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# Using Index Options to Improve the Performance of Dynamic Asset Allocation Strategies

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It has been long argued that equity managers can use derivatives markets to help implement a systematic risk management process designed to enhance the performance of their portfolio (see for example Ineichen (2002) for a recent reference). These derivatives instruments can be used in the context of completeness portfolios that are designed not to interfere with the original portfolio composition, so that they can be used to generate what has been labeled *portable beta benefits* (Amenc et al. (2004)).

Consider for example the case of long/short equity hedge fund managers. Since the vast majority of these managers favor stock picking as a way to generate abnormal return in a pure bottom-up process, they 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.

Futures contracts can be used to correct for such intended biases, and ensure that the portfolio factor exposure is consistent with the manager's active views. In case the manager is a pure stock picker who has no views on systematic factors, it is recommended that he/she uses derivatives products to systematically neutralize the exposure of the portfolio with respect to the pervasive risk factors. In the absence of a systematic risk management process, and since a bottom-up selection process is not likely to lead to a *market* and *factor* neutral portfolio, it is not obvious to extract from the portfolio performance anything but a very noisy signal on the managers' pure stock picking ability.

There actually exists a second possible form of an active asset allocation strategy involving implementing an option-based portfolio strategy, of which the sole objective is to modify the asset allocation risk profile in the portfolio. In particular, it is well-known that 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 consider the use of options in equity portfolios from a different angle in that we show how suitably designed option strategies can also be used to enhance the performance of a market timing 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.

The remaining part of 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 argue that tactical asset allocators would strongly benefit from using 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. In a third section, we conduct a numerical experiment leading to the implementation of the option overlay strategy. 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.[1] 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. For example Blair (2002), 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

[1] 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.

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.

***Where does Predictability come from?***

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."

If financial economists have reached an agreement on the existence of some predictability in asset returns, they may not necessarily agree on the origin of such predictability. 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 (1989)).

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 $u(c_t)+\beta u(c_{t+1})$, where $\beta < 1$ is a parameter describing the preference for present over future consumption, one obtains the following standard pricing equations (see, for example, Cochrane (2000)):

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

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

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.[2] 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).

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

As stated in the introduction, 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 Tactical Asset Allocation (TAA) program by eliminating the few worst returns of a fund track record. For example, it is clear that adding out-of-the-money put options to a long-only portfolio allows for an efficient ex-ante management of extreme risks. In what follows, we show that using an option overlay portfolio can also serve a return enhancement purpose, which may complement the standard risk reduction benefits.

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

[2] 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 $E_t(m_{t+1}x_{t+1}) = E_t(m_{t+1})E_t(x_{t+1}) + \text{cov}_t(m_{t+1}, x_{t+1})$. This exposure is a function of leverage that also often varies with the business cycle.

the risk-free rate is small. All these reasons explain why even a well-designed TAA strategy usually performs poorly (only slightly 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. In what follows, we consider as an illustration the case of a European market timer who uses the benchmark Dow Jones EURO STOXX 50 Index. [3]

Let us assume that 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:

$$C_t = S_t \times N(d) - e^{-r(T-t)} K \times N(d - \sigma\sqrt{T-t}) \tag{3}$$

with

$$d = \frac{\log \frac{S_t}{K} + (r + \frac{1}{2}\sigma^2)(T-t)}{\sigma\sqrt{T-t}} \tag{4}$$

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, $\sigma$ the volatility, *T* the time to maturity. We also recall the expression for the sensitivities of the call price with respect to time:

$$\Theta = \frac{\partial C}{\partial t} = -\left[\frac{S\sigma}{2\sqrt{T-t}} N'(d) + Ke^{-r(T-t)} N(d)\right] \tag{5}$$

[3] The Dow Jones EURO STOXX 50 Index 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.

From equation (5), it can be noted 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.

While this portfolio of short options should add performance in calm periods when TAA strategies generally do not outperfom dramatically, 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 add the benefits of risk reduction to the benefits of return enhancement, one may implement a dynamic hedging strategy of the option portfolio using index futures. Because dynamic trading can prove costly in the presence of transaction costs and is beyond the realm of expertise of most equity portfolio managers, we instead choose to hedge the risk associated to the short option positions by adding long positions in further out-of-the-money options.[4] 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 an 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.

In Exhibit 1, we present the payoff and profit/loss (P & L) for the option portfolio overlay. For simplicity of exposure, we consider in this exhibit, and also in exhibit 2, a situation where all options have the same maturity date. As can be seen from the exhibit below, the strategy generates a profit when the underlying variable does not move far away from the current value. On the other hand, the loss is limited in case of a large move of the underlying asset.

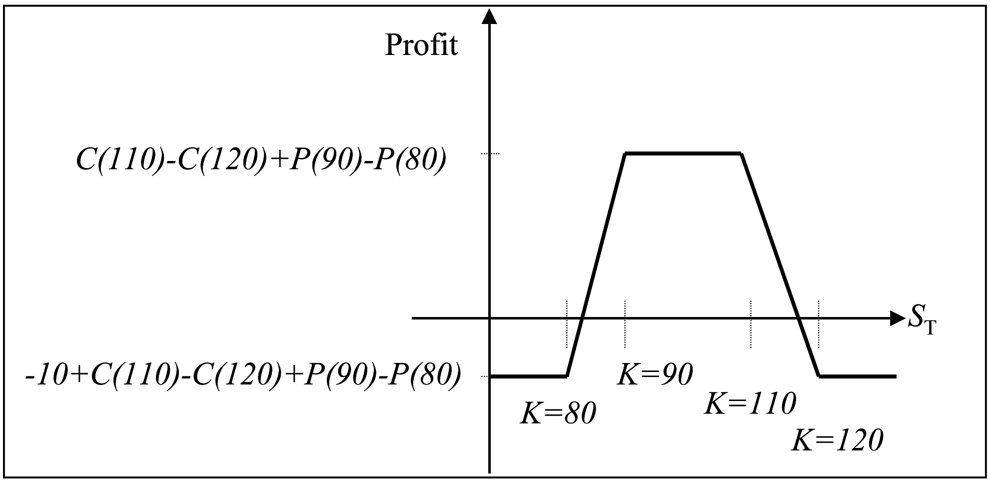
[4] Because the portfolio contains options with various maturities, and because these options may not be held until maturity, the strategy still involves some amount of residual risk that could be dynamically hedged.

**Exhibit 1: Profit and Loss on the Option Overlay Portfolio as a Function of the Terminal Value $S_T$ of the Index.** This exhibit shows the payoff as well as the P&L of the option overlay portfolio designed to enhance the performance of a TAA strategy in periods of low volatility, under the assumption of an identical maturity for all options. 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 2 below shows the typical profit and loss diagram of this option portfolio as a function of the value of the underlying asset at maturity.

**Exhibit 2: 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 the option overlay portfolio designed to enhance the performance of a TAA strategy in periods of low volatility, under the assumption of an identical maturity for all options. 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.



## A NUMERICAL EXAMPLE OF IMPLEMENTATION OF AN OPTION OVERLAY STRATEGY

It can be argued that a realistic performance for a successful allocator is consistent with a hit ratio around 65% (see for example Amenc et al. (2003)). In this section we first consider the performance of an active asset allocator with a reasonable level of predictive ability captured by a hit ratio equal to 2/3. Hence the fictitious active allocator we focus on correctly predicts whether equity markets will outperform cash in 2 cases out of 3.

To this end, we calculate the profit generated by an investor who is using the EONIA as a benchmark, and who is willing to allocate a fraction $x$ to equity (proxied here by the DJ EURO STOXX 50 index) at the beginning of each month in a short/long manner when he/she expects equity markets to outperform the riskfree rate. For example, in case $x=10\%$, the allocation is 10% in DJ EURO STOXX 50 and 90% invested at EONIA in each month when the DJ EURO STOXX 50 index is expected to outperform cash, and the allocation is -10% in DJ EURO STOXX 50 and 110% invested at EONIA in each month when the DJ EURO STOXX 50 index is expected to underperform cash.[5]

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

**Exhibit 3: Performance of TAA Portfolio.** This table contains information on the performance of the TAA strategy with benchmark invested in cash and trading performed on index futures. The mention NA (not applicable) is displayed when the relevant performance measure does not apply to a particular portfolio.

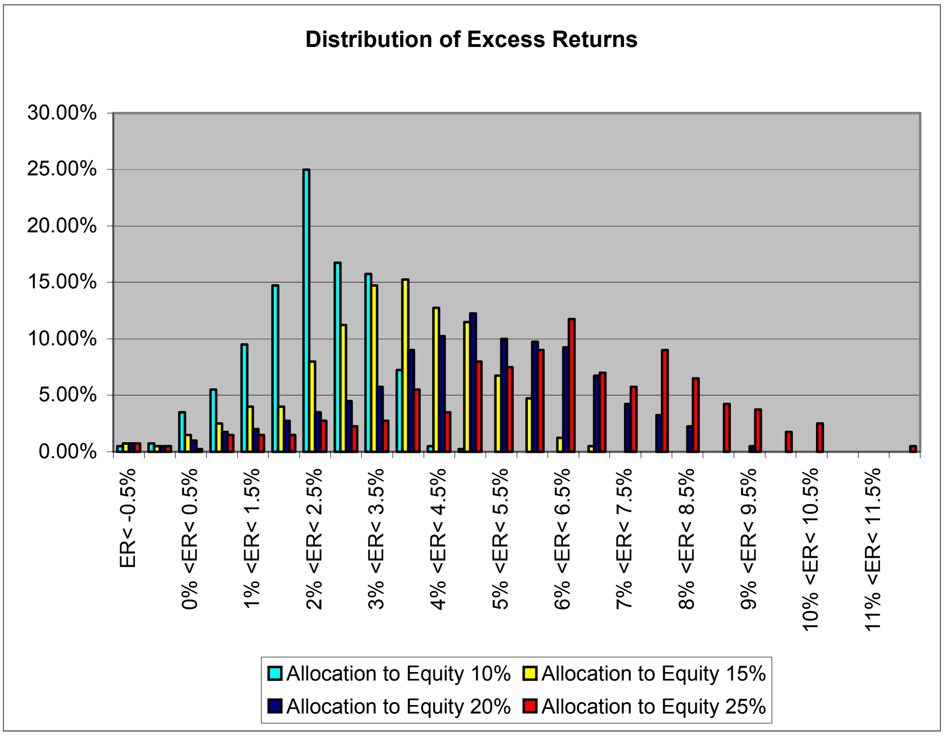
| Allocation to Equity | 0% (100% EONIA) | 10% | 15% | 20% | 25% |
|---|---|---|---|---|---|
| Annualized Return | 3.81% | 5.83% | 6.94% | 8.04% | 9.15% |
| Annualized Std Deviation | 0.25% | 2.57% | 3.85% | 5.13% | 6.41% |
| Sharpe | NA | 0.788 | 0.813 | 0.826 | 0.833 |
| % Negative Returns | NA | 25.00% | 27.78% | 30.56% | 30.56% |
| Monthly Drawdown | NA | -0.98% | -1.57% | -2.17% | -2.76% |
| Highest Monthly Return | NA | 2.12% | 3.08% | 4.05% | 5.01% |

As can be seen from the results in exhibit 3, active asset allocation decisions allow the investor to outperform the benchmark, represented here by a portfolio 100% invested in cash (EONIA).

To test the robustness of the results, we repeat 500 times the experiment by drawing randomly the successful months, while maintaining a 2/3 hit ratio level. Exhibit 4 below shows the distribution of excess performance obtained by an active allocator, as we let successful 2/3 of the months vary across the sample.

[5] At all times, we assume that 95% of the portfolio is invested in EONIA, the remaining 5% being left available to cover margin calls induced by trading in futures.

**Exhibit 4: Robustness Analysis.** This figure shows the distribution of performance obtained by a style timer with a 2/3 hit ratio as we let the months found to be successful vary across the entire sample.




As can be seen from exhibit 4, the performance of the allocator is not a mere artifact of a particular choice of the winning months in the sample. This shows the robustness of abnormal performance that can be generated by a realistic timing strategy.

In what follows, we implement an option overlay strategy that is designed to enhance the performance of the tactical asset allocation portfolio.[6]

Specifically, each month we select options on the DJ EURO STOXX 50 index with strike prices symmetrically distributed around the at-the-money level. The decision rule that we systematically apply is as follows:

- For each month *m*, short-term (i.e., expiring in month *m+1*) call and put options to be sold are chosen so that the strike price is the closest to current index price + 50 (case of a call option) or current index price -50 (case of a put option). For each month *m*, longer-term (i.e., expiring in month *m+2*) call and put options to be purchased are chosen so that the strike price is the closest to the current index price +100 (case of a call option) or current index price -100 (case of a put option)
- The quantities in the top and bottom strangle strategies are optimized so as to maximize the net theta of the overall position, while satisfying a dollar-neutrality

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

constraint.[7] As a result, the payoff may somewhat differ from the equally-weighted scheme presented in exhibit 3, while maintaining the constraint that the "size" of the bottom strangle equals the "size" of the top strangle, so as to ensure a proper hedging of extreme risks. An example of an option portfolio could be: short 100 put options with 30 day maturity and strike price 90, short 150 call options with 30 day maturity and strike price 110, long 100 put options with 90 day maturity and strike price 80 and long 150 call options with 90 day maturity and strike price 120.

We then select the leverage of the option overlay strategy so as to make it commensurate with the scale of the underlying TAA strategy. We obtain theta and delta estimates by using the Black-Scholes model after extracting an implied volatility estimate from options settlement prices.[8] We then perform a systematic rebalancing at the beginning of each month, i.e., positions at the beginning of month *m* systematically closed out at the beginning of month *m+1* using the settlement prices. Exhibit 5 shows the performance of this option overlay strategy when added to the TAA strategy.

**Exhibit 5: Impact of Adding an Option Overlay Strategy.** This table contains information on the impact of adding an option overlay to the TAA portfolio. The mention NA (not applicable) is displayed when the relevant performance measure does not apply to a particular portfolio.

| Allocation to equity | 0% (100% EONIA) | 10% | 15% | 20% | 25% |
|---|---|---|---|---|---|
| Annualized Return | 3.81% | 7.04% | 8.15% | 9.25% | 10.36% |
| Annualized Std Deviation | 0.25% | 2.65% | 3.89% | 5.15% | 6.42% |
| Sharpe | NA | 1.219 | 1.115 | 1.057 | 1.020 |
| % Negative Returns | NA | 22.22% | 27.78% | 27.78% | 27.78% |
| Monthly Drawdown | NA | -1.01% | -1.61% | -2.20% | -2.80% |
| Highest Monthly Return | NA | 2.12% | 3.08% | 4.04% | 5.00% |

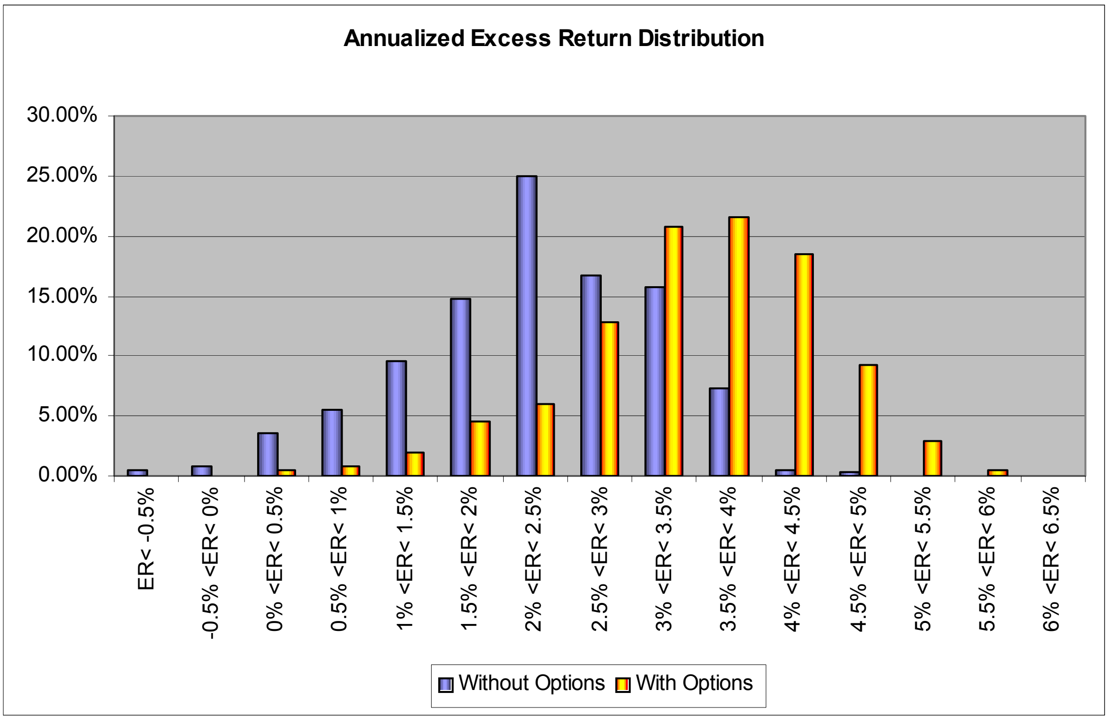
As can be seen from the comparison between Exhibit 4 (performance of the market timer without an option overlay) and Exhibit 5 (performance of the market timer using an option overlay), the option overlay acts as a return enhancer for the tactical allocation portfolio. For example, in the case when allocation to equity is equal to 10%, the performance is increased in the sample by 121 basis points in terms of average returns (7.04% annualized return versus 5.83%), without a significant increase in the level of risk (2.65% annualized volatility versus 2.57%).

[7] Imposing a dollar-neutrality constraint allows us to focus on a pure portable beta strategy as the manager does not have to borrow or lend cash for the option overlay. It should be noted that rounding is performed on the number of lots so that dollar-neutrality is approximate and not exact.

[8] We thank Eurex for having provided us with a detailed database of settlement prices of options written on the DJ EURO STOXX 50 index over the period.

To test the robustness of the results, we again repeat 500 times the experiment by drawing randomly the successful months, while maintaining a 2/3 hit ratio level. Exhibit 6 below shows the distribution of excess performance obtained by an active allocator (case of a 10% allocation to equity) with and without the option overlay, as we let the 2/3 of the months when the active bet proved to be successful vary across the sample.

**Exhibit 6: Annualized Excess Returns of the TAA Strategy with and without the Option Overlay for a 10% Allocation to Equity.** This figure shows the distribution of annualized excess of the TAA strategy with and without the option overlay portfolio as we let the 2/3 of the months when the active bet proved to be successful vary across the sample.




As can be seen from exhibit 6, the benefits of the option overlay strategy are robust with respect to the choice of successful months in the sample. A better understanding of how the option overlay can enhance the performance of the underlying TAA strategy when the TAA strategy fails to perform well can perhaps be seen from the fact that the addition of the option overlay proves beneficial to the performance in 70% of cases when the absolute value of the TAA portfolio return is lower than 0.25%.

## 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 beta vehicles.

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