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Portable Alpha and Portable Beta Strategies in the Euro Zone

Implementing Active Asset Allocation Decisions using Equity Index Options and Futures

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Abstract:

While stock picking strategies are in principle meant to exploit evidence of predictability in individual stock specific risk, most equity managers, as a result of their bottom-up security selection decisions, often end up making discretionary, and most of the time unintended, bets on market, sector and style returns as much as they make bets on individual stock returns. In this paper, we show how portfolio managers in the Euro-zone can benefit from using derivatives markets to actively manage their asset allocation decisions in a systematic manner. Using a robust econometric process based on a non-linear multi-factor thick and recursive modeling approach, we report statistically and economically significant evidence of predictability in Dow Jones EURO STOXX 50 excess return. These econometric forecasts can be turned into active portfolio decisions and implemented via Eurex index futures to generate active asset allocation *portable alpha* benefits. We also show that adding active sector rotation decisions to asset allocation decisions allows one to significantly lower the portfolio volatility as a result of the benefits of bet diversification: We finally explain how active portfolio managers can benefit from using suitably designed Eurex option strategies as *portable beta* vehicles. In particular, option portfolios can be used to enhance the performance of tactical asset allocation programs by consistently adding value during the periods of low volatility when timing strategies are known to perform rather poorly. The benefits of active asset allocation decisions reported in this paper originate from the combination of a robust econometric and portfolio process on the one hand, and an efficient trading of low cost investible products such as Eurex index futures and options on the other hand. This strongly suggests that most long-short managers could use a similar methodology to enhance the performance of their portfolios without having to rely on the alleged superior performance of any specific predictive model.

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While stock picking strategies are in principle meant to exploit evidence of predictability in individual stock *specific risk*, equity managers, as a result of their bottom-up security selection decisions, often end up making discretionary, and most of the time unintended, bets on market, sector and style returns as much as they make bets on individual stock returns.[i] These unintended bets are unfortunate as they can have a dramatic, positive or negative, impact on the portfolio return, and their presence introduces an undesirable element of luck in the performance generating process.

Consider for example the case of long/short equity managers. The vast majority favor stock picking as a way to generate abnormal return. Long/short managers do not generally actively manage their market exposure, and most of them end up having a net long bias. This can be seen for example from the correlation of HFR Equity Hedge (a prominent index for long/short hedge fund managers) with the S&P500, which turns out to be equal to 0.63 based on monthly data over the period 1990-2000. This is due to the fact that these managers, most of them being originally long-only mutual fund managers, typically feel more comfortable at detecting undervalued stocks than overvalued stocks. This long bias, which is not the result of an active bet on a bullish market trend but merely the result of a lack of perceived opportunities on the short selling side, has undoubtedly explained a large fraction of the performance of these managers in the extended bull market periods of the 90s. On the other hand, it has very significantly hurt their performance in the past few years of market downturns. Similarly, long/short managers, even those who target market neutrality, have unintended time-varying residual exposure to a variety of sectors or investment styles (growth or value, small cap or large cap) resulting from their bottom-up stock picking decisions. Since very few managers are both *market* and *factor* neutral, it is not obvious to extract from their performance anything but a very noisy signal on their pure stock picking ability.

In this paper, we show how long/short managers in the Euro zone can use derivatives markets to help actively manage their asset and sector allocation decisions in a systematic manner so as to enhance the performance of their portfolio. It should be emphasized at this point that the benefits of active asset allocation decisions that we present in this experiment are not based on the use of any specific econometric model with unusually superior predictive power. In the interest of underlining a methodology that could be used by a set of long-short managers endowed with reasonable econometric skills, we use in this paper an econometric approach, known as “thick modeling”, which is based on a process that consists of selecting at each date a “council” of models to make predictions, as opposed to using a single model. In other words, the benefits of active asset allocation decisions reported in this paper originate from the combination of a robust econometric and portfolio process on the one hand, and an efficient trading of low cost investible products such as Eurex index futures and options on the other hand. This strongly suggests that most long-short managers could use a similar methodology to enhance the performance of their portfolios without having to rely on the alleged superior performance of any specific predictive model.

Active management of asset allocation decision actually comes in two forms. The first possible form of an active asset allocation strategy involves adding market and/or sector timing alpha benefits to original stock picking based active decisions. Long/short managers can also choose to use market, sector or style timing as an alternative way to generate alpha in the absence of confidence in their ability to generate consistent performance through stock picking. In this paper, we show how to form a pure overlay portfolio that is designed to capture excess return through tactical asset and factor allocation decisions on the European markets, using active management of betas to generate (portable) alphas. We focus on pure active allocation decisions implemented through trading in index derivatives markets so as to study the performance of an overlay that is not impacted by stock picking decisions, which should remain the sole focus of attention from bottom-up managers.

The second possible form of an active asset allocation strategy involves implementing an option-based portfolio strategy, of which the sole objective is to decrease asset allocation risk in the portfolio. In particular, options on equity indices can be used to truncate return distributions with an aim at eliminating the few worst (and best) outliers generated from managers' forecast errors. In this paper, we show how suitably designed option strategies can be used to enhance the performance of an active asset allocation strategy, the objective being to design a program which would consistently add value during the periods of calm markets, which are typically not favorable to timing strategies. In recent years, the core-satellite portfolio approach has become increasingly popular among investors who attempt to add portable alpha benefits to their portfolio without modifying their passive exposure to a reference index. In the section detailing the second possible form of an active asset allocation strategy, we look at it from a different perspective. More specifically, we explain how active portfolio managers can benefit from using suitably packaged derivatives satellite portfolios as portable beta vehicles.

This paper is organized as follows. In a first section, we present the case for tactical asset allocation (TAA) decisions. In a second section, we present some evidence of predictability in Euro equity markets. In a third section, we show how this predictability can be exploited in a systematic way to generate superior performance through dynamic trading in index futures. In a fourth section, we argue that long/short managers can also use options on equity indices to implement truncated return strategies that aim at enhancing the performance and/or at reducing the risk of a TAA program. A fifth section extends the analysis to sector rotation decisions, while concluding remarks can be found in a last section.

THE CASE FOR TACTICAL ASSET ALLOCATION DECISIONS

It is well known that derivative products can be used by long/short managers in all sorts of ways to improve the risk-return profile of their portfolio. In particular index futures can be used for hedging purposes by long/short managers who specialize in stock picking and have no views on market trends, and therefore want to hedge away their residual market exposure. Hedging market risk means setting the beta of the long/short portfolio equal to zero. While this is desirable for a stock picker who has no view on the market direction, this may not be optimal from an active portfolio management standpoint, as it does not take into account useful conditioning information.

There is actually now a consensus in empirical finance that expected asset returns, and also variances and covariances, are, to some extent, predictable based on conditioning information (see for example Keim and Stambaugh (1986), Campbell (1987), or Ferson and Harvey (1991)). In this section, we show how these insights can be exploited by long/short managers to improve existing policies based upon unconditional estimates.

Tactical Asset Allocation broadly refers to active strategies that seek to enhance portfolio performance by opportunistically shifting the asset mix in a portfolio in response to the changing patterns of return and risk. Practitioners started to engage in tactical asset allocation strategies as early as the 1970s. The exact amount of investment currently engaged in tactical asset allocation is not clear, but it is certainly growing very rapidly. For example, Philip, Rogers and Capaldi (1996) estimated that around $48 billion was allocated to domestic TAA in 1994, while Lee (2000) estimates that more than $100 billion was dedicated to domestic TAA at the end of 1999.

TAA can be regarded as a 3 steps process:

- Step 1: forecast asset returns by asset classes
- Step 2: build portfolios based on forecasts (i.e., turn signals into bets)
- Step 3: conduct out-of-sample performance tests

Forecast Asset Returns by Asset Class

One first needs to distinguish between *forecast-based* TAA and *fact-based* TAA. The former approach consists in forecasting returns by first forecasting the values of economic variables (scenarios on the contemporaneous variables). The latter approach to forecasting returns is based on knowledge of lagged variables.

One also needs to distinguish between *discretionary TAA*, where predictions about asset returns are based upon an expert's forecast ability and *systematic TAA*, where predictions about asset returns are based upon a model's forecast ability. In turn, one should distinguish, within the class of systematic TAA, between parametric and non-parametric models.

Typical parametric models are linear regression models, where a set of predictive variables is used in a lagged regression analysis (see Bossaerts and Hillion (1999) for the use of statistical criteria to select return forecasting models). In the interest of robustness, the rule of thumb in that approach is to select a small number of predictive variables (say 2 or 3), based on economic analysis, as opposed to data mining (screening a large set of candidate variables and selecting the model via maximization of the in-sample R-squared). The simplest form of this model is the standard linear regression framework with constant coefficients.

Given that the financial markets clearly exhibit non-stationary behavior, as well as non-linear dependency on factors, several dynamic models or non-linear approaches have been offered in the literature.[ii] For example, in the presence of concern over parameter instability, one can use a Kalman filter analysis, which is a general form of a linear model with dynamic parameters, where priors on model parameters are recursively updated in reaction to new information (see Hamilton (1994)). Another form of linear dynamic models is the class of conditional linear models, which are attractive from a theoretical standpoint but involve additional parameters and often result in lower out-of-sample performance (Ghysels (1998)). There also exist a number of non-linear models, including in particular logit regression models (see for example Bauer and Molenaar (2002) for an application of logit models to financial markets forecasts). A variety of non-parametric models have also been tested in the context of TAA strategies. Harvey et al. (2000) investigate the predictability of emerging market returns based on neural networks. Another example of non-parametric predictive models can be found in Blair (2002), who considers a kernel regression approach, where forecasts are obtained from non-linear filtering of previous returns based on exogenous variables.

Build Portfolios Based on Forecasts

Once predictions of expected returns are available, one needs to turn these active bets into portfolio decisions. This can be done without an optimizer, by investing in equal- or value-weighted portfolios with highest expected returns. On the other hand, one may instead use an optimizer, and typically maximize portfolio expected return with constraints on tracking error risk with respect to a pre-defined benchmark.

The literature on optimal portfolio selection has also recognized that predictability in returns can be exploited to improve on existing policies based upon unconditional estimates. While Samuelson (1969) and Merton (1969, 1971, 1973) have paved the way by showing that optimal portfolio strategies are significantly affected by the presence of a stochastic opportunity set, optimal portfolio decision rules have subsequently been extended to account for the presence of predictable returns (see in particular Barberis (2000), Campbell and Viceira (1998), Campbell et al. (2000), Brennan, Schwartz and Lagnado (1997), Lynch and Balduzzi (1999), Lynch (2000), Brandt (1999) and Ait-Sahalia and Brandt (2001)). Roughly speaking, the prescriptions of these models are that investors should increase their allocation to risky assets in periods of high expected returns (market timing) and decrease their allocation in periods of high volatility (volatility timing). Kandel and Stambaugh (1996) argue that even a low level of statistical predictability can generate economic significance and abnormal returns may be attained even if the market is successfully timed only 1 out of 100 times.

Recent research has also emphasized the need to account for model and parameter uncertainty (see for example Kandel and Stambaugh (1996), Barberis (2000), Avramov (2002), or Cvitanic et al. (2002)).

Conduct Out-of-Sample Performance Tests

Two popular tests have been devised to assess timing ability, one is the *quadratic model* of Treynor and Mazuy (1966), the other is the *switch-point regression model* of Hendrikkson and Merton (1981). These models aim at testing the non-linearity of the relationship between portfolio and benchmarked returns: if a manager can time the market, the sensitivity of portfolio returns to market returns should be higher (lower) during up (down) markets.

At the econometric level, the performance of a forecast model can be measured in terms of the ex-post correlation between forecast and actual return, as well as the correlation between ex-post class rank and predicted rank. Also a hit ratio can be calculated as a measure of the quality of directional forecast (percentage of time predicted direction is valid).

At the portfolio level, standard measures of relative portfolio performance can be applied. One typically computes the average (ex-post) excess return over the benchmark, as well as the best and the worst timing performance (taking into account transaction costs and possibly including price impact). One may also compute a hit ratio as the percentage of times the TAA active portfolio beats the passive benchmark.

A relevant measure of relative risk is the tracking error, i.e., the volatility of excess return over the benchmark. A composite ratio, the equivalent of the Sharpe ratio for relative performance evaluation, is the information ratio, calculated as the average excess return divided by the tracking error.

EVIDENCE OF PREDICTABILITY IN THE EURO MARKET

While it is common sense that perfect forecasts of asset returns are impossible, most financial economists agree that aggregate asset returns are to some extent predictable. For example, Campbell (2000), in a survey paper on the state of modern asset pricing theory, explains that if financial economists typically do not believe in the benefits of stock picking, they generally agree on the benefits of timing decisions based on the presence of a predictable component in asset class returns: "The evidence for predictability survives at reasonable if not overwhelming levels of statistical significance. Most financial economists appear to have accepted that aggregate returns do contain an important predictable component."

Where does Predictability come from?

There are actually two possible interpretations behind the presence of predictability and the success of TAA strategies, depending on whether one believes that the dynamics of expected returns is explained by rational or behavioral components.

The rational interpretation of the dynamics of asset returns states that expected returns reflect rational risk premiums and they change over time as risk premiums change. Risk premiums are made of two components, quantity of risk and price of risk, both of which tend to vary with the business cycle. Therefore, one interpretation of the success of TAA strategies is that asset returns are predictable because the business cycle is predictable (the slope of the term structure, among other variables, has been found to predict the business cycle (Harvey (1988)).

More specifically, consider a standard specification of a general asset pricing model where asset prices are derived as a solution to an optimization program for a representative investor who has rational preferences over their present and future consumption c_t and c_{t+1}. If one further assumes that the investor's intertemporal consumption preferences can be expressed using a time-additive expected utility representation $u(c_t) + bu(c_{t+1})$, where $b < 1$ is a parameter describing the preference for present over future consumption, one obtains the following standard pricing equations (see, for example, Cochrane (2000)):

$$p_t = E_t(m_{t+1} x_{t+1}) \tag{1}$$

where the stochastic discount factor (or pricing kernel) m_{t+1} can be written as $m_{t+1} = b \dfrac{u'(c_{t+1})}{u'(c_t)}$.

Equation (1) stipulates that the price p_t at date *t* of a financial claim delivering the random payoff x_{t+1} at date *t+1* is given by the conditional expectation at date *t* of the product of the stochastic discount factor m_{t+1}, which can intuitively be thought of as performing a time and risk-adjustment, and the payoff x_{t+1}.

In other words, since we know by equation (1) prices can be regarded as (discounted risk-adjusted) expected values of expected cash flows, they can be predicted as long as one or several of the following three ingredients can be predicted. The first ingredient is the (aggregate) expected cash flow x_{t+1}, which is persistent and slowly time varying like the business cycle. The other ingredient is the market risk premium (related to risk-adjustment through the pricing kernel), a function of marginal utility of the representative agent *u'(c)*, which tends to be high at business cycle troughs, and low at business cycle peaks. The last ingredient is the level of interest rates (related to time-adjustment through the pricing kernel), which reflects expectations of real interest rates, real economic activity and inflation.[1] Given that these three ingredients are all linked with the business cycle, they can be predicted if the business cycle is predictable to some extent, and this is not inconsistent with the efficient market hypothesis.

The competing, behavioral, interpretation of the success of TAA strategies is that the performance does not result from an ability to predict the dynamics of rationally motivated changes in prices but an analysis of the reactions of the market to its publication. The market is guided by the information (informational efficiency) but certain players can hope to manage the consequences better than others (inefficiency or reactional asymmetry). This approach, which has given rise to numerous academic studies (e.g., de Bondt and Thaler (1985), Thomas and Bernard (1989), McKinley and Lo (1990)), provides the ground for under and over reactions to news (momentum and contrarian effects) or herding and glamour effects (e.g., growth at a reasonable price has become growth at any price).

In-Sample Evidence of Predictability

In this section we first report some evidence of in-sample predictability in Euro equity returns based on predictive variables that have a potential for capturing both the rational and behavioral elements of predictability in European aggregate stock returns. We use the benchmark Dow Jones EURO STOXX 50 Index that charts the top 50 blue chip stocks from the twelve countries participating in the EMU. It is a price index weighted according to the free-float market capitalization of each component stock and its value is updated and disseminated every 15 seconds.

To forecast DJ EURO STOXX 50 index excess returns over the one-month LIBOR rate, we screen a universe of meaningful variables. These variables are chosen on the basis of previous evidence of their ability to predict asset returns, as well as their natural influence on asset returns.

Rather than trying to screen hundreds of variables through stepwise regression techniques, which usually leads to high in-sample R-squared but low out-of-sample R-squared (robustness problem), it is usually preferred to select a short list of economically meaningful variables, which are known to have a natural impact on stock returns.

Most of these variables can be found within the following three broad categories.

1. Variables related to interest rates

    a. Level of the term structure of interest rates, proxied by the short-term rate: Fama (1981) as well as Fama and Schwert (1977) show that this variable is negatively

[1] At the individual stock level, there is actually a fourth ingredient, the firm risk exposure, which can be measured through the covariance between the asset payoff and the stochastic discount factor, as can be seen from the identity $E_t(m_{t+1}x_{t+1}) = E_t(m_{t+1})E_t(x_{t+1}) + \mathrm{cov}_t(m_{t+1}, x_{t+1})$. This exposure is a function of leverage that also often varies with the business cycle.

correlated with future stock market returns; it serves as a proxy for expectations of future economic activity.

   b. Slope of the term structure of interest rates, proxied by the term spread: an upward sloping yield curve signals expectations of an increase in the short-term rate, usually associated with an economic recovery.

2. Variables related to risk

   a. Quantity of risk, proxied by historical volatility (intra-month volatility of stock returns) or expected volatility (implicit volatility from option prices).

   b. Price of risk, proxied by credit spreads on high yield debt: it captures the effect of default premiums (Fama and French (1998)), which track long-term business cycle conditions (higher during recessions, lower during expansions).

3. Variables related to relative cheapness of stock prices, proxied by dividend yields: it has been shown that the dividend yield is associated with slow mean reversion in stock returns across several economic cycles (Keim and Stambaugh (1986), Campbell and Shiller (1998), Fama and French (1998)). It serves as a proxy for time variation in the unobservable risk premium since a high dividend yield indicates that dividends have been discounted at a higher rate.

We also include a shortlist of additional variables that are known to have a natural impact on equity returns, including a US large cap index (S&P500), a commodity index (Goldman Sachs commodity index[iii]) and a currency index (US $ major currency index[iv]). Finally, we also include a "sentiment" variable, a measure of imbalance between market volume on puts versus calls such as the ratio of volume of call to volume of put options.[v]

We have aimed at including variables related not only to the Euro equity market, but also to the US equity markets because i) of the significance of U.S. equity markets over stock markets worldwide, and ii) some of these variables are not available with a sufficiently long history on European markets. Overall, we have been focused on 10 variables, some of which relate to Euro equity markets, others to US equity markets (see exhibit 1 below for the detailed list of variables). Monthly data on these variables has been gathered via DataStream (Thomson Financials) over the period extending from August 1994 to July 2003, and, as a first step analysis, we have run in-sample first pass regressions of DJ EURO STOXX 50 excess return over one-month LIBOR onto these one month lagged variables. The results of this analysis can be found in Exhibit 1.[vi]

Exhibit 1: List of Selected Variables and their Lagged Impact on Euro Equity Returns. This table provides the list of variables that have been tested for their ability to predict European stock returns, as well as the slope

coefficients, associated t-statistics and R-squared from a simple regression of DJ EURO STOXX 50 excess return over one-month LIBOR onto these one month lagged variables on the period August 1994 to July 2003.

Variable	Type of Variable	Coefficient	T-Stat	R-Squared
S&P 500	Momentum Equity	-0.0027	-0.0192	0.00%
US $ Major Currency Index	Momentum Currency	0.0015	1.5497	1.81%
Goldman Sachs Commodity Index	Momentum Commodity	0.0006	2.3612	3.57%
S&P 500 Dividend Yield	Dividend yield	-0.0069	-0.0966	0.01%
FTSEuroFirst 80 Dividend Yield[vii]	Dividend yield	0.0000	0.4407	0.22%
Default Spread US	Risk (price)	0.0104	0.2880	0.08%
EURIBOR 3 Months Offered Rate	Interest rates	0.0312	2.7109	5.67%
Term Spread US (10 years - 3 months)	Interest rates	0.0006	0.0866	0.01%
Term Spread Euro (3 months - 10 years)	Interest rates	-0.0661	-0.1423	0.03%
Put/Call Ratio US (S&P 500 Index Options)	Sentiment	-0.0602	-2.0811	2.37%

A number of things can be noted from this analysis. First, most US-based variables do not appear to have a significant predictive power on Euro equity index at the one-month level. For example, one month lagged values of S&P return and dividend yield, or US default and term spread, do not show up on the sample as significantly impacting excess returns on the DJ EURO STOXX 50 index. This suggests that the impact of US equity markets on European equity markets is more instantaneous and does not transpire at the one-month lag. On the other hand, the US put-call ratio seems to have a significant predictive power in a simple linear regression framework. Other significant variables include commodity prices, short-term euro rate, and also the currency index. These preliminary results seem to suggest some evidence of predictability in Euro equity markets.

There are, however, a number of reasons why one should go beyond such a simplified analysis. First, some of these variables may not show predictive power at the one-month lag level, while being more significant when taken at a different lag. More importantly, a single-factor linear specification is not likely to be the best specification. In particular, it is possible that a non-linear model involving more than one of the afore-mentioned variables (including potentially those which do not show up as significant in a single linear regression setup) turn out to have a significant predictive power. Also, and perhaps more importantly, predictability should be tested on an out-of-sample basis, with a process focused on finding the best possible trade-off between quality of fit and robustness. These are the reasons why we turn next to a more sophisticated approach for finding evidence of predictability in Euro equity markets.

GENERATING ALPHA THROUGH TAA DECISIONS IN THE EURO MARKET

In this section, we show how to implement a sophisticated and robust econometric approach to forecast European equity returns and to build long/short portfolios based on these forecasts, implemented by trading index futures. The strategy is implemented using DJ EURO STOXX 50 index futures, for which data is available since June 1998.

Thick and Recursive Modeling Approach

Given that we are searching for evidence of predictability in index returns with the goal of implementing a tactical allocation strategy, we attempt to find the best possible trade-off between quality of fit and robustness. In particular, given the wide range of filters applied to select factors and models, there is of course a potential concern over the pitfalls of data mining. We try to mitigate this problem by using a *recursive modeling* and *thick* approach.

The *recursive modeling* approach consists of using a 3 stage procedure involving a calibration period, a training period and a trading period. This procedure, suggested for example by Pesaran and Timmerman (1995), directly relates to the critique made by Bossaerts and Hillion (1999), who showed the insufficiency of in-sample criteria to forecast out-of-sample information ratios. For example, for a forecast starting in August 2000, we first decompose the period August 1994 to July 2000 (6 years) into 2 sub-periods, a calibration period and a training period. In the c*alibration period*, we use a 4-year rolling window of data (starting August 94) to calibrate the model, i.e., estimate the coefficients. For the t*raining period*, we use a 2-year rolling window of data (starting in August 98) to back test the model, i.e., generate forecasts and compute hit ratios.[viii] Finally, we select the model at the end of the training period and use it subsequently in the 3-year *trading* period (August 2000 to July 2003).

In this paper, we actually extend Pesaran and Timmermann (1995) recursive modeling approach to account for model uncertainty. Pesaran and Timmermann (1995) select in each period only one forecast, i.e., the forecast generated by the best model selected on the basis of a specified selection criteria (such as adjusted R2, BIC, Akaike, Schwarz) which weights goodness of fit against parsimony of the specification. We follow Granger (2000) and label this approach “thin” modeling in that the forecast for excess returns and consequently the performance of the asset allocation strategy are described over time by a thin line. One limit of thin modeling is that model uncertainty is not considered. In each period the information coming from the discarded models is ignored for the forecasting and portfolio allocation exercise. This choice seems to be particularly strong in the light of the results obtained by Bayesian line of research, which stresses the importance of the estimation risk for portfolio allocation (see for example Barberis (2000) or Kandel and Stanbaugh (1996)). A natural way to interpret model uncertainty is to refrain from the assumption of the existence of a ”true” model and attach instead probabilities to different possible models. This approach has been labeled “Bayesian Model Averaging” (see, for example, Avramov (2001)). Bayesian methodology reveals the existence of in-sample and out-of-sample predictability of stock returns, even when commonly adopted model selection criteria fail to demonstrate out-of-sample predictability.

The main difficulty with the application of Bayesian Model Averaging to problems like ours lies with the specification of prior distributions for parameters in all possible models of interest. Recently, Doppelhofer et al. (2000) have put forward an approach labeled "Bayesian Averaging of Classical Estimates" (BACE) which overcomes the need of specifying priors by combining the averaging of estimates across models, a Bayesian concept, with classical ordinary least square (OLS) stimation, interpretable in the Bayesian camp as coming from the assumption of diffuse, non-informative, priors. In a related line of research, Aiolfi and Favero (2002) argue that portfolio allocation strategies based on a thick modeling strategy systematically (i.e., averaging across the different portfolio choices driven by predictions of excess returns) overperforms portfolio allocation strategies based on thin modeling. In this paper, we apply the BACE approach by selecting at each date a "council" of models to make predictions, as opposed to using a single model. As outlined in the introduction, the use of a process that is based on a "council" of models to make predictions, as opposed to using a single model, strongly suggests that most long-short managers could use a similar methodology to enhance the performance of their portfolios without having to rely on the alleged superior performance of any specific predictive model.

We now explain in more details the econometric process that we have implemented.

Econometric Process

To forecast DJ EURO STOXX 50 index excess returns, we use the shortlist of 10 aforementioned variables introduced in the previous section. We test not only the explanation power of the one-month lag $Z_{i,t-1}$, but also of the squared lag $Z_{i,t-1}$, (a measure of volatility), the moving average $\frac{1}{3}Z_{i,t-1}+\frac{1}{3}Z_{i,t-2}+\frac{1}{3}Z_{i,t-3}$, relative changes $\ln Z_{i,t-1}-\ln Z_{i,t-2}$ (when relevant) and stochastically detrending $Z_{i,t-1}-\frac{1}{12}\left(Z_{i,t-2}+Z_{i,t-3}+Z_{i,t-13}\right)$.[ix]

Because we believe there is more robustness in forecasting signs than absolute values, we favor a Logistic Probability Unit, or Logit, approach over standard linear regression models. Logit models indeed use less information than the OLS model because the dependent variable takes on a value of zero or one, instead of the whole range of positive and negative returns. An additional feature of logit estimation is that it makes a non-linear transformation of the input data that decreases the influence of outliers. Given that outliers and noisy data are a serious source of concern for financial forecasts, logit models should outperform linear models.

In this class of models, the dependent variable *y* (excess return of the DJ EURO STOXX 50 index over the one-month LIBOR) may take on only two values, 1 (meaning positive) or 0 (meaning negative). A simple linear regression of *y* on a set of regressors *x* is not appropriate, since among other things, the implied model of the conditional mean places inappropriate restrictions on the residuals of the model. Furthermore, the fitted value of the dependent variable from a simple linear regression is not restricted to lie between zero and one.

Instead, we adopt a specification that is designed to handle the specific requirements of binary dependent variables. We model the probability of observing DJ EURO STOXX 50 index outperforming the one-month LIBOR rate as

$$\Pr\left(y=1 \middle| x; b\right) = \frac{e^{-x'b}}{\left(1+e^{x'b}\right)} \tag{2}$$

where *x* is a vector of independent variables chosen from the shortlist of 10 possible predictive variables, and β a vector of parameters. The coefficient standard errors are estimated using quasi-maximum likelihood methods, which are more robust in the presence of heteroskedasticity (White (1990)).

The next step involves the selection of a set of models that will be used to forecast DJ EURO STOXX 50 excess returns. The process for model selection is based on two types of indicators. Indicators of type 1 are meant to represent the in-sample performance of the forecasting model, measured in terms of t-stats and Schwartz Information Criterion (SIC). The SIC allows one to penalize the different models for the number of degrees of freedom more harshly than the adjusted R-squared. To increase our confidence in the model's robustness, we do not consider models with more than 4 variables.[x] Indicators of type 2 are meant to represent the out-of-sample forecasting power measured in terms of hit ratio (accuracy of the direction).

During the trading period, we allow for a dynamic updating procedure of the models. On each date we select a group of models based on the following criteria: (1) all variables in the model are significant at the 5% confidence level; (2) they have been significant at the 5% level in 95% of the previous 12 months; (3) hit ratios in the training sample are higher than 0.55. Criterion (1) ensures that we are selecting a valid model; criterion (2) ensures that the model has shown robustness through time; and criterion (3) ensures that the model has shown a minimal ability for correct forecasting. A last step consists of eliminating redundant models from the shortlist of selected models. More specifically, we do not allow models that show a 100% agreement to be part of the same "council".

Portfolio Process and Results

We use this econometric procedure presented to generate predictions on expected excess return for the DJ EURO STOXX 50 index, and implement optimal trading decisions on DJ EURO STOXX 50 index futures consistent with these econometric forecasts.

In a thick modeling approach, one is left with *n* potentially conflicting predictions at each date. In a logit regression framework, predictions are presented as the percentage probability that equity outperforms cash. Let us denote by p_i the predicted probability for model *i*. Two important quantities of interest are the average forecast probability and the standard deviation of the forecast.

$$m_p = \frac{1}{n}\sum_{i=1}^{n} w_i p_i \tag{3}$$

$$s_p = \sqrt{\frac{1}{n}\sum_{i=1}^{n} w_i \left(m_p - p_i\right)^2} \tag{4}$$

where w_i is the weight associated to model i. This weight can be a function of the model's perceived ability to forecast. Given that no obviously relevant weighting scheme is available in our context, since the filter we have applied implies a relative level of homogeneity in the models (in-sample measures of) performance, we set this weight equal to *1/n*.

The prediction rule is as follows: when m_p is larger than 50%, it means that on average the models in the council predict that the DJ EURO STOXX 50 index will outperform the one-month LIBOR rate. We take the confidence in the prediction to be a function of how far above or below the neutral value 50% the average m_p is. In particular, we distinguish between two types of situations, cases when the average forecast probability is more than one standard deviation away from 50% (lower confidence in the forecast), and cases when the average forecast probability is less than one standard deviation away from 50% (higher confidence in the forecast).

The results we obtain on the period August 2000 to July 2003 are summarized in Exhibit 2.[xi] The average hit ratio over the period is equal to 2/3, which is significantly greater than 50% (null hypothesis of no predictability) at the 2.5% confidence level.

Exhibit 2: Econometric Forecasts for a TAA Strategy. In column 2 information can be found on the number of models in the council at each date after application of various filters. Column 3 tells us about the level of t-stat across models and variables. Column 4 is the average forecast probability; it provides information about the predicted sign (prediction that the DJ EURO STOXX 50 index outperforms the one-month LIBOR when the value is higher than 50%). Column 5 contains a measure of dispersion of different models' forecasts (standard deviation of forecast probabilities). Column 6 provides hit ratios (equal to 1 if the correct sign is forecast, equal to 0 otherwise). Numbers in italic and boldfaced relate to cases when the average forecast probability is less than a standard deviation away from 50%.

Date	No of Models	Average T-Stat	Prob(y>0)	Sigma	Hit Ratio
Aug-00	2	2.55	57.48%	8.12%	***0***
Sep-00	3	2.57	56.81%	10.73%	***1***
Oct-00	4	2.79	52.69%	12.93%	***0***
Nov-00	4	2.66	47.45%	10.70%	***0***
Dec-00	4	2.54	47.98%	13.11%	***1***
Jan-01	4	2.43	41.96%	13.50%	***1***
Feb-01	4	2.34	44.89%	11.96%	***1***
Mar-01	4	2.39	44.19%	4.79%	1
Apr-01	3	2.30	45.77%	10.68%	***1***
May-01	3	2.55	50.99%	25.59%	***1***
Jun-01	3	2.57	79.42%	5.96%	0

Jul-01	1	2.21	79.24%	0.00%	0
Aug-01	2	2.57	17.83%	2.40%	1
Sep-01	3	2.54	48.67%	5.73%	***1***
Oct-01	3	2.50	61.92%	5.37%	0
Nov-01	5	2.80	56.66%	43.18%	***1***
Dec-01	4	2.73	48.35%	36.72%	*0*
Jan-02	3	2.56	23.61%	24.86%	1
Feb-02	5	2.84	3.21%	3.90%	1
Mar-02	4	2.82	4.70%	2.21%	0
Apr-02	4	2.73	4.70%	5.42%	1
May-02	4	2.65	14.52%	15.63%	1
Jun-02	4	2.77	19.28%	12.72%	1
Jul-02	7	2.60	36.99%	11.79%	1
Aug-02	9	2.50	30.52%	14.57%	1
Sep-02	9	2.65	37.87%	8.53%	0
Oct-02	8	2.68	28.49%	14.17%	1
Nov-02	8	2.85	27.05%	8.07%	0
Dec-02	8	2.67	44.04%	17.80%	***0***
Jan-03	9	2.57	28.77%	7.20%	1
Feb-03	11	2.56	22.73%	13.02%	1
Mar-03	13	2.72	19.15%	21.53%	1
Apr-03	13	2.65	27.72%	29.62%	*0*
May-03	16	2.55	76.46%	28.17%	***1***
Jun-03	14	2.70	74.49%	20.19%	1
Jul-03	16	2.81	68.43%	24.36%	***1***

In the context of standard TAA, the strategy is dynamically shifting portfolio weights in two asset classes, equity (e.g., DJ EURO STOXX 50) and cash (one-month LIBOR). It should be emphasized that portfolio decisions need to be consistent with the choice of a benchmark. There are actually 3 possible benchmarks, and corresponding portfolio processes, for a TAA strategy.

- Case 1: The benchmark is 100% cash. The allocation to equity goes from -50% to 50%, which implies the need of shorting when allocation to equity is lower than 0%.
- Case 2: The benchmark is 100% DJ EURO STOXX 50. The allocation to equity then goes from [100%-y%, 100%+y%], which implies the need of leveraging when allocation to equity is greater than 100%.
- Case 3: The benchmark is 50% DJ EURO STOXX 50 and 50% cash. The allocation to equity goes from [50%-y%, 50%+y%]. This stays within the realm of standard long-only mutual fund regulation as long as y<50%.

The variable y allows us to control the level of aggressiveness of the strategy depending of the confidence level and/or investors' constraints.

In this paper, we describe the performance of these 3 strategies. In all cases, we actually implement a decision rule that makes the level of leverage a function of confidence in the forecast model. Our measure of confidence in the forecast is a function of the agreement of selected models in the council. More specifically, we use the following rule to define optimal allocation to equity in the case 1 where the benchmark is 100% cash. Note that case 2 (respectively, case 3) is obtained by simply adding 100% (respectively, 50%) to the equity allocation defined in case 1.

- If the average forecast probability is more than one standard deviation away from 50%, we interpret this as a signal of higher confidence in the prediction and we allocate equity equal to m_p*-50%* and allocate cash equal to *100%-(*m_p*-50%) = 150%-*m_p*.*
- If the average forecast probability is less than one standard deviation away from 50%, we interpret this as a signal of lower confidence in the prediction and we allocate equity equal to *(*m_p*-50%)/2* and allocate cash equal to *100%-(*m_p*-50%)/2 = 125%-*m_p*/2.*

We have also tested a more aggressive version of this portfolio process, where the allocation to equity is equal to *2(*m_p*-50%)* and *(*m_p*-50%)*, in the higher and lower confidence cases, respectively.

In exhibit 3 an overview of the results can be found.

Exhibit 3: Performance of TAA Strategies. This table contains information on the performance of various TAA strategies on the period Aug 2000 to July 2003, with 3 different choices for a benchmark, and 2 levels of aggressiveness, as described in the body of the text. The mention NA (not applicable) is displayed when the relevant performance measure does not apply to a particular portfolio.

mark	One- Month Libor			DJ EURO STOXX 50			50% One- Month Libor + 50% DJ EURO STO		
	Benchmark	Less Aggressive	More Aggressive	Benchmark	Less Aggressive	More Aggressive	Benchmark	Less Aggressive	More Aggre
ative Return	12.12%	27.52%	43.67%	-52.65%	-43.43%	-33.15%	-25.12%	-12.38%	-5.48%
lised Return	3.82%	8.28%	12.74%	-21.43%	-16.39%	-11.35%	-8.80%	-3.91%	-1.46%
lised Volatility	0.25%	5.55%	11.13%	25.73%	22.45%	20.22%	12.84%	10.08%	9.19%
e	NA	0.804	0.801	-0.981	-0.900	-0.750	-0.983	-0.766	-0.574
ative Returns	NA	13.89%	13.89%	61.11%	61.11%	61.11%	38.89%	47.22%	61.11%
Monthly Drawdown	NA	-3.39%	-7.04%	-15.37%	-13.31%	-13.28%	-7.55%	-6.56%	-8.38%
lised Tracking Error	NA	NA	NA	NA	5.61%	11.22%	NA	5.64%	9.63%
ation Ratio	NA	NA	NA	NA	0.898	0.449	NA	0.869	0.763

The economic significance of the timing strategy can be seen from the overperformance of the portfolio. For example, in case 1 of an absolute return strategy with a benchmark 100% invested in cash, the annual performance is a solid 8.28% for a 5.55% volatility.

In the interest of realism, we now complete the first results obtained from the above-mentioned simulation with a back test using index futures and risk-free assets and taking into account transaction fees as well as administration and management fees. Such an approach has the advantage of being very close to the market’s real conditions. We focus on the less aggressive strategy in case 1 of a benchmark equal to 100% in one-month LIBOR. This allows us to better appreciate the pure portable performance of a timing strategy based on the forecasts.

The results detailed hereafter have been generated by a TAA portfolio designed to significantly outperform the LIBOR 1 Month while exhibiting a relatively low volatility. From this perspective, we have invested more than 90% of the initial capital in money market funds. Our tactical bets have resulted in purchasing or selling DJ EURO STOXX 50 index futures (FESX) once a month. Our back test has been implemented using the following data and trading rules:

Holdings over the period:

- About 90% of the “monies” (level of investment obtained after deducting liquid assets held to meet deposits and margin calls) permanently invested in Money Market Mutual Funds;
- Traded Futures: DJ EURO STOXX 50 futures listed on EUREX (FESX)
- Maximum gross leverage recorded over the period = 1.52 (average = 1.16).

- *Trading Rules applied in this back test:*

- Recommendations released from the 7th business day of each month (see table 1 to view the exhaustive list of recommendations given from July 2000 to June 2003);
- Orders executed at the last trade price of the first business day after releasing recommendations.

- *Fees:*
  - Administration fees amounting to 54 bps a year (settled on a monthly basis – 0.045%)
  - Management fees equal to 90 bps a year (settled on a monthly basis – 0.075%);
  - Standard transaction fees for futures.

The holdings in DJ EURO STOXX 50 futures have been rebalanced or simply readjusted once a month. In exhibit 4 an overview of the results can be found.

Exhibit 4: Performance of TAA Strategies. This table contains information on the performance of the TAA strategy with benchmark invested in cash when implemented on index futures. The mention NA (not applicable) is displayed when the relevant performance measure does not apply to a particular portfolio.

	Reference Portfolio	Simulation with Indices	Back Test
Cumulative Return	12.12%	27.52%	22.98%
Annualized Return	3.82%	8.28%	7.07%
Annualized Std Deviation	0.25%	5.55%	5.69%
Sharpe	NA	0.80	0.58
% Negative Returns	NA	13.89%	16.67%
Worst Monthly Drawdown	NA	-3.39%	-3.04%

The results show that the presence of trading costs and various kinds of fees (administrative fees and management fees) does not significantly impact the performance of the trading strategy. This is evidence that index futures are a natural choice for implementing a timing strategy as the trading costs involved are notoriously low. The annualized return goes down from 8.28% to 7.07%, while the volatility is essentially not affected.

USING EQUITY INDEX OPTIONS TO IMPROVE THE PERFORMANCE OF A TACTICAL ASSET ALLOCATION PROGRAM

While long/short managers can use index futures contracts to help reduce a portfolio's volatility, options on equity indices can also be used to implement truncated return strategies that aim at enhancing the performance and/or at reducing the risk of a TAA program by eliminating the few worst (and best) returns of a fund track record.

Trendless periods of the market cycle are typically difficult market environments for TAA strategies. There are actually a number of reasons why this is the case. First, it is of course easier to predict significant market moves, as opposed to small changes in trends that can easily be confused with noise. Besides, if the market experiences a series of short-term reversals within the one-month time frame, the model's prediction, based on last month data, will fail at forecasting the right direction. Finally, even if the model yields correct predictions, they are of little use if the spread of the risk asset return over the risk-free rate is small. All these reasons explain why even a well-designed TAA strategy usually performs poorly (only slighter better than the risk-free rate) in periods of low volatility.

We now explain how suitably designed option strategies can be used to enhance the performance of a TAA strategy. The objective is to design a program that would consistently add value during periods of calm markets, while not significantly impacting TAA's ability to add value during turbulent market environments. This means that the enhancement program must not lose much during the market turbulence that typically leads to TAA profits. In what follows we examine the suitability of embedding option positions in a portfolio whose characteristics should achieve these desired objectives.

For the strategy to perform well in periods of low volatility, it has to involve short positions in options. Consider the following example. Assume the DJ EURO STOXX 50 index is at a (normalized) 100 level. Let us further assume we sell a call option with a 110 strike and a put option with a 90 strike price. Such a strategy, which is known as a "top strangle"; allows an investor to take a short position on volatility. If the market goes through a calm period so that the index price remains within the 90-110 range, none of the options will be exercised and the option portfolio will generate a profit due to the time-decay. Intuitively, the profit comes from the loss in value of unexercised options as they come close to maturity. Formally, this can be seen from a standard option pricing model, such as the Black-Scholes-Merton formula which reads for a plain vanilla European call option:

$$C_t = S_t \times ?\,(d) - e^{-r(T-t)} K \times N(d - s\,\sqrt{T-t}) \qquad (5)$$

with

$$d = \frac{\log \frac{S_t}{K} + (r + \frac{1}{2} s^{\,2})(T-t)}{s\,\sqrt{T-t}} \qquad (6)$$

where the notation is as follows: C is the call price, *S* the underlying asset price, *K* the strike price, *r* the risk-free rate, s the volatility, *T* the time to maturity.

We also recall the expression for the sensitivities of the call price with respect to changes in the key variables:

$$\Delta = \frac{\partial C}{\partial S} = N(d) \qquad (7)$$

$$\Gamma = \frac{\partial^2 C}{\partial S^2} = \frac{1}{Ss\,\sqrt{T-t}} N'(d) \qquad (8)$$

$$\Theta = \frac{\partial C}{\partial t} = -\left[\frac{Ss}{2\sqrt{T-t}} N'(d) + Ke^{-r(T-t)} N(d) \right] \qquad (9)$$

From equation (9), it can be noted in particular that the sensitivity with respect to time (theta) is a negative quantity, and the same would apply for a put option. This makes sense; everything else being equal, the passage of time implies a loss in time value for the option. As a result, a portfolio involving short positions in options (both calls and puts) has a positive theta, and a profit is generated by the mere passage of time, provided of course that the options remain out-of-the-money and are left unexercised.

We actually would like to choose the strike prices and the number of options in the portfolio so as to achieve delta neutrality, hence building a market neutral position that will not be impacted by small positive or negative changes in the index level. It should be noted that this option overlay strategy requires dynamic trading as it will prove necessary to rebalance the portfolio so as to maintain delta-neutrality as a result of changes in the underlying asset level. This need for rebalancing will be all the more likely as the net gamma of the portfolio (second derivatives of the portfolio value with respect to changes in underlying asset price) increases. Since gamma can equivalently be defined as the "rate of change" in delta, as gamma increases, the delta of the option becomes more sensitive to underlying price movements. A desirable feature of the option position is therefore to enjoy a relatively low net gamma.

Provided that a portfolio of short positions in options can be designed to meet the aforementioned criteria (zero delta, low gamma and positive theta), this achieves the first goal of the enhancement program: add performance in calm periods when TAA strategies generally do not outperfom dramatically.

On the other hand, the risk of one or the other option being exercised remains in case of a large change in the index value. Should this happen, the profitability of the underlying TAA strategy would be significantly impacted. In an attempt to mitigate such a risk, we add long positions in further out-of-the-money options. To get back to the previous example, we would buy a call option with say a 120 strike price and a put option with say a 80 strike price. Such a strategy is known as a "bottom strangle". If these options are chosen to be of longer maturity (e.g., 45-90 days versus 30-35 days), then the net theta of the option portfolio would be positive and the strategy would still profit from the time decay, while adding a protection to the underlying TAA position in case the index goes below 80 or above 120 in our example.[xii] Again, the overall portfolio should be designed so as to achieve as close as possible to dollar neutrality, delta neutrality and gamma neutrality, so as to avoid the need for too significant rebalancing.

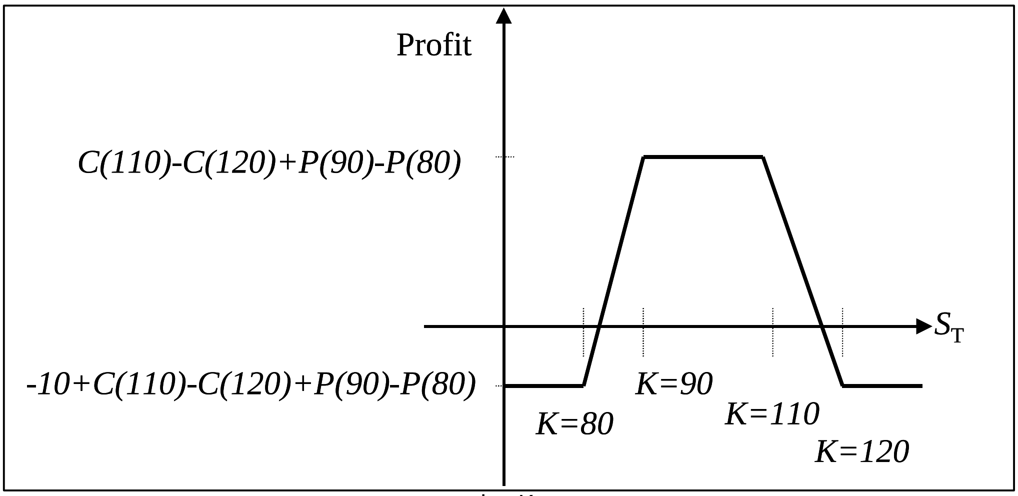
In exhibit 5, we present the payoff and profit/loss (P/L) on the ingredients of the option portfolio overlay. As can be seen from the exhibit below, the strategy generates a profit when the underlying variable does not move away far from the current value. On the other hand, the loss is limited in case of a large move of the underlying asset.

Exhibit 5: Profit and Loss on the Option Overlay Portfolio as a Function of the Terminal Value S_T of the Index. This figure shows the payoff as well as the P&L of a combination of a top and a bottom strangle designed to enhance the performance of a TAA strategy in periods of low volatility. The notation C(K) (respectively, P(K)) stands for the price, i.e. premium, at the initial date of a call option (respectively, a put option) written on the index with a strike price K.

	S_T<80	80<S_T<90	90<S_T<110	110<S_T<120	120<S_T
Payoff short call 110	0	0	0	-(S_T-110)	-(S_T-110)
Payoff short put 90	-(90-S_T)	-(90-S_T)	0	0	0
Payoff Top Strangle	S_T-90	S_T-90	0	110 -S_T	110 -S_T
P&L Top Strangle	S_T-90+C(110)+P(90)	S_T-90+C(110)+P(90)	C(110)+P(90)	110-S_T+C(110)+P(90)	110-S_T+C(110)+P(90)
Payoff long call 120	0	0	0	0	S_T-120
Payoff long put 80	80-S_T	0	0	0	0
Payoff Bottom Strangle	80-S_T	0	0	0	S_T-120
P&L Bottom Strangle	80-S_T-C(120)-P(80)	-C(120)-P(80)	-C(120)-P(80)	-C(120)-P(80)	S_T-120-C(120)-P(80)
Portfolio Payoff	-10	S_T-90	0	110 -S_T	-10
Portfolio P&L	-10+C(110)-C(120)+P(90)-P(80)	S_T-90+C(110)-C(120)+P(90)-P(80)	C(110)-C(120)+P(90)-P(80)	110-S_T+C(110)-C(120)+P(90)-P(80)	-10+C(110)-C(120)+P(90)-P(80)

Exhibit 6 below shows the typical pay-off of this option portfolio as a function of the value of the underlying asset at maturity.

Exhibit 6: Profit and Loss on the Option Overlay Portfolio as a Function of the Terminal Value S_T of the Index. This figure shows the P&L of a combination of a top and a bottom strangle designed to enhance the performance of a TAA strategy in periods of low volatility. The notation C(K) (respectively, P(K)) stands for the price, i.e. premium, at the initial date of a call option (respectively, a put option) written on the index with a strike



price K.

The change in value of the option portfolio is approximately given by:

$$dP = \Theta dt + \Delta dS + \frac{1}{2}\Gamma(dS)^2 \qquad (10)$$

or in case of a delta-neutral portfolio:

$$dP = \Theta dt + \frac{1}{2}\Gamma(dS)^2 \qquad (11)$$

In what follows, we implement an option overlay strategy that is designed to meet these requirements. Specifically, each month we select options on the DJ EURO STOXX 50 index with strike prices symmetrically distributed around the at-the-money level. We aim at implementing a short position in short-term out-of-the-money options (both calls and puts). We also add a long position in longer-term and further-out-of-the-money call and put options. Then, we select the quantity traded in each option in the overlay portfolio so as to make it commensurate with the underlying index position, while seeking delta neutrality and maximizing the theta for a given (small) net initial value. Exhibit 7 provides an example of such a portfolio.

Exhibit 7: Example of Option Portfolio. This table provides the Black-Scholes (B-S) price, as well as the delta, gamma and theta of all options in the overlay portfolio. These numbers are based upon the assumption of a $100 underlying index price, a 5% risk-free rate and a 25% volatility. The quantity of each option in the portfolio has been designed so as to achieve a highest possible theta for a small initial value, while meeting a delta-neutrality constraint.

	Strike Price	Maturity (days)	B-S Price	Delta	Theta	Gamma	Quantity	Position
Call	120	90	1.981	0.274	-4.449	0.027	25	long
Put	80	90	0.127	-0.026	-0.499	0.005	10	long
Call	110	30	0.372	0.11	-4.449	0.0026	100	short
Put	90	30	0.192	-0.06	-0.032	0.017	73	short

Portfolio			-0.421	-0.03	326.349	-0.776		

As can be seen from this example, we manage to obtain a portfolio with relatively low initial value (dollar-neutral objective), with a net delta very close to zero (delta-neutral objective), for a relatively low gamma and a high theta. The daily gain from holding this portfolio due to the time decay, assuming the options are not exercised, is equal to 326.349/365= $0.894.

Exhibit 8 shows the value of the same portfolio a month later, assuming none of the options have been exercised, and assuming that the underlying asset price, risk-free rate and volatility have remained at a constant level.

Exhibit 8: Value of the Option Portfolio one Month Later. This table provides the Black-Scholes price, as well as the delta, gamma and theta of all options in the overlay portfolio one month later. These numbers are based upon the assumption of a $100 underlying index price, a 5% risk-free rate and a 25% volatility, and assuming that none of the options have been exercised.

	Strike Price	Maturity (days)	B&S Price	Delta	Theta	Gamma	Quantity	Position
Call	120	60	0.201	0.049	-4.449	0.01	25	long
Put	80	60	0.036	-0.01	-0.481	0.003	10	long
Call	110	0	0	0	0	0	100	short
Put	90	0	0	0	0	0	73	short
Portfolio			5.385	1.125	-116.035	0.28		

The gain from adding this option portfolio is 5.385 - (-0.421) = $5.806 over the one month period. This addition generates a return enhancement for the TAA portfolio, without increasing the exposure of the portfolio with respect to extreme risks thanks to the addition of the long position in the option portfolio.

Exhibit 9 shows the performance of this option overlay strategy…

Exhibit 4: Performance of TAA Strategies. This table contains information on the performance of the TAA strategy with benchmark invested in cash when implemented on index futures. The mention NA (not applicable) is displayed when the relevant performance measure does not apply to a particular portfolio.

	Benchmark Libor	TAA with Options	TAA without Options
Cumulative Return	12.12%	27.51%	22.98%
Annualized Return	3.82%	8.28%	7.07%
Annualized Std Deviation	0.25%	5.58%	5.57%
Sharpe		0.80	0.58
Downside Risk (3.00%)		4.78%	4.46%
Sortino (3.00%)		1.10	0.91
% Negative Returns		13.89%	16.67%

To be completed

2. GENERATING ALPHAS THROUGH SECTOR ROTATION STRATEGIES

TAA strategies were traditionally concerned with allocating wealth between two asset classes, typically shifting between stocks and bonds. More recently, more complex *style* timing strategies have been successfully tested and implemented.

The Case for Tactical Style and Sector Allocation Strategies

These strategies are based on the recognition that Sharpe's CAPM (1964) needs to be extended to account for the presence of other pervasive risk factors, i.e., size and book-to-market factors (Fama and French (1992)):

$$
\begin{aligned}
R_{i,t} - r_{f,t} &= \underbrace{b_{i,M}\left[R_{M,t} - r_{f,t}\right]}_{\text{systematic - market}} \\
&+ \underbrace{b_{i,B/M}\left[R_{B/M,t} - r_{f,t}\right] + b_{i,size}\left[R_{size,t} - r_{f,t}\right]}_{\text{systematic - style}} + \underbrace{e_{i,t}}_{\text{specific}}
\end{aligned}
\qquad (12)
$$

Such a decomposition of returns allows for a natural extended classification of active portfolio strategies (see Exhibit 10). *Market Timing or Tactical Asset Allocation Strategies* aim at exploiting evidence of predictability in market factor; *Style Timing or Tactical Style Allocation (TSA) Strategies* aim at exploiting evidence of predictability in style factors; *Stock Picking Strategies* aim at exploiting evidence of predictability in individual stock specific risk.

Exhibit 10: Classification of Active Portfolio Strategies

	Systematic - market	Systematic - style	Specific
Form of active strategy	***Tactical Asset Allocation***	***Tactical Style Allocation***	***Stock picking***
Mutual fund – stock picking	X (discretionary)	X (discretionary)	X
Hedge fund – stock picking	0	X (discretionary)	X
Mutual fund – market timing	X (discretionary or systematic)	0	0
TSA – long only	X (systematic)	X (systematic)	0
TSA – market neutral	0	X (systematic)	0

It is perhaps surprising that, on the one hand, most long/short equity managers still favor stock picking as a way to generate abnormal return, while, on the other hand, thirty years of academic studies have shown that there is little evidence of predictability in the specific component of stock returns in the absence of private information. It should be noted that TSA is not a new concept. Most mutual fund managers actually make discretionary, and sometimes unintended, bets on styles as much as they make bets on stocks. In other words, they perform TAA, TSA and stock picking at the same time in a somewhat confusing "mélange des genres". As in many other contexts, we have evidence that specialization pays. In particular, Daniel, Grinblatt, Titman and Wermers (1997] find evidence that mutual funds showed some stock selection ability, but no discernable ability to time the different stock characteristics in terms of book-to-market or size.

More recently, several authors have emphasized the benefits of focusing on style timing exclusively. In particular, Fan (1995), Sorensen and Lazzara (1995), Kao and Shumaker (1999), Avramov (2000) or Bauer and Molenaar (2002) report strong evidence of predictability in equity style returns and underline the performance of strategies that involve dynamic trading in various equity styles. Related papers also include Gerber (1994), Case and Cusimano (1995), Fisher, Toms and Blount (1995), Mott and Condon (1995), Levis and Liodakis (1999), Oertmann (1999), Reiganum (1999), Amenc and Martellini (2001), Cooper et al. (2001), Ahmed, Lockwood and Nanda (2002), Amenc, El Bied and Martellini (2003), or Amenc et al. (2003).

In a similar spirit, Cavaglia and Moroz (2002) provide evidence that local industry returns are predictable. They present the performance of simulated strategies and demonstrate that active sector rotation across countries provides an additional source of alpha beyond simplistic country rotation strategies. They present a forecasting approach to predicting the relative performance of industries in each of 22 developed country equity markets and demonstrate that a blend of style signals provides an effective way to predict the return performance of these assets. The out-of-sample portfolio performance of investment strategies based on these forecasts for the 1991-2001 period would have provided annual gross returns in excess of the world benchmark return of 400 bps a year with one-way turnover of 50 percent.

In a related paper, Johnson and Sakoulis (2003) show how financial and economic variables can be employed in a time varying dynamic sector allocation model for U.S. equities. They find that using the Kalman filter to estimate time varying sensitivities to predetermined risk factors results in significantly improved sector return predictability over static or rolling parameter specifications. A simple trading strategy developed here using Kalman filter predicted returns as input provides for potentially robust long run profit opportunities.

Sorensen and Burke (1986) and Beller, Kling, and Levinson (1998) also found that U.S. industry returns can be predicted by using either past return performance or macroeconomic fundamentals; they cautioned, however, that the extent of asset return predictability may not offset transaction costs sufficiently to maintain the paper profits when their models are implemented. Capaul (1999) found conflicting evidence about the effectiveness of using traditional style factors for global industries. For instance, he found that low-P/B (price-to-book) industries underperformed high-P/B industries in the 1991-98 period; similarly, buying "large" global industries appeared to be more attractive than buying "small" global industries.

Implementing Sector Rotation Strategies using Eurex Sector Index Futures

While active sector rotation is a popular strategy among investors, it is operationally intensive and expensive when implemented with individual stocks. In what follows, we argue that futures on sector indexes are a natural cost-efficient way for active sector rotation.

In this section, we design a long/short strategy that generates abnormal return from timing between various sectors of a European index while maintaining a zero exposure with respect to the global index.

In an effort to calibrate models on asset classes for which liquid investible products are available, we have chosen to focus on the following two sector indices, DJ EURO STOXX Banks and DJ EURO STOXX Telecom. Investible products (futures and options) on these indices were introduced by Eurex in March 2001.

Given that we are searching for evidence of predictability in equity style returns with the goal of implementing a sector rotation strategy, we focus on the best possible trade-off between quality of fit and robustness. We show how to implement a systematic sector strategy on the basis of a sophisticated econometric approach similar to the one used in the context of the DJ EURO STOXX 50 TAA strategy.[xiii]

The results we obtain are summarized in Exhibit 11. The average hit ratio over the period is equal to 64%, which is significantly greater than 50% (null hypothesis of no predictability) at the 5% level. Interestingly, if we exclude cases when the average forecast probability is less than one standard deviation away from 50% (i.e., numbers in italic and boldfaced in column 6), the hit ratio reaches a spectacular 0.875 value (over 16 months).

Exhibit 11: Econometric Forecasts for a Sector Rotation Strategy. In column 2 information can be found on the number of models in the council at each date after application of various filters. Column 3 tells us about the level of t-stat across models and variables. Column 4 is the average forecast probability; it provides information about the predicted sign (prediction that the DJ EURO STOXX Bank index outperforms the DJ EURO STOXX Telecom Index when the value is higher than 50%). Column 5 contains a measure of dispersion of different models' forecasts (standard deviation of forecast probabilities). Column 6 provides hit ratios (equal to 1 if the correct sign is forecast, equal to 0 otherwise). Numbers in italic and boldfaced relate to cases when the average forecast probability is less than a standard deviation away from 50%.

Date	No of Models	Average T-Stat	Prob(y>0)	Sigma	Hit Ratio
Aug-00	2	2.34	68.98%	21.99%	***1***
Sep-00	2	2.41	48.34%	5.05%	***0***
Oct-00	3	2.45	62.38%	2.71%	1
Nov-00	3	2.53	27.65%	5.29%	1
Dec-00	2	2.54	89.21%	2.48%	1
Jan-01	3	2.62	68.26%	11.12%	1
Feb-01	3	2.64	92.44%	4.34%	1
Mar-01	1	2.48	92.97%	0.00%	1
Apr-01	3	2.43	57.75%	28.29%	***1***
May-01	8	2.48	90.45%	4.61%	1
Jun-01	8	2.58	98.61%	1.95%	1
Jul-01	8	2.58	88.58%	4.86%	1
Aug-01	10	2.60	65.61%	15.31%	0
Sep-01	10	2.63	69.11%	12.46%	1
Oct-01	10	2.65	25.63%	17.43%	1
Nov-01	11	2.73	60.64%	18.80%	***0***
Dec-01	8	2.72	80.37%	7.28%	0
Jan-02	6	2.75	43.52%	18.28%	***0***
Feb-02	11	2.66	38.23%	20.80%	***0***
Mar-02	9	2.65	29.09%	16.41%	1
Apr-02	3	2.71	53.32%	3.89%	***1***
May-02	4	2.79	60.15%	4.17%	1
Jun-02	7	2.86	56.51%	6.16%	1
Jul-02	10	2.73	56.24%	12.05%	***0***
Aug-02	10	2.68	56.98%	16.82%	***0***
Sep-02	9	2.82	56.15%	12.35%	***0***
Oct-02	8	2.80	67.28%	22.72%	***0***
Nov-02	6	2.73	61.86%	16.95%	***1***
Dec-02	9	2.82	70.77%	23.78%	***0***
Jan-03	8	2.80	59.39%	22.07%	***1***
Feb-03	8	2.71	58.40%	23.10%	***0***
Mar-03	10	2.64	45.55%	26.72%	***0***
Apr-03	12	2.51	45.36%	29.59%	***1***
May-03	13	2.59	50.90%	34.03%	***1***
Jun-03	9	2.70	63.97%	23.99%	***1***
Jul-03	8	2.68	58.49%	19.45%	***1***

Our portfolio process is similar to the one introduced in a TAA context. More specifically, we use the following rules to define a market-neutral sector rotation strategy:[2]

- If the average forecast probability is more than one standard deviation away from 50%, the allocation to the DJ EURO STOXX Bank index is equal to m_p*-50%* and the allocation to the DJ EURO STOXX Telecom index is equal to *50%-*m_p*.*
- If the average forecast probability is less than one standard deviation away from 50%, the allocation to the DJ EURO STOXX Bank index equals *(*m_p*-50%)/2* and the allocation to the DJ EURO STOXX Telecom index equals *(50%-*m_p*)/2.*

We have also tested a more aggressive version of this portfolio process, where the allocation to the DJ EURO STOXX Bank index is equal to *2(*m_p*-50%)* and *(*m_p*-50%)*, in the higher and lower confidence cases, respectively. In exhibit 12 an overview of the results can be found.

Exhibit 12: Performance of a Sector Rotation Strategy. This table contains information on the performance of a sector rotation strategy (bank sector versus telecom sector) for 2 levels of aggressiveness, as described in the body of the text. The mention NA (not applicable) is displayed when the relevant performance measure does not apply to a particular portfolio.

	Benchmark = One-Month Libor	Less Aggressive	More Aggressive
Cumulative Return	12.12%	41.46%	77.04%
Annualized Return	3.82%	11.74%	19.66%
Annualized Std Deviation	0.25%	5.12%	10.11%
Sharpe	NA	1.547	1.567
% Negative Returns	NA	11.11%	19.44%
Worst Monthly Drawdown	NA	-1.09%	-2.44%

Mixing TAA and Sector Rotation Benefits

In this section, we also consider the benefits of a double-alpha strategy involving both TAA and sector rotation decisions. We focus on the case of the benchmark invested 100% in cash for the TAA strategy, and a less aggressive portfolio process in both cases. The results are displayed in exhibit 13.

Exhibit 13: Performance of a Strategy Mixing Sector Rotation and TAA. This table contains information on the performance of a strategy mixing sector rotation (bank sector versus telecom sector) and TAA in the less aggressive version, as described in the body of the text. The mention NA (not applicable) is displayed when the relevant performance measure does not apply to a particular portfolio.

	Benchmark = One-Month Libor	DJ EURO STOXX Sector Rotation	Less Aggressive DJ EURO STOXX + One-Month Libor	Composite Portfolio
Cumulative Return	12.12%	41.46%	27.52%	34.65%
Annualised Return	3.82%	11.74%	8.28%	10.01%
Annualised Std Deviation	0.25%	5.12%	5.55%	3.32%
Sharpe	NA	1.547	0.804	1.866

[2] Market neutral can imply dollar-neutrality or beta-neutrality. Here we consider dollar-neutrality for simplicity of exposure.

% Negative Returns	NA	11.11%	13.89%	11.11%
Worst Monthly Drawdown	NA	-1.09%	-3.39%	-1.45%

As can be seen from Exhibit 13, mixing asset and sector allocation decisions allows one to significantly lower the portfolio volatility while maintaining the level of average returns. This is due to the benefits of bet diversification: active asset and sector allocation bets are wrong in about one-third of the cases, but they are not necessarily wrong on the same dates.

CONCLUSION

In this paper, we explain how active portfolio managers, who attempt to generate abnormal profits through bets on well-identified risks for which they feel they have reliable views, can benefit from using suitably packaged derivatives satellite portfolios as portable alpha and beta vehicles.

These portfolios, based on active asset allocation decisions, can be used either as standalone absolute return alpha providers, or as overlay portfolios customized to help them modify the exposure of their portfolios with respect to a variety of sources of risks on which they have no desire to bet. In particular, we provide an example of a short volatility strategy that allows a manager to enhance the performance of a base investment strategy.

The benefits of active asset allocation decisions that we present in this experiment are not based on the use of any specific econometric model with unusually superior predictive power. The approach followed in this paper is actually based on a process that consists of selecting at each date a “council” of models to make predictions, as opposed to using a single model. We actually believe that the benefits of active asset allocation decisions originate more from the combination of a robust econometric process and an efficient trading of low cost investible products such as Eurex index futures and options, rather than the use of any given mysterious model with extraordinary performance. This strongly suggests that most long-short managers could use a similar methodology to enhance the performance of their portfolios.

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[i] On the other hand, some long-short managers use quantitative techniques to implement a systematic risk management process allowing them to actively manage their exposure to a variety of risk factors.

[ii] Ideally, one would like to account for both the presence of no- linear dependencies and dynamic coefficients. There is however few examples of tractable non-linear dynamic models.

[iii] The Goldman Sachs Commodity Index is a world production-weighted commodity index comprised of 25 liquid, exchange-traded futures contracts.

[iv] The US $ major currency index is a daily trade-weighted currency index which measures nominal exchange rate strength of the US dollar relative to a basket consisting of Canada, Japan, Euro, Denmark, Norway, Sweden, Switzerland, UK, Mexico, Australia, New Zealand, China, Hong Kong, Korea, Singapore and Taiwan.

[v] One may also include economic variables. One problem there is the risk of posterior adjustment, which refers to the fact that the estimate of an economic variable (e.g., inflation) for a previous date can be adjusted several months after a first estimate is first released. As a result, economic series in databases may contain cleaner data than what is actually available in real-time.

[vi] In principle, we could have used a longer time-period, but this would have severely limited the number of variables that could be included in the analysis. Given that our emphasis is on economic impact of predictability, we have chosen to focus on a process that can be similar to the one that would be used in actual investment practice.

[vii] We would have rather used the Dividend Yield on the DJ EuroStoxx index, but that data was not available to us.

[viii] Hit ratios are the percentage of times the predicted sign equals the actual sign of the style return. We test whether hit ratios are significantly greater than ½ (benchmark case of no model): in the case of 24 observations, a hit ratio of at least 63% (respectively, 67%) is significantly greater than ½ at the 10% (respectively, 5%) level. We also compute the associated t-statistics to check whether the variable had a statistically significant explanatory power.

[ix] It is well known (e.g., Stambaugh (1999)) that asymptotic distribution theory on which statistical inference is based provides a poor approximation to the actual finite-sample distribution of test-statistics when the predictor is persistent. To avoid spurious regression problems, it is therefore useful to check whether the independent and dependent variables are stationary, using a standard unit root test, the Dickey-Fuller (1979) test (see also and Phillips and Perron (1988)).

[x] We have also checked that multi-colinearity was not an issue, as the maximum correlation between two variables does not exceed 60% in the sample.

[xi] By August 2000, we mean a forecast performed on July 7th, for the period ranging from July 7th to August 7th.

[xii] A similar strategy is presented in Arnott and Miller (1996), with the difference that no optimisation is performed over the composition of the portfolio.

[xiii] One difference is that we had to increase the number of variables used in the process from August 2000 to March 2002 as there was no model before April 2002 that could meet the criteria when we limited ourselves to the 10 variables used in a TAA context.