Z-Regression (Panel B). But the predictability is more dispersed. While Z-Regression's forecasts for Swiss bonds' explain almost one-fifth in variation of realized returns, the predictability is barely nil for U.S. bonds. What is even more striking in Table 5 is the stark contrast between results in Panel A (IAPT) and B (Z-Regression). None of the regression slopes of the IAPT predictions is significant. This demonstrates that the cross-sectional restrictions of the IAPT can only lead to predictable variation through assets' exposure to the time-varying risk factors. With the main factor in both models being the market factor and with the bond indices having markedly lower market exposure[18] than the stock indices, the predictability of the instrumental variables can not boil down to predictability of expected bond market returns as it does in the unrestricted Z-Regressions.

Still, the RMSE of the bond markets are fairly identical using either model of expected returns – notwithstanding the differing degrees of predictive content. The RMSE of the bonds hover between 1% and 3%. This is markedly lower than for the stocks as reported in Table 4, but these figures have to be viewed in light of the lower volatility in bond returns.

[17] At the 10% level.

[18] The bond index exposure to the market factor is low even for our choice of using a *bond* market factor. But it is a factor constructed from the G7 bond markets, which excludes Switzerland. Hence, one reason for the low bond market exposures is obvious: While the Swiss and European stock markets are a substantial component of the world stock market factor, Swiss bonds are not even included in the

Assets	RMSE	α $t(\alpha)$	β $t(\beta)$	R^2
		PANEL A: IAPT		
Bonds EMU	1.46%	0.004	-0.897	2.62%
		(1.292)	(-1.037)	
Bonds U.S.	2.74%	0.008	-0.141	0.32%
		(2.019)	(-0.358)	
Bonds CH	1.08%	0.000	0.175	0.04%
		(0.181)	(0.131)	
FX Fwd. EUR	0.91%	0.001	-0.616	1.02%
		(0.478)	(-0.643)	
FX Fwd. USD	2.80%	0.007	0.543	5.80%
		(1.637)	(1.569)	
		PANEL B: Z-REGRESSIONS		
Bonds EMU	1.49%	0.004	-1.350	7.21%
		(1.695)	(-1.763)	
Bonds U.S.	2.73%	0.008	-0.190	0.52%
		(2.042)	(-0.458)	
Bonds CH	1.16%	0.002	-2.644	18.71%
		(1.365)	(-3.034)	
FX Fwd. EUR	0.91%	0.001	-0.626	1.05%
		(0.472)	(-0.651)	
FX Fwd. USD	2.79%	0.007	0.549	6.00%
		(1.634)	(1.598)	

Regression results and RMSE for a regression of realized excess returns, $r_{i,t}$, on models' forecasts $E^{\text{Model}}\left(r_{i,t}|\boldsymbol{Z}_{t-1}\right)$:

$$r_{i,t} = \gamma_{0,i} + \gamma_{1,i} \cdot E^{\text{Model}}\left(r_{i,t}|\boldsymbol{Z}_{t-1}\right) + \xi_{i,t}$$

for the 42 out-of-sample estimates obtained for the sample from February 1998 to July 2001.

Table 5: Out-of-sample predictability of bonds-model

4 Portfolio Strategies

International portfolio theory prescribes to widen the set of investable assets by currencies (usually in the form of forward contracts whose returns are equivalent to the excess returns of the foreign money markets). Optimal portfolios are then obtained from a simultaneous optimization of asset and currency positions where "optimal" means mean-variance efficient (Jorion and Khoury 1996; Adler and Dumas 1983).

However, such an approach is not commonplace in the asset management industry. First of all, unconstrained mean-variance optimization is not widely used, not even for domestic portfolios. One reason is that real-world portfolios are usually constrained with regard to the size and the sign of individual positions. What is more, the mean-variance framework has no regard for estimation error in its inputs. To the contrary, it is very sensitive to input values[19] (Best and Grauer 1991; Michaud 1989). Instead of using some ad-hoc constraints on portfolio weights and still (mis-)taking the estimated return moments for the true values we used the Bayesian approach of Black and Litterman (1992)[20] to obtain the expected returns which we inputted into the mean variance optimization[21].

Secondly, for international portfolio managers there are additional concerns: Expected currency changes (which are the main driver behind expected *returns* on the forwards)[22] are hard to predict (Solnik 1999; Gärtner 1997; Obstfeld and Rogoff 1996)

G7 bond factor. Neither is the currency component of the returns measured in Swiss franc.

[19]Especially the vector of expected returns, see also Merton (1980) on the difficulties of accurately estimating expected returns.

[20]To be precise, the Black-Litterman method is based on the mixed estimation of Theil (1973, pp. 349ff).

[21]Though, one ad-hoc choice had to be made: The Black-Litterman method requires a pre-specified benchmark portfolio which we have choosen to be equally weighted in both assets and currencies.

[22]Please note the distinction made between currency changes and returns on forwards. Only the forward positions are assets while "currencies" in the sense of exchange rates are not assets but numeraires as succinctly stated by Grinold and Kahn (2000, p. 527). These more theoretical – but nonetheless intriguing! – aspects will be explored in greater detail in a separate paper.

which aggravates the "error maximization problem" (Michaud 1989) in mean-variance optimization which was alluded to above. In addition, the idea of simultaneously optimizing positions in assets and currencies might run counter to a division of labor between, say, equity analysts and currency economists[23]. Often, the currency specialist is only brought in as an overlay manager who hedges and possibly speculates with currencies *given* the positions taken by the asset manager. In a typical overlay setting, the asset manager gets neither feedback on the currency hedges nor does he anticipate them. We apply our dynamic TAA strategies to several variants of currency allocations so that they reflect the following cases of currency integration in the investment process:

- Mean-variance optimization, simultaneously across assets and currencies, that is the theoretical optimum
- Suboptimal case of forming a mean-variance asset portfolio and doing a subsequent currency overlay
- The special case of unitary (1:1) currency hedging of foreign assets

4.1 (Sub-)Optimal currency allocations

In this section we describe shortly the intuition and the computation of three typical cases of (sub-)optimal currency allocations. They are a sub-set of the five cases evaluated by De Santis, Gerard, and Hillion (1999). A very intuitive treatment of this topic is given by Jorion and Khoury (1996, Chapter 7). All three cases boil down to constructing some mean-variance efficient portfolio. They are distinct in the way to which subset of assets and currencies the mean-variance mechanics are applied. As inputs

[23] This argument applies already at the level of asset portfolios where analysts are usually specialized along the lines of bonds, stocks, countries, sectors or even further subdivisions. The divide between investment analysts and currency economists seems to be even bigger, though.

we use a vector of (conditionally) expected returns which is partitioned into assets A and foreign currency forwards C:

$$\vec{\mu} = \begin{bmatrix} \vec{\mu}_{\text{A}} \\ \vec{\mu}_{\text{C}} \end{bmatrix} \tag{10}$$

For our purpose, that vector will be filled with the output from the expected return models discussed in section 3 – respectively the Bayesian updates of these expectations obtained from the Black-Litterman method (see section 4.2). For the covariance matrix we write

$$\boldsymbol{\Sigma} = \begin{bmatrix} \boldsymbol{\Sigma}_{\text{A,A}} & \boldsymbol{\Sigma}_{\text{A,C}} \\ \boldsymbol{\Sigma}_{\text{C,A}} & \boldsymbol{\Sigma}_{\text{C,C}} \end{bmatrix} \tag{11}$$

with obvious partitioning. Please note that the "cross-covariance sub-matrix" is symmetric and we can write $\boldsymbol{\Sigma}_{C,A} = \boldsymbol{\Sigma}'_{C,A}$. In our application we use an unconditional estimate of the second moments using the same rolling window sample of historical data as in the return estimation. For further interpretation of the optimal weights derived below, it is useful to define the following two matrices which can be motivated from a linear (OLS) projection of the asset returns on the currency forwards. This projection yields the minimum variance hedge ratios stacked in the matrix $\boldsymbol{B}$:

$$\boldsymbol{B} = \boldsymbol{\Sigma}_{\text{C,C}}^{-1}\boldsymbol{\Sigma}_{\text{C,A}} \tag{12}$$

By virtue of the projection's orthogonality conditions, the variance-covariance matrix of the assets *conditional* on the currency hedges can be written as

$$\boldsymbol{\Sigma}_{\text{A,A|C}} = \boldsymbol{\Sigma}_{\text{A,A}} - \boldsymbol{B}'\boldsymbol{\Sigma}_{\text{C,C}}\boldsymbol{B} \tag{13}$$

Please note, that all the inputted estimates of $\vec{\mu}$ and especially $\mathbf{\Sigma}$ are based on excess returns as discussed in section 2.

The output of the portfolio optimization is a vector of portfolio weights, $\vec{w}^*$, which has been normalized so that they sum to one (or minus one):

$$\vec{w}^* = \frac{\vec{w}}{\vec{w}'\,\mathbf{1}} \tag{14}$$

When we describe each strategy's weights below, we will always refer to the non-normalized weights, $\vec{w}$, for ease of notation. Please note that the normalization above uses the *absolute* sum of portfolio positions whereas standard textbook treatments just scale by the sum (Campbell, Lo, and MacKinlay 1997, p. 188, eq. 5.2.28). This is motivated in that we are looking at dynamic portfolio strategies of a single investor – who may also want to short his overall exposure to risky assets[24]. We would like to emphasize further that our normalization was chosen in order to ensure that every portfolio's (excess) return is calculated with respect to the same notional value. We deem this convention is closer to practical applications than specifying some level of risk-aversion as, for example, in Jorion and Khoury (1996, Chapter 7).

Simultaneous optimization over assets and currencies yields the standard solution for mean-variance efficient portfolios[25]. By definition, this is the benchmark case of fully optimal currency integration in the asset allocation process. Given the parti-

[24]The IAPT used in section 3.1.1 could be derived within a framework of equilibrium with net-positive asset supply (rendering it an international ICAPM actually). Then the optimal portfolio weights needed to be positive. But this line of reasoning would not apply to the Z-Regressions described in 3.1.3. Hence we do not strive for consistency here. See also Ostdiek (1998) for equilibrium conditions consistent with negative market premia in conditional pricing models.

[25]Please note that there are a multitude of solutions depending on the investor's risk-aversion. We pin down our solution by normalizing the portfolio positions.

tioning between assets and currencies, the standard formula for the optimal weights

$$\vec{w}^{\text{MV}} = \boldsymbol{\Sigma}^{-1}\vec{\mu}$$

can be decomposed:

$$\vec{w}^{\text{MV}} = \boldsymbol{\Sigma}^{-1}\vec{\mu} = \begin{bmatrix} \vec{w}_{\text{A}}^{\text{MV}} \\ \vec{w}_{\text{C}}^{\text{MV}} \end{bmatrix} = \begin{bmatrix} \boldsymbol{\Sigma}_{\text{A,A|C}}^{-1}\,\vec{\mu}_{\text{A}} - \boldsymbol{\Sigma}_{\text{A,A|C}}^{-1}\,\boldsymbol{B}'\,\vec{\mu}_{\text{C}} \\ \boldsymbol{\Sigma}_{\text{C,C}}^{-1}\,\vec{\mu}_{\text{C}} - \boldsymbol{B}\,\vec{w}_{\text{A}} \end{bmatrix} \tag{15}$$

This partitioning makes it possible to interpret the optimal portfolio: The positions in assets and currencies are mutually dependent on each other's parameters. The asset weights are determined by the weights of a mean-variance portfolio obtained from the variance-covariance of *hedged* assets ($\boldsymbol{\Sigma}_{\text{A,A|C}}$) and an adjustment for the corresponding costs of hedging ($\vec{\mu}_{\text{C}}$). The currency positions re-iterates a well known theme from minimum-variance hedging: The first component reflects the *mean*-variance optimal speculative position, the second component is made up by the *minimum*-variance hedge of the asset positions ($\vec{w}_{\text{A}}$).

Currency Overlay: The simultaneous optimization discussed above prescribes a constant feedback between asset and currency positions, which might appear a little bit complicated and clumsy for the practical interaction between specialized portfolio analysts. A shortcut which is often used in practice is to let the asset manager focus on his investments – without any regard for currency issues – and to have a separate currency specialist *subsequently* take foreign exchange positions (both for hedging and for speculation). This leads to the following portfolio:

$$\vec{w}^{\mathrm{OV}} = \begin{bmatrix} \vec{w}_{\mathrm{A}}^{\mathrm{OV}} \\ \vec{w}_{\mathrm{C}}^{\mathrm{OV}} \end{bmatrix} = \begin{bmatrix} \boldsymbol{\Sigma}_{\mathrm{A,A}}^{-1}\, \vec{\mu}_{\mathrm{A}} \\ \boldsymbol{\Sigma}_{\mathrm{C,C}}^{-1}\, \vec{\mu}_{\mathrm{C}} - \boldsymbol{B}\, \vec{w}_{\mathrm{A}} \end{bmatrix} \tag{16}$$

Here asset weights ($\vec{w}_{\mathrm{A}}$) are independent from any currency parameters. Please note that the asset managers does not even anticipate the actions of the currency manager. This loss in his degrees of freedom implies that such an overlay management is not optimal. It would only be consistent with the optimal situation if asset returns were independent from currencies ($\boldsymbol{\Sigma}_{\mathrm{A,C}} = \mathbf{0} \Rightarrow \boldsymbol{B} = \mathbf{0}$). In our setup, the overlay manager does not only hedge but is also allowed to enter speculative positions[26]

Unitary Hedging: So far, we have always meant minimum-variance hedging when referring to currency hedging. In practice, this is not only fraught with parameter uncertainty, it is also confronted with the idea of "unitary hedging". Whereas the former prescribes a hedge-ratio equal to the β of a linear projection, the latter advocates a one-to-one hedge ratio (Perold and Schulman 1988). Following Jorion and Khoury (1996) and De Santis, Gerard, and Hillion (1999) we construct the unitary hedging portfolio as holding the mean-variance optimal proportions of (unhedged) market indices and shorting their respective currencies in corresponding amounts:

$$\vec{w}^{\mathrm{UH}} = \begin{bmatrix} \vec{w}_{\mathrm{A}}^{\mathrm{UH}} \\ \vec{w}_{\mathrm{C}}^{\mathrm{UH}} \end{bmatrix} = \begin{bmatrix} \boldsymbol{\Sigma}_{\mathrm{A,A}}^{-1} \vec{\mu}_{\mathrm{A}} \\ -\vec{w}_{\mathrm{A}}^{\mathrm{UH}} \end{bmatrix} \tag{17}$$

In practice, such a one-to-one relation requires that each asset can be unanimously associated with one currency. Under certain assumptions, this could be motivated within the general mean-variance framework. Namely, each asset's (multivariate) re-

[26]See De Santis, Gerard, and Hillion (1999) who construct this variant plus a "hedging-only" version.

gression coefficient with a particular currency should be one and zero with respect to the other currencies. Furthermore, there should be no PPP risk, hence risk premia earned on holding currency exposures would be zero. The first assumption would justify the particular hedge ratio (1:1), the second the absence of speculative currency positions. But as recently demonstrated by Diermeier and Solnik (2001), stocks are exposed to more than one currency and this applies not only to multi-national blue chips.

4.2 Estimation error kept in check by Black-Litterman

In the previous section we describe various methods of portfolio formation. They differ with regard to the currency decisions, but they all have some (unrestricted) mean-variance criterion in common. Two difficulties arise when implementing such mean-variance portfolio strategies. Theoretically, it can be shown that the portfolios are very sensitive to input parameters, particularly the mean (Best and Grauer 1991). And from the results of section 3.3 we know how hard it is to make these forecasts. Imprecise measurement of mean returns is generally recognized and not a particular feature of our two models (Merton 1980). From a practitioner's point of view, unrestricted mean-variance efficiency poses additional problems – even if it were otherwise accurate. Usually, asset managers are prevented from holding short positions or they need to adhere to certain strategic weights within small tactical bands. Mean variance portfolios however frequently resort to optimizing the risk-return trade-off by entering unlimited short-positions, sometimes of a significant size. Even though mean-variance efficiency is a theory of diversification, it is not necessarily preempted from entering positions which would appear ridiculously large from an intuitive point of view, they are only be justified by the accuracy (and sole relevancy!) of the input parameters $\vec{\mu}$ and $\mathbf{\Sigma}$.

A common response to the second problem is to solve the for the mean-variance optimum numerically so that restrictions on the investment weights can be specified. Typical restrictions include the non-negativity of investment weights (no short sales). De Santis, Gerard, and Hillion (1999) restrict their portfolios this way. But such a restricted optimization does not yet account for estimation error in the input parameters. Instead, we use the Black and Litterman (1992) method where the estimated mean returns enter the optimization only after a Bayesian updating with respect to some prespecified "neutral" weights. This way we keep both a check on distortions arising from estimation error and we can define how a "reasonable" portfolio should look like. The latter is achieved by the choice of neutral benchmark. As a matter of simplicity, an equally-weighted portfolio of all five investments (bond, respectively stock indices of three countries plus two foreign currencies) has been defined to be "neutral". Please note that this implies outright positions (20% each) in the two currency forwards. With regard to the currency strategy – in particular the question of currency hedging – this choice might not appear to be very "neutral"[27] But our results (not reported here) are not substantially altered by other choices, for example by changing the benchmark towards an equal weighting of assets while shorting the currencies (that means unitary hedging).

The idea of Black and Litterman goes back to the method of mixed estimations of Theil (1973). A recent demonstration of its use has been given by Drobetz (2001) and Lee (2000, Chapter 7). Here, we follow the original notation of Black and Litterman (1992). At the core of the Black-Litterman method is a Bayesian updating of prior return expectations into posterior expectations. The latter will then embody both the information of the new estimates but only to the extent that they *reliably* differ from the prior expectations. Two things are still missing: We have neutral investment weights,

[27]With "neutral" being always defined with respect to some reference portfolio, there is no way around that.

but no prior expectations. And we need to specify what "reliably different" means.

The prior expectations are already there, namely in the form of the investment weights. They can be backed out from the weights by assuming that these weights are consistent with mean variance efficiency and the estimated covariance matrix $\mathbf{\Sigma}$ by reversing the mean-variance optimization:

$$\vec{\mu}^{\text{Neutral}} = \delta\,\mathbf{\Sigma}\,\vec{w}^{\text{Neutral}} = \delta\,\mathbf{\Sigma}\,\left(\frac{1}{n}\right)\mathbf{1} \tag{18}$$

Where δ is the coefficient of investors' relative risk aversion[28]. Henceforth we will set $\delta = 1$. Please note that δ affects only the reverse optimization, our portfolios are all normalized so that their weights sum to unity – not with regard to a particular degree of risk aversion. As reported by Drobetz (2001), changing this parameter is only of minor importance for the Black-Litterman updates. The last equality in (18) applies only for our choice of defining an equal-weighting of the n investments as neutral, $w_i^{\text{Neutral}} = \frac{1}{n}$.

"Reliably different" is defined in the manner that extraneous information is specified in a mixed estimation (Theil 1973). It is assumed that the information on a vector of true parameters $\overrightarrow{ER}$ takes the form

$$\overrightarrow{ER} = \overrightarrow{ER_x} + \vec{\varepsilon}_x \tag{19}$$

where ER_x is the extraneous point estimate, in our case the output $\vec{\mu}^{\text{Model}}$ of the models discussed in section 3, and $\vec{\varepsilon}_x$ models the degree of uncertainty surrounding that point estimate[29]. It is assumed to be normally distributed with mean zero and diagonal

[28] If investors utility is defined over mean and variance of returns, this would imply: $U(\mu, \sigma^2) = \mu - \frac{\delta}{2}\sigma^2$

[29] Black and Litterman (1992) and Theil (1973) allow for a more general formulation where subjective beliefs can be expressed over linear combinations of the parameters. In the notation of Black and Litterman: $PE[R] = Q + \varepsilon$ where P is a matrix describing the linear combinations. In our setting, we are only concerned with absolute views covering all returns. Hence their P equals the identity matrix $\boldsymbol{I}$.

covariance matrix $\mathbf{\Omega}$[30]. In our case, the choice of $\vec{\varepsilon}$ is obvious: We take the RMSE between realized and expected returns, as defined in equation (9) *and measured in-sample*[31]. To be precise, we set

$$\mathbf{\Omega} = \frac{1}{\sqrt{T}} \overrightarrow{\text{RMSE}}' \, \boldsymbol{I} \tag{20}$$

where T is the number of observations used for the in-sample estimates (here: $T = 143$) and N is the number of investments (here: $N = 20$). This is a particular definition of ours with which we adapted the Black-Litterman model to our setting. The rest follows directly from their paper (setting their P equal to the identity matrix, see our footnote 29.). The updated vector of expected returns is

$$\vec{\mu}^{\text{BL}} = \left[(\tau\mathbf{\Sigma})^{-1} \, \mathbf{\Omega}^{-1}\right]^{-1} \left[(\tau\mathbf{\Sigma})^{-1} \, \vec{\mu}^{\text{Neutral}} \, \mathbf{\Omega}^{-1} \, \vec{\mu}^{\text{Model}}\right] \tag{21}$$

where $\tau = T = 143$ scales $\mathbf{\Sigma}$ in order to reflect the distribution of the means based on the central limit theorem. The updated vector of expected returns $\vec{\mu}^{\text{BL}}$ is then inputted into the portfolio formulas discussed in section 4.1.

4.3 Currency decisions matter more than TAA

Now we have everything in place to answer our main question: Does the implementation of a TAA (based on macroeconomic conditioning variables) matter more than strategic currency hedging? From section 3.3 we already know that returns are predictable by our instrumental variables, but only at modest levels. The level of predictability differs between bonds and stocks and also between the choice of the return

[30]The diagonality assumption is only made by Black and Litterman (1992) whereas Theil (1973) derives his method also in the general case of correlated degrees of uncertainty.

[31]Of course, this measure is going to understate the out-of-sample uncertainty. But it is probably the best we can do in our setup.

model. Still, there seems to be some potential for TAA – reaffirming the results known from other studies (Solnik 1993; De Santis, Gerard, and Hillion 1999) in our particular sample. Two things remain to be seen: To what extent can this statistical predictability be translated into superior returns? And how do these TAA returns measure up against performance differences arising from different currency allocations?

From the return models we generate 42 out-of-sample estimates of expected returns over the sample from February 1998 to July 2001. Analogously we estimate 42 historical covariance matrices using the same in-sample periods (rolling 12 year windows) as for the expected returns. Then we calculate the various portfolios described in the previous sections using these estimates (and their Black-Litterman refinements) for each month. Tables 6 and 7 summarize average, max and min weights for each asset in the stock, respectively bond market strategies. From weights and realized returns we generate a history of (ex-post) portfolio excess returns over 42 months over which we calculated the following performance statistics: Average excess return, volatility and Sharpe Ratio[32] as well as minimum and maximum return (all expressed in percents per month).

Our performance results are summarized in Table 8. The first two columns report the statistics obtained by constructing a mean-variance portfolio jointly optimized over assets and currencies but using "raw" (non-Black-Litterman) estimates. As we already doubted before, these portfolios tend to take extremely large positions which is mirrored by the large minimum and maximum returns (yes, these figures are percent per month!). What is worse, their Sharpe Ratio does in most cases not even come close to what a passive equally weighted portfolio would have achieved as shown in the next column. This demonstrates that unrestricted mean-variance portfolios do not only en-

[32]Please note that multiplying the Sharpe Ratio by $\sqrt{T} = \sqrt{42} \approx 6.5$ yields the t-stat on whether the portfolio's average excess return is different from zero.

ter extreme positions, but that their performance can easily become disastrous if the inputs are estimated with high uncertainty.

The equally weighted portfolio's performance reported in the third column on Table 8 is also our neutral benchmark used for the Black-Litterman portfolios whose statistics are reported in the remaining columns[33]. Before discussing the Black-Litterman results in detail, we would like to mention that for each strategy there is barely no difference between portfolios formed on return estimates from the IAPT and the Z-Regression (please note that both generated similar RMSE's which are a key factor in determining Black-Litterman deviations from the benchmark.) To facilitate our discussion we will henceforth not differentiate between both in the discussion of the portfolios' performance.

Columns 4 and 5 report statistics on the jointly optimized mean-variance portfolio using Black-Litterman expectations. Indeed, it seems that our TAA can improve performance – as measured by Sharpe Ratio – but only slightly. For the stocks strategy (Panel A) the Sharpe Ratio increases from 0.53 (equally weighted benchmark) to 0.55 using either return model. For the bonds model the increase is similar, if anything a little bit more pronounced, from 1.07 to 1.15 and 1.12 respectively. What is intriguing is that the strongest increase occurs for the IAPT which exhibits the worst (namely nil) out-of-sample predictability in our results of section 3.3. Obviously, the uncertainty surrounding the estimates – as expressed by their RMSE in Table 4 and 5[34] – keeps a substantial check on Black-Litterman deviations from the strategic weights. This is demonstrated by the numbers in columns 4 and 5 of tables 6 and 7 showing that

[33] As already discussed above, please note that this portfolio implies outright positions (20% each) in the two currency forwards. With regard to the currency strategy – in particular the question of currency hedging – this choice might not appear to be very "neutral". But our results are not substantially altered by other choices, for example by changing the benchmark towards an equal weighting of assets while shorting the currencies (that means unitary hedging).

[34] Please note that the RMSE figures reported in both tables are calculated out-of-sample while the Black-Litterman inputs are calculated from in-sample fitted values. Ballpark-wise they are in the same ranges.

the Black-Litterman weights deviate only plus/minus two percentage points from the neutral equal weighting.

Results on currency overlay strategies are reported in columns 6 and 7 of Table 8. For both stocks and bonds, the performance is not drastically altered, albeit slightly worse, by the sub-optimal currency overlay method when compared to the joint optimization reported before. Our setup of the currency overlay management, does still enter speculative positions and minimum-variance hedges of currency as in the joint optimization, but this time there is no feedback to the asset positions (see section 4.1).

It should be noted that only some of the bond strategies have an average excess return which is significantly different from zero: The passive equal weighting and the Black-Litterman portfolios using mean-variance as well as currency overlays. This can be seen by multiplying the Sharpe Ratios by $\sqrt{T} = \sqrt{42} \approx 6.5$. Given our 42 observations, Sharpe Ratios should be at least 0.30 or higher to attain t-stats larger than 1.95. All of the stocks strategies, including the non-Black-Litterman mean-variance portfolio with its high but volatile returns, fall short of this threshold.

The importance of the currency hedging decision becomes clear when looking at the last two columns where we report results on the unitary hedged TAA strategies. Here, Sharpe Ratios shrink dramatically for stocks and bonds, down to 0.32 respectively 0.25. In the case of the stocks this is due to both a decrease in average return and an increase in volatility. For the bonds, average return is reduced by about three-quarters down to about 1% while the unitary hedging leaves volatility almost unchanged[35].

[35]Compared with the joint optimization.

				Black-Litterman Expectations					
	Mean-Variance		EW	Mean-Variance		Currency Overlay		Unitary Hedge	
	IAPT	Z-Reg.	(passive)	IAPT	Z-Reg.	IAPT	Z-Reg.	IAPT	Z-Reg.
Stocks EMU									
Avg.	98%	−9%	20%	21%	20%	29%	29%	36%	35%
Max	1207%	705%	20%	22%	21%	31%	30%	39%	38%
Min	−41%	−1287%	20%	19%	19%	27%	27%	34%	34%
Stocks U.S.									
Avg.	102%	174%	20%	20%	20%	34%	34%	42%	42%
Max	1343%	4583%	20%	21%	21%	38%	37%	47%	45%
Min	−83%	−810%	20%	18%	19%	30%	31%	38%	39%
Stocks CH									
Avg.	41%	199%	20%	21%	21%	18%	18%	22%	22%
Max	472%	3289%	20%	23%	23%	20%	21%	25%	25%
Min	−26%	−261%	20%	19%	19%	15%	16%	19%	20%
Forex Fwd. EUR									
Avg.	141%	130%	20%	20%	20%	10%	10%	−36%	−35%
Max	6386%	5083%	20%	25%	25%	17%	16%	−34%	−34%
Min	−901%	−1881%	20%	17%	17%	5%	6%	−39%	−38%
Forex Fwd. USD									
Avg.	−396%	−461%	20%	19%	19%	8%	8%	−42%	−42%
Max	1037%	1405%	20%	23%	22%	12%	12%	−38%	−39%
Min	−7367%	−10173%	20%	15%	15%	6%	6%	−47%	−45%

Average, max and min weights of each asset in stock market strategies for the 42 months from February 1998 to July 2001. Portfolio decisions are revised each month based upon estimates of conditionally expected returns using either the IAPT model or the Z-Regression and unconditional second moments from data over 143 months prior to the portfolio formation. Black-Litterman expectations use an equally weighted portfolio (EW) as neutral, prior belief.

Table 6: Asset weights of stock market strategies

				Black-Litterman Expectations					
	Mean-Variance		**EW**	**Mean-Variance**		**Currency Overlay**		**Unitary Hedge**	
	IAPT	Z-Reg.	(passive)	IAPT	Z-Reg.	IAPT	Z-Reg.	IAPT	Z-Reg.
				Bonds EMU					
Avg.	272%	56%	20%	21%	20%	32%	32%	38%	37%
Max	5348%	1171%	20%	23%	24%	40%	38%	47%	44%
Min	−178%	−701%	20%	18%	18%	28%	28%	32%	33%
				Bonds U.S.					
Avg.	430%	148%	20%	20%	20%	44%	44%	51%	51%
Max	9237%	1226%	20%	22%	22%	51%	52%	60%	62%
Min	−198%	−241%	20%	16%	17%	35%	36%	41%	42%
				Bonds CH					
Avg.	24%	−55%	20%	20%	20%	10%	10%	12%	11%
Max	544%	178%	20%	22%	23%	14%	14%	16%	16%
Min	−234%	−1172%	20%	17%	16%	4%	2%	5%	3%
				Forex Fwd. EUR					
Avg.	−110%	13%	20%	20%	20%	10%	10%	−38%	−37%
Max	1128%	1225%	20%	23%	23%	12%	12%	−32%	−33%
Min	−2816%	−813%	20%	18%	18%	9%	9%	−47%	−44%
				Forex Fwd. USD					
Avg.	−588%	−156%	20%	19%	19%	4%	4%	−51%	−51%
Max	1943%	430%	20%	24%	24%	5%	5%	−41%	−42%
Min	−15242%	−1663%	20%	15%	15%	2%	2%	−60%	−62%

Average, max and min weights of each asset in bond market strategies for the 42 months from February 1998 to July 2001. Portfolio decisions are revised each month based upon estimates of conditionally expected returns using either the IAPT model or the Z-Regression and unconditional second moments from data over 143 months prior to the portfolio formation. Black-Litterman expectations use an equally weighted portfolio (EW) as neutral, prior belief.

Table 7: Asset weights of bond market strategies

				Black-Litterman Expectations					
	Mean-Variance		**EW**	**Mean-Variance**		**Currency Overlay**		**Unitary Hedge**	
	IAPT	Z-Reg.	(passive)	IAPT	Z-Reg.	IAPT	Z-Reg.	IAPT	Z-Reg.
PANEL A: STOCKS									
Avg.	15.14%	3.26%	0.56%	0.59%	0.59%	0.72%	0.71%	0.45%	0.45%
Vol.	83.81%	79.07%	3.64%	3.69%	3.70%	4.67%	4.68%	4.95%	4.95%
S.R.	0.18	0.04	0.15	0.16	0.16	0.15	0.15	0.09	0.09
Max	531.97%	271.51%	7.05%	7.21%	7.21%	8.59%	8.57%	8.29%	8.28%
Min	−37.54%	−389.68%	−11.32%	−11.37%	−11.46%	−14.05%	−14.11%	−15.25%	−15.29%
PANEL B: BONDS									
Avg.	2.64%	1.17%	0.35%	0.37%	0.36%	0.45%	0.44%	0.08%	0.08%
Vol.	23.35%	8.49%	1.14%	1.11%	1.13%	1.39%	1.40%	1.15%	1.16%
S.R.	0.11	0.14	0.31	0.33	0.32	0.33	0.32	0.07	0.06
Max	117.51%	40.63%	2.41%	2.43%	2.46%	2.82%	2.87%	2.83%	2.83%
Min	−56.05%	−17.46%	−1.99%	−2.05%	−2.03%	−2.69%	−2.66%	−3.01%	−3.07%

All statistics are calculated from the monthly excess returns of portfolio strategies over the 42 months from February 1998 to July 2001. Portfolio decisions are revised each month based upon estimates of conditionally expected returns using either the IAPT model or the Z-Regression and unconditional second moments from data over 143 months prior to the portfolio formation. Black-Litterman expectations use an equally weighted portfolio (EW) as neutral, prior belief. SR is the Sharpe Ratio, $\frac{\text{Avg.}}{\text{Vol.}}$. Multiplying the Sharpe Ratio by $\sqrt{T} = \sqrt{42} \approx 6.5$ yields the t-stat on whether the portfolio's average excess return is different from zero.

Table 8: Performance measures of TAA strategies

5 Summary

International portfolio managers need to address the strategic question of how to integrate the currency allocation in the investment process. In particular, they need to decide whether to engage in hedging their currency exposure or not (Jorion and Khoury 1996; Perold and Schulman 1988; Odier and Solnik 1993). In addition, there is abounding evidence that expected returns vary with the business cycle which is in turn partly predictable by macroeconomic variables (Fama and French 1989; Ferson and Harvey 1993; Campbell 2000). Prior research suggests that this performance can be improved by making use of this predictability (Solnik 1993; De Santis, Gerard, and Hillion 1999). We have examined the *relative* importance of both issues by constructing dynamic TAA strategies for different types of currency hedging where we look separately at the Swiss franc returns of portfolios of stocks and bonds. Our question can be framed as the comparison of the impact of a *strategic* currency allocation with that of a *tactical* asset allocation. And the results reaffirm the claim made by Brinson, Hood, and Beebower (1986) – in a purely domestic setting – that strategic asset allocation is the main determinant of portfolio performance.

In particular we found that there is a moderate but for some assets significant out-of-sample predictability – especially stocks. We inputted a set of five typical macroeconomic indicators in two different models of expected return and found that the results are ambiguous: Due to the mechanics of the cross-sectionally restrained factor pricing model (IAPT), time-variation can only boil down to asset returns via their exposure to the time-varying risk factor premia. A purely statistical regression of returns on instruments is not constrained in this way and here we found remarkably high out-of-sample correlations between realized and expected returns for some assets, for example up to 0.42 for Swiss bonds and 0.39 for Swiss stocks. As an aside it should be mentioned that the predicted out-of-sample risk premia in the IAPT are strikingly similar for our two sets of test assets (stocks and bonds).

An unrestricted mean-variance optimization tends to be misled by the estimation errors. Hence we inputted the forecasts only after a Bayesian updating with the Black-Litterman method which accounts explicitly for the estimation errors. Given the high uncertainty of the forecasts, this limits the potential of the TAA by construction: As shown in tables 6 and 7, the Black-Litterman method allows only for small deviations from the benchmark.

Our major findings on the relative importance of currency allocations and the potential of TAA are summarized in Table 8. Once the portfolio construction is kept in check by the Black-Litterman method, a clear picture emerges: Our macro-based Black-Litterman TAA offers only marginal improvements in Sharpe Ratios. Especially the decision to adopt a unitary hedging leads to a dramatic fall in portfolios' risk-return ratios. Intriguingly, the currency overlay management does not perform significantly worse than the theoretically optimal joint optimization over assets and currencies. This suggests that currency overlay management is indeed a second best-solution, but it seems to be only a close second. It remains to be seen, whether the increased need for co-ordination among asset and currency positions in the optimal full mean-variance case would not even off-set such a small margin of differential performance as the one documented in our study.

A G7 basket weights

The global G7 basket variables used in our study (dPE, TRM, rMB) are all constructed by weighting the respective local variables by their GDP[36]. Three issues merit a further explanation: The measurement of GDP, avoidance of look-ahead bias and the creation of the Euro, which economically rendered the G7 to a G5.

We use annual figures obtained from the OECD on real GDP's calculated with PPP exchange rates as of 1990 (and 1995 for later dates). This choice reflects the idea that basket weights should proxy for the size of the countries' real economy. In results not reported here we also analyzed other weighting schemes, in particular we also looked at using market capitalization weights. Without going into too much details, we can say that our results are largely invariant to the choice of weighting. The point is, that for our purpose the basket weights matter only to the extent that the tracking of economic conditions by the basket variables is diverging. If all local variables move closely together – probably because they track common economic conditions in an ever more integrating global economy – the weights do not affect the pricing content of the basket by much.

In order to avoid look-ahead bias we use only GDP data of the previous year and only as of April in order to account for the publication of the data. Basket values for January to March use weights based on GDP data from two years ago.

The introduction of the Euro in January 1999 has resulted in merging the economic variables[37] from France, Germany and Italy. In addition it has enlarged the scope of the economy whose condition is projected by them: The eleven EMU countries comprises also non-G7 countries[38]. Hence we have chosen to weigh the Eurozone variables, as

[36]The G7 consist of Canada, France, Germany, Italy, Japan, the U.K. and the U.S.

[37]The point could be made that this argument holds only for interest rate and currency baskets, not for the PE ratio. Still we have decided to apply the reasoning outlined here also to the PE basket.

[38]Austria, Belgium, Finland, Ireland, Luxembourg, Netherlands, Portugal, Spain.

of January 1990, with the GDP of the EMU. It could be argued that this leads to a structural break with regard to this jump in the weights of what formerly entered only through the GDP's of France, Germany and Italy. But first of all they already make up about two-thirds of the EMU in terms of GDP. And secondly, yes there is a structural break. While the German Bundesbank exercised a leading role in pre-EMU times it never had to account for the economies of Ireland and Portugal as the European Central Bank has to (and does) now. Hence there would be no sense in smoothing out this jump. Lastly, as already indicated in the previous paragraph, the results are invariant.

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