Tactical Asset Allocation on Market Neutral Hedge Funds[1]

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Abstract

The objective of the thesis is to show through an empirical work how alpha drivers can be used tactically with beta drivers to provide solid out-performance compared to a chosen benchmark. Given the fact that financial theory and empirical research cast doubt on the alpha generating process based on stock-picking abilities by Fund Manager, I substitute that methodology with a quantitative approach. Using a robust econometric process based on a non-linear multi-factor thick and recursive modeling approach that takes into account structural breaks in the data generating process, I found statistically and economically significant evidence of returns predictability for the DJ Euro Stoxx 50 excess returns. My modeling approach is capable of accounting for model specification uncertainty, possible shifts in the forecasting model and low probability events. Based on this predictability poIr, I back test the implementation of Asset Allocation Strategies simulating three Market Neutral Hedge Funds on different asset classes and degree of risk aversion. I back test these portfolios trading Index futures to generate alpha drivers, and an optimized option strategy to generate beta drivers. Transaction, administration and management fees are included in order to be very close to market's real conditions. As a conclusion, out-performance on risk-adjusted returns is obtained through the implementation of a dynamic, robust and complete econometric process, during periods of downward and upward markets.

1 Introduction

My motivation to work on hedge funds is two-fold. The first reason is rather obvious; hedge funds have been a phenomenon of the 1990s and they increased from a hundred of players ten years ago to several thousand today with double-digit annual growth rate. The second reason is that as hedge funds dislike disclosing information about their investment process and market bets due to legal reasons and investment strategy opportunities, a first approach to disentangle this black box is just to build hedge fund portfolios under real market conditions, resembling as closely as possible their payoff characteristics.

One common issue in the market place, especially in Private Banking institutions, is that hedge funds are offered to clients as Alpha generator's products. This means that, portfolio managers will add value to the performance of funds using stock picking strategies, which are meant to exploit evidence of predictability in individual stock specific risk as a result of their bottom-up security selection abilities. In order to built their forecasts, micro and macroeconomics assumptions must be made for at least ten years in advance, and sometimes many of those restrictive and subjective assumptions leads to wrong investment decisions. Furthermore, most of the time portfolio managers end up making unintended bets on markets, sector or style returns as much as they make bets on individual stock returns. These unintended bets can have a dramatic, positive or negative, impact on the portfolio return, which introduces an "element of luck" on the performance generating process. In the same tandem, financial theory casts doubt on stock picking abilities. For instance, Malkiel (1995) and Gruber (1996) evidenced that most academic studies since the 1960s agree that portfolio managers do not systematically or significantly outperform the market.

What I propose in this thesis is to change the investment process by which investors design their asset allocation strategy. I built an investment process aimed at avoiding subjective forecast, eliminating predictions about asset returns based upon an expert's forecast ability.

I employ, in spirit of Pessaran and Timmerman (1995), a dynamic model that try to quantify financial and macroeconomics factors which are believed to be relevant by investors when they take investment decisions. The authors make the assumption that investors did not have information about a good forecasting model but they Ire aware of the factors that could give information about the business cycle of the economy. They developed a dynamic modeling approach that is suitable of predicting the directional time-variation in excess returns. In econometrics terms, the approach entails a recursive estimation procedure that allows for continuous permutations among the determinants in accordance with a predefined model selection criterion.

As markets and information move constantly, those factors that are important today could be irrelevant next period. In this way, the objective of this methodology is to understand the way investors buy and sell assets and then, setup an efficient tactical asset allocation strategy which could bring better risk-adjusted returns.

In the interest of underlining the methodology employed, which could be used by a set of long-short managers endowed with reasonable econometric skills, I use in this thesis 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 here 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.

I incorporate two new issues from the financial literature to further the robustness of the econometric model. First, among a set of explanatory variables known to explain variation of business cycles, I also include variables that have information of extremely noisy episodes. These variables help the model learn from the past and add a new underlying distribution to the predictable business cycle variation, which help predict new components related to major exogenous shocks. For instance, I create a dummy variable that takes one when excess returns are more than 3 or 4 sigmas and zero otherwise. Second, the majority of the finance literature on predictability of stock returns assumes a time-invariant relationship between state variables and returns. I strongly believe that taking into account structural breaks in the input data is an important factor to consider when making excess returns forecasts. Breaks or jumps in the parameters that relate security returns to state variables could arise due to a number of factors, such as major changes in market sentiments, burst or creation of speculative bubbles, regime switches in monetary and debt management policies. Thus, I use a two stage approach[2], by which the investor monitors and tests for breaks in real time and, then uses an estimation window based on more actualized data to generate return forecasts. At each point in time the procedure essentially addresses the question of how much historical information should be used in estimating a regression model. When adopted recursively through time, the testing procedure yields a sequence of estimation windows whose lengths effectively indicate the memory of the returns model under consideration.

Based on my dynamic, robust and complete econometric model, I back test the model through the execution of two distinct Tactical Asset Allocation Strategies. The first possible form of an active asset allocation strategy involves adding market timing alpha benefits as an alternative way to generate alpha in the absence of confidence in the ability to generate consistent performance through stock picking. In this thesis, I 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. I 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.

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[2] Pesaran and Timmermann (1999).

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. Here, I 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, I look at it from a different perspective. More specifically, I explain how active portfolio managers can benefit from using suitably packaged derivatives satellite portfolios as portable beta vehicles.

Last but not least, I build three Hedge Fund Portfolios consistent with a chosen benchmark, 100% Money market, 100% Index Future and an equal weighted combination of the two, using two different degree of risk aversion (less and more aggressive). Moreover, I control the level of aggressiveness of the strategy depending upon the confidence level I have to take decision on investments.

Based on this systematic approach and through the use of cost-effective financial derivatives, I aim at avoiding noisy investment strategies such as stock picking strategies, in order to generate sustainable portable Alpha and beta drivers.

The thesis is organized as follows. In a first section, I distinguish between strategic and tactical asset allocation (TAA) decisions, understand the difference of alpha and beta drivers and mention some warning in terms of alpha drivers. In a second section, I present some evidence of predictability in Euro equity markets. In a third section, I 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, I 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. Concluding remarks can be found in a last section.

2 Tactical Asset Allocation

With the objective of building Hedge Fund Portfolios, I want to state the difference between the Strategic Asset Allocation implemented by the management of the investment company and the Tactical Asset Allocation (TAA) developed by the professional investment team, as Ill as, a clear understanding of what is the meaning of a TAA with the aim of getting Alpha vs. Beta drivers. Of course, “there is not such a thing as a free lunch”, so I also warm for the dangerous or doubts that exist on the ability to generate these drivers. Then, given the fact that I have a clear cut on TAA strategies, I mention different alternatives or methodologies by which TAA are developed.

2.1 Strategic vs. Tactical Asset Allocation

The aim of strategic asset allocation is to meet the goals of the organization under normal market conditions over a full market cycle. For instance, a pension fund will implement a strategic asset allocation to ensure that there are sufficient assets to pay the fund’s pension obligations; a mutual fund will develop a strategic asset allocation based on the risk tolerance of their client base and on regulation constrains. The long-term nature of strategic asset allocation means that a strategy is not designed to beat the market; its objective is not to add extra investment returns. Even though it is not always true in practice, its long-term goal should not be derailed by financial market cycles. Many times, boards of the organization engage in market timing, arguing that they have sufficient insight into the financial markets to gain extra returns, but they end up mixing strategic with tactical asset allocation, which is the job of the investment team.

Tactical asset allocation (TAA) is intended to take advantage of the financial markets when opportunities appear to be out of line. It is designed to facilitate a fund’s long-term goals by seeking added value. TAA also looks to actively managed alternatives to passive benchmark risk, generating alpha drivers, which are generating excess returns over a broad financial index. As a result, tactical asset allocation is implemented to beat the market and to change the distribution of returns of the strategic asset allocation.

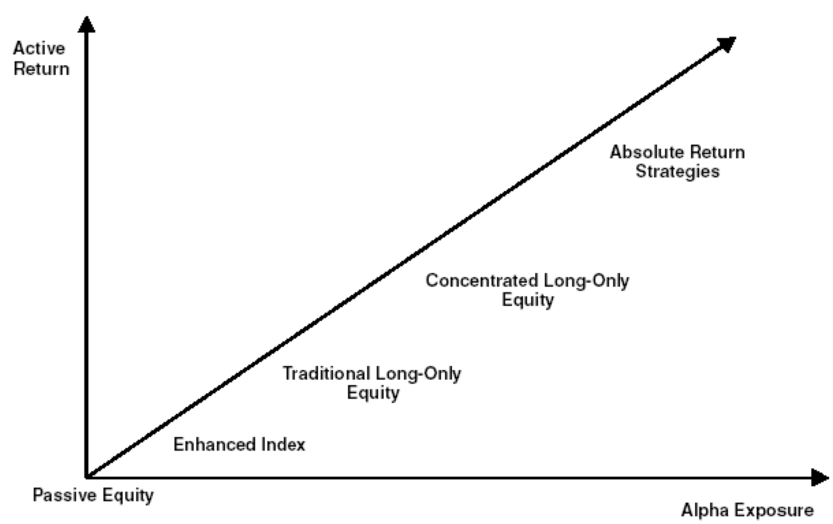
2.2 Alpha vs. Beta drivers

In order to implement a Tactical Asset Allocation strategy, it is key to understand the different objectives and strategies of getting Alpha and Beta drivers. To do so, a simple way is to consider the management of a total fund as two different TAA strategies, which are beta and alpha drivers.

On the one hand, the board of an organization establishes the asset class targets and the benchmarks associated with those targets, which are the beta drivers for the fund. Beta drivers determine a fund's overall exposure to the financial markets. On the other hand, alpha drivers determine a fund's deviation from beta drivers. Alpha drivers can be measured by actively managed accounts relative to a beta risk benchmark, it can also be measured by an underweight or overweight to a benchmark; this represents the tactical asset allocation strategy.

In the following plot[3], it can be seen the relationship between alpha and beta exposures on equity asset class. The x-axis measures active risk and the y-axis measures active returns, while at the zero point are beta drivers through passive equity funds. Close to passive strategy are enhance index and traditional investments, and further out along the x-axis alpha drivers can be seen, mainly absolute returns strategies (hedge funds). In the y-axis, it is shown that a positive relationship exists between alpha drivers and returns.

Alpha versus Beta Exposure



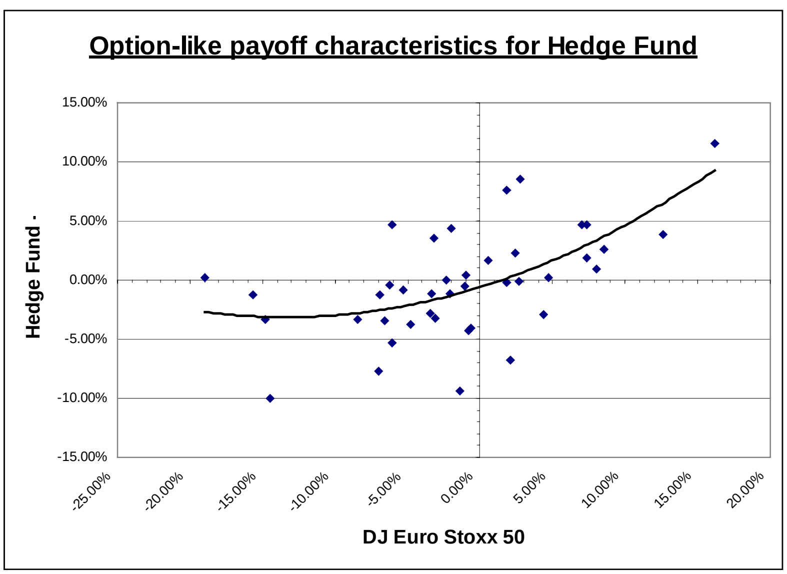
A typical example of a beta driver is an Index Fund, which closely tracks a clear benchmark without trying to beat the market. Actually, as time goes by, this fund under performs its benchmark due to transaction costs and management fee, but the risk is the market or benchmark risk. The correlation and the beta of this fund is the same as the market. Many times, I find within the mutual fund industry or traditional investment that investment professionals apply fundamental stock-picking skills to outperform their benchmarks. While these products are marketed as actively managed funds, they are also beta drivers and not alpha drivers because the correlation and the beta are still one. These traditional investments are fully invested most of the time and only go long in the asset; they don't take leverage and have a relative performance objective.

[3] Taken from the paper "Alpha smyces and Active Management".

Alpha drivers are identified by their high tracking error to a benchmark or simply by their lack of a benchmark. Hedge funds are a good example of products considered as alpha drivers. Their lack of connection with the financial markets allows them to focus on alpha risk rather than beta risk. They can go long and short in the underlying asset or futures, they use leverage to take opportunistic exposure, they have absolute performance objective and take a flexible investment approach and look for low correlation with market indices. For instance, a long/short equity hedge fund can add value by buying undervalued and selling overvalued assets, in which case both sides could be profitable. The shorted asset is even more profitable because there are fewer people willing or able to exploit this segment. This segment of HF does not rely on upward movement in markets to add value, it avoids market risk by implementing market neutral strategy, which means long and short positions compensate each other but get the specific risk to generate alpha drivers.

Another difference that must be pointed out is the shape for beta and alpha drivers return distributions. In the first case, returns behave linearly with the market, which means that when the market goes up the fund's returns increase and vice versa. In the latter case, performance distribution is not linear in nature, on the contrary, they are non-linear return functions that exhibit option like payoff characteristics. This special kind of distribution can add value if the alpha generated can be ported and combined with traditional investments.

The graph below shows these return characteristics of option-like payoff for one of the hedge fund portfolios I built over the DJ Euro Stoxx 50. It can be seen that the performance of the HF is better than that of the Index not only in upward markets but also in downside markets, given a payoff like a call option.



2.3 Caution and problems with Alpha drivers

Recent empirical evidence has challenged whether alpha drivers deliver pure alpha. Jensen and Rotenberg (2003) studied the beta component of hedge fund, and they found a high degree of correlation within each HF strategy, from 42% for market neutral to 66% for event-driven. These high levels of correlation among HFs indicate that managers generate similar economic exposure – beta exposure- within each HF strategy.

In the same way, other authors highlight that Long Short HF managers do not actively manage their market exposure, and most of them end up having a net long bias. 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 than overvalued stocks. Moreover, they argue that these managers have unintended time-varying residual exposure to a variety of sector or investment styles as a result of a noisy ability of stock picking. When portfolio managers execute their bottom-up security selection decisions, often they end up making discretionary, and most of the time unintended bets on markets, sector and style returns as much as they make bets on individual stock returns.

2.4 Steps process in TAA decision

The first step I need to develop is to build a quantitative, qualitative or a combination of both, model that generates asset returns forecasts. One way to build the data generating process is to develop a forecast-base TAA $\hat{\gamma}_{t+1} = \phi(\hat{\chi}_{j,t+1})$, where $\hat{\chi}_{j,t+1}$ variables are estimated in order to make a forecast on asset returns. A different procedure is to build a fact-based TAA $\hat{\gamma}_{t+1} = \phi(\chi_{j,t})$, where the $\chi_{j,t}$'s are already known variables from the market. These two TAA process can be implemented using a Systematic TAA, where asset returns predictability is based on quantitative models, or using a Discretionary TAA, where predictions are done by financial experts.

Typical linear models are used (OLS) with constant coefficients, and more dynamic models implement the Kalmar filter, which incorporates uncertainty over parameter instability. There are also a number of non linear models like Logit[4] or Probit methodology that take into account the non linear dependence on explanatory factors.

The second step is to build portfolios based on asset returns forecasts, which can be done using an optimizer or using some clear rule to allocate assets, i.e. in terms of market value, liquidity or valuation ratios. There is a considerable amount of finance literature showing that optimal portfolio selection processes can benefit from predictability of returns[5].

[4] Bauer and Molenaar implement an example using Logit models.
[5] Barberis (2000), Campbell and Viceira (1998), Brennan, Schartz and Lagnado (1997). and Lynch (1999) and (2000).

The last step is to conduct out-of-sample performance tests. There are many tests and procedures that deal with performance but the most direct way is to test if the percentage of time forecast direction is right (Hit Ratio).

3 Evidence on Predictability of Excess Returns

Many financial studies conclude that stock returns can be predicted by means of publicly available information, using financial and economics time series with an important business cycle component. However, the interpretation of this is far from clear. Some people argue that predictability of returns reflects time varying expected returns, which means that it works within the efficient market hypothesis, and some others believe that if it exists is due to market inefficiency. Pesaran and Timmerman (1995) support the idea that it must be interpreted in the context of an inter-temporal equilibrium model of the economy.

A practical approach to discover if returns are predictable or not is to analyze if portfolio managers Ire able to obtain excess returns over the index on a historical basis, or to make a simulation using historical data on a set of factors and back test it as many years as possible to obtain robust results. With regard to the latter methodology it is important to clearly formulate the rules to forecast returns to avoid hindsight.

Pessaran and Timmerman (1995) run a simulation to forecast returns for the US stock market, making the assumption that investors did not have information about a good forecasting model but they Ire aware of the factors that could give information about the business cycle of the economy. At each point in time, in a recursive manner, investors use only historical information to select a model according to a predefined model selection criterion and then use the best model to make a one-step forecast for excess returns. With these predictions in mind, investors allocate their money in stocks or bonds depending on whether excess returns on stocks are predicted to be positive or negative. The authors apply statistical and financial criteria to choose models based upon all possible permutations on the set of explanatory variables. They do not make assumptions on the data generating process, it can change through time in the same way that the models can change in different months.

The starting point of the analysis is the long tradition in finance that links movements in stock returns to business cycle indicators[6]. Factors considered as linked with stock returns are short and long interest rates, dividend yields, industrial production, company earnings, liquidity measures, and inflation rate. Macro variable data is lagged 2 months and financial variables one month.

The procedure for chosen models is as follows: they took data from 1954:1 to 1992:11, used 6 years of monthly data to calibrate the model and calculate the parameters for explanatory variables, from 1954:12 to 1992:12. They chose the model that maximized the discriminate function of a given model selection criteria, and used the parameter values to make a one-step forecast for excess returns. To forecast the next month the procedure is repeated and the data is moved one month ahead. Even though this mechanism is computationally demanding, it clearly simulates the search procedure, which an investor could have carried out in real time. The amount of regressions run was 202,752, and the conclusion is that they found strong evidence on returns predictability

[6] See Prime (1946), Ross (1960), and Morgan and Thomas (1962).

on all information criteria or functions taken in consideration (Akaike, Schwarz, R2 adjusted, Sharpe and wealth maximization)

Similarly, Campbell (2000), in a survey paper on the state of modern asset pricing theory, explains, "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."

3.1 Economic Significance of Predictability

In finance literature, the efficient market hypothesis is often interpreted as the impossibility of constructing a trading rule, based on publicly available information to obtain excess returns. Predictability of stock returns in itself does not, however, guarantee that an investor can earn profits from a trading strategy based on such forecasts. In order to see if the predictive power can help to obtain extra returns, transaction costs and management fees must be considered and applied within the simulation. As the strategy is to switch from equity to risk free bond or vice versa depending upon return forecasts, transaction costs could become determinant when testing for excess returns.

The predictability of returns to be exploitable depends not only on the evolution of the business cycle, but also on the magnitude of the shock. Based on empirical evidence, it seems easier to have a better prediction power on excess returns during switching regimes and changes of macroeconomic environment than during normal periods.

3.2 What can be predicted and why

The more traditional approach in financial theory to value a risky asset is to discount appropriately its future cash flows at a certain interest rate. The equation can be written as follows,

$$p_{t=0} = \sum_{t=1}^{\infty} (\hat{cf}_t) \frac{1}{(1 + r_t + \pi_t)}$$

At this stage, asset-pricing models enter into the picture. One of the most recognized model pricing is CAPM, which considers only the systematic risk to be rewarded by the market.

The Arrow-Debreu pricing theory proposes to price an asset by valuing the portfolio of state claims with the same state-by-state future payoff pattern. In this case, the discounting procedure is performed state-of-nature by state-of-nature with the price of the relevant Arrow Debreu security providing the equilibrium discount factor.

Instead of changing the denominator of the basic pricing equation, Certainty Equivalent theory states that an asset can be valued by changing the numerator of the expected future cash flows so that it can be discounted at the risk free interest rate.

Rather than changing the denominator or the numerator of the pricing equation, risk neutral valuation or martingale theory simply changes the probability measure by which the expectations of future cash flows is taken, in such a way that discounting at the risk free rate is legitimate.

All these models have the disadvantage of either being one period model or being static. Based on the intuition of Arrow Debreu securities, CCAPM incorporates a dynamic setup that links financial markets and the real side of the economy based on rational expectations. Its equation can be stated as follows,

$$p_{t=0} = \mathrm{E}_t \sum_{t=1}^{\infty} \delta^t \left(\frac{MU_1(\hat{c}_{t+\tau})}{MU_1(c_t)} * \hat{Y}_{t+\tau} \right)$$

which states that risky assets are valued as the sum of future dividend payments discounted by the risk free interest rate and by the marginal rate of substitution betIen consumption tomorrow and today. Dividend payments represented by $\hat{Y}_{t+\tau}$ are linked to the business cycle, and the marginal rate of substitution $\frac{MU_1(\hat{c}_{t+\tau})}{MU_1(c_t)}$ represents the risk premium paid by agents depending upon the benefit the asset can represent in different states of nature.

Last, but not least, the Arbitrage Pricing Theory framework uses a set of stable factors that are determinants of all asset returns to obtain the return-generating process. It is important that the estimating betas from past data are obtained under stationary assumptions, which can be found only at the level of portfolios and not at individual levels.

Even though each pricing model makes different assumptions and has a specific framework under which they price risky assets, all of them take into account the same ingredients. Firstly, the expected future cash flow at aggregate level, which is persistent and mean-reverting, is like the business cycle. Secondly, risk premium, a function of inter-temporal marginal utility of consumption, which is high at business cycle troughs and low at business cycle peaks. The last element is the level of interest rate, which gives expectations of real interest rate, real economic activity and inflation. As these three elements are all linked to the business cycle, they can be predicted if the business cycle is predicted to some extent, and this is consistent with the efficient market hypothesis.

Finance theory does, however, suggest that in markets with risk-averse agents stock returns would vary with the state of the business cycle, Lucas (1978) and Balvers, Cosimano and MacDonald (1990). Taken together, these statements suggest that a plausible analysis of investors' predictions of stock returns in real time should be based on business cycle variables, taking appropriate account of the specification uncertainty that surrounds modeling stock returns at the end of each forecasting period.

3.3 Set of Explanatory Variables

My objective is to build a long/short equity hedge fund, which will be based on a quantitative approach so that I can implement a tactical asset allocation using futures and options strategies. I will show in-sample predictability in Euro equity returns based on predictive variables that have a potential for capturing the fundamental of pricing models. I use the Dow Jones Euro Stoxx 50 Index that incorporates the 50 blueship stocks in the Euro Zone. This index is a price-weighted index according to the free-float market capitalization of each of its components. In order to make prediction over the excess returns of the equity index over the LIBOR 1M interest rate, I considered the same explanatory variables as in their paper, but I incorporated a dummy variable to learn from past mistakes.

As it is not stated in their paper, I assume that the DJ Euro Stoxx 50 index is taken as total return index, which incorporates dividend payments. I download the data from the same data provider as in the paper, DataStream (Financial Thompson). I take all the variables from the same data provider.

As dependent variable I took the spread of the DJ Euro Stoxx 50 Index expressed in Euro currency onto the LIBOR 1M rate for a period of 10 years, from 1994:1 to 2003:12. The evolution of the cumulative returns for the excess returns and a summary of descriptive statistics can be seen in Figure 1 in the Appendix, which shows a break in the middle of the year 2000.

For explanatory variables, I also take the same timeframe and I segment it into the three ingredients discussed above for prediction of business cycles.

1. Variables related to interest rate:

   - ✓ Level of the term structure of interest rates, proxy by the short term rate: Fama (1981) as Ill as Fama and Schwert (1977) show that this variable is negatively correlated with future stock market returns; it serves as a proxy for expectations of future economic activity,

   - ✓ Slope of the term structure of interest rates, proxies 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,

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

- ✓ Price of risk, proxies by credit spread 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 valuation of stock prices, proxies 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.

These variables are chosen from finance literature, which explains variation of business cycles, risk premium and risk free interest rate.

There are additional variables included that one can consider as natural influence for international capital markets: US S&P 500 Index, a commodity index (Goldman Sachs commodity index[7]) and a currency index (USD major currency index[8]). I also include a sentiment variable from the option markets, the ratio of volume of put and call.

I also include dummy variables in the estimated equations. As in Pesaran and Timmermann (1998), I ask whether an investor would regard events of big sigma as exceptions, which cannot be explained by linear or simple regressions relating excess returns to a set of business cycle indicators. In this way, I include into my model variables that have information about extremely noisy episodes that could help to predict future events. These variables help the model learn from the past and add a new underlying distribution to the predictable business cycle variation, which helps to predict new components related to major exogenous shocks.

[7] The GSCI is a world production weighted commodity index comprised of 25 liquid, exchange traded futures contracts.

[8] The USD major currency index is a daily trade weighted currency index, which measures nominal exchange rate strength of the US relative to a basket consisting of 16 countries.

3.4 Evidence of In-sample Predictability

I develop a basic and intuitive analysis to understand the effect of explanatory variables on the Euro Zone equity excess returns. I organize time series in ascending order and stratify them into three equal groups, the first will be the average of low numbers, the second will be the average of the medium numbers and the third will be the average of higher numbers. In this way, I will be able to obtain the intuition of the effect in different scenarios of the explanatory variables onto excess returns.

For instance, in the table below, I analyze the effect of the US high yield debt credit spread onto the European excess returns. Maximum and minimum values can be seen in each of the three scenarios (low, middle, high). When the credit spread of US corporate bonds increases (high scenario), the excess returns in the Euro Zone are negative by 2.32% on average on a monthly basis, in excess of the unconditional mean. On the contrary, when the credit spread decreases, equity returns out-performs the LIBOR 1M interest rate by 1.67% on average on monthly bases, in excess of the unconditional mean. This intuition confirms the idea that when there is high credit spread in the US, as a proxy for price of risk, equity returns under-perform the interest rate returns.

US spread - %	Low		Medium		High		Unconditional Values
	Min	Max	Min	Max	Min	Max	
Difference between conditional and unconditional values	0.43	0.69	0.70	1.65	1.66	3.74	
	Mean		***Mean***		***Mean***		***Mean***
Excess returns	1.67%		0.56%		-2.32%		0.61%

In the case of the level of interest rate, represented by the Euribor 3M, I can see that when the interest rate is high, the mean excess returns are negative on average on a monthly basis by 0.35%, in excess of the unconditional mean. Here, the effect of the level of interest rate on excess returns is also clear.

Level of Euribor 3M	Low		Medium		High		Unconditional Values
	Min	Max	Min	Max	Min	Max	
Difference between conditional and unconditional values	2.03	3.43	3.45	4.72	4.76	7.36	
	Mean		***Mean***		***Mean***		***Mean***
Excess returns	0.10%		0.22%		-0.35%		0.61%

I include in the Appendix, tables for all other variables, and I conclude that excess returns increase when[9],

- ✓ Short term interest rates are low and do not change much
- ✓ The dividend yield is decreasing or low
- ✓ The term structure is upward sloping and steepenning
- ✓ Implicit volatility is decreasing or low
- ✓ The S&P 500's returns are positive
- ✓ The currency index is depreciating
- ✓ The commodity index is increasing

This simple and intuitive way of seeing the correlation among variables and excess returns is a very useful tool for helping a portfolio manager in his/her discretionary decision making process. I will put this idea in a more formal way when I develop the econometric model to predict when equity returns in the Euro Zone out-perform the risk free interest rate.

3.5 Evidence of Out-of-sample Predictability

Before developing a robust econometric model to forecast excess returns, I test out-of-sample some simple econometric models and consider them as not value added or benchmark models.

In order to do so, I take the excess returns time series and check for unit roots to see whether the series is stationary, and given the time series is stationary I choose those points when the volatility is low, where the data doesn't show spikes. After that, I run simple regressions incorporating as factors my set of explanatory variables. Once I have a good model based on t-statistics and R2, I check for autocorrelation, heteroskedasticity problems and stability in coefficients. Using these parameters, I calculate estimations for the dependent variable and obtain hit ratio out-of-sample for the following 3.5 years. Surprisingly, I obtain a hit ratio of 63%, only 2/3% less than those values published in many papers on this subject. The table 2 in the Appendix[10] shows one when the dependent variable is estimated with the same sign and zero otherwise.

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[9] In the case for the US and Euro term spread table, it is not clear the effect of positive slope over excess returns. But when I see the values of max and min in excess returns, it becomes clear that they are positively correlated.

[10] Absolute values for the estimation of dependent values have no significance, but what is important is the estimation whether equity returns will out-perform or under-perform that of the risk free rate.

4 Methodology and Econometric Model

4.1 Introduction

In this chapter of my thesis, I devote some pages to discussing different alternatives that are considered in the literature when implementing the econometric process. I extend the work of AMM in that I make my forecasts of excess returns over the DJ Euro Stoxx 50 taking into account breaks and structural changes, which change the size of window data used to estimate parameters. This procedure allows us to adjust input data to a new data generating process faster than any other method, and to obtain better results when I implement the tactical asset allocation strategy in hedge fund portfolios.

4.2 Thick vs. Thin Recursive Modeling Approach

Pesaran and Timmermann (1995) developed a dynamic modeling approach that is more suitable to predict the directional time-variation in the excess returns of the US S&P 500 Index. In econometrics terms, the approach entails a recursive estimation procedure that allows for continuous permutations among the determinants in accordance with a predefined model selection criterion. The advantage of this method is that all possible models are constantly reevaluated in order to reflect an investor's continuous search for the best approximation of the "true" model based on historical information only. The purpose of this computationally intensive procedure is to minimize possible ex post data-snooping biases.

Pesaran and Timermann select in each period only one forecast, i.e. the one generated by the best model selected on the basis of a specified selection criteria which weights goodness of fit against parsimony of the specification. Based on Granger (2000) this approach is labeled "thin" modeling in that forecasts over time are described by a thin line (one model). The main disadvantage of thin modeling is that model uncertainty is not considered. In each period the information from the discarded models is ignored for the forecasting and portfolio allocation. This choice seems to be particularly strong in light of the results obtained by the Bayesian line of research, which stresses the importance of the estimation risk for portfolio allocation[11]. 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"[12]. It 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 this lies with the specification of prior distributions for parameters in all possible models of interest. Recently, Doppelhofer (2000) put forward an approach labeled "Bayesian

[11] See for example, Barberis (2000), Dande and Stanbaugh (1996).
[12] See Hoeting (1999), Raftery (1997) and Avramov (2001).

Averaging of Classical Estimate" (BACE) which overcomes the need to specify priors by combining the averaging of estimates across models. Aiolfi and Favero (2000) demonstrate that portfolio allocation strategies based on a thick modeling strategy systematically over perform portfolio allocation strategies based on thin modeling. In my thesis, I apply the BACE approach by selecting at each date a "council" of models to make predictions, as opposed to using a single model.

4.3 Stability and Structural Breaks

The majority of the finance literature on predictability of stock returns assumes a time-invariant relationship between state variables and returns. This stability assumption has played an important role in the more recent development of the asset allocation implications of predictability of returns. For example, Kandel and Stambaugh (1996) derive the optimal portfolio weights in a Bayesian setting where investors account for uncertainty about parameter values but assume that these remain constant over time. Brennan, Schwarz and Lagnado (1997) also assume constant regression coefficient in their solution to a multi-asset strategic asset allocation problem. Finally, Brandt (1999) assumes a constant relationship between state variables and time-varying investment opportunities.

As a general rule, when parameter breaks are thought either to be very rare or of a very small magnitude, the usual method is to use an expanding window and augment an already selected sample period with new observations. This recursive method aims to obtain a more efficient estimate of the same fixed coefficients by using more information as it becomes available. In a more flexible framework, if the parameters of the regression model are not believe to be constant over time, frequently a rolling window of observations with a fixed size is used to generate forecasts. This procedure only makes sense if the underlying process is unstable.

I prefer to use the proposition of Pesaran and Timmermann (1999), which is a two-stage approach. In the first stage, the investor monitors and tests for breaks in real time and, in the second stage uses an estimation window based on more actualized data to generate return forecasts. For real time monitoring of breaks in the forecasting model, I implement the "reversed ordered Cusum" approach which applies Cusum tests (Variance and mean of the data generating process) to observations reversed in time so that the last observation is placed first, the penultimate observation second and so on. At each point in time the procedure essentially addresses the question of how much historical information should be used in estimating a regression model. This is the question naturally asked if one is interested in forecasting time-series that are subject to breaks.

The unconditional methods such as rolling or expanding window allow the window size to vary as a deterministic function of time. In contrast, the conditional approach implemented here treats the window size as a parameter based on the estimated point of the most recent break.

Breaks or jumps in the parameters that relate security returns to state variables could arise due to a number of factors, such as major changes in market sentiments, burst or creation of speculative bubbles, regime switches in monetary and debt management policies (for example, from money supply targeting to inflation targeting, or short to long debt instruments).

4.4 Reversed Ordered Cusum Method

An alternative to the estimation of multiple breakpoints is to simply estimate the point of the most recent break. Such an approach has the advantage that it lends itself to methods for estimating a single break. While this idea can thus be adapted to a variety of approaches, I will use the Cusum (mean) and Cusum Squared (Variance) procedure proposed by Brown (1975) as recursive structural stability tests. These tests are usually applied to observations running forward from start to finish at a given time interval. However, the application of such a forward Cusum test is not appropriate because it will not be effective when there are multiple breaks. To deal with this shortcoming, I take the proposition that simply reverses the observations in time before proceeding with the application of the Cusum testing procedure. This process is known as reversed ordered Cusum test.

I use the following notation to denote the observation matrices with the order of the observations reversed in time, starting from the τ th observation (so that the size of the estimation window is given by $T-\tau+1$):

$$\tilde{\mathbf{Y}}_{T,\tau} = (y_T, y_{T-1}, ..., y_{\tau+1}, y_\tau)', \qquad \tilde{\mathbf{X}}_{T,\tau} = (\mathbf{x}_T, \mathbf{x}_{T-1}, ..., \mathbf{x}_{\tau+1}, \mathbf{x}_\tau)'$$

and define the (backward) recursive least squares estimates as

$$\hat{\beta}_\tau = (\tilde{\mathbf{X}}'_{T,\tau}\tilde{\mathbf{X}}_{T,\tau})^{-1}\tilde{\mathbf{X}}'_{T,\tau}\tilde{\mathbf{Y}}_{T,\tau}, \quad \tau = \tilde{T}, \tilde{T}-1, ..., 2, 1.$$

The choice of the shortest estimation window selected, namely $T-\tilde{T}+1$, is arbitrary but one would expect it to be set around two to three times the dimension of β to avoid extreme variation in the parameter estimates, $\hat{\beta}_\tau$.

The standardized recursive residuals from the regression that is reversed in time are

$$\hat{v}_\tau = (y_\tau - \hat{\beta}'_{\tau-1}\mathbf{x}_\tau)/d_\tau, \qquad \tau = \tilde{T}, \tilde{T}-1, ..., 2, 1,$$

where

$$d_\tau = 1 + \mathbf{x}'_\tau(\tilde{\mathbf{X}}'_{T,\tau}\tilde{\mathbf{X}}_{T,\tau})^{-1}\mathbf{x}_\tau, \quad \tau = \tilde{T}, \tilde{T}-1, ..., 2, 1,$$

and reversed Cusum squared test statistic given by

$$WW_{\tau,T} = \sum_{j=P+1}^{\tau} \hat{v}_j^2 \Big/ \sum_{j=P+1}^{T} \hat{v}_j^2 .$$

4.5 Description of my Methodology and Econometric Model

As I want to forecast excess returns in order to implement a tactical asset allocation strategy, I aimed to find a balance between in-sample goodness of fit (represented by R2) and robustness (represented by out-of-sample predictability – Hit Ratio).

I consider the set of explanatory variables mentioned before. I try to avoid screening among many explanatory variables through the application of pair-wise regressions, which leads to good in-sample goodness of fit but not good out-of-sample predictability. The set of variables considered are selected on the basis of previous evidence of their ability to predict asset returns, or their natural influence on asset returns. Some papers allow for all the possible combinations among variables to create models, but I constrain the number of combinations through a procedure by which "good variables" are first selected. After that, I allow for combination but only up to two explanatory variables in order to have a more robust and parsimonious model specification. I acknowledge that combinations of more number of variables would give better econometrics results, but not necessarily better forecasting results.

I test for a sub-set of variables that allows for a good trade-off between quality of fit and robustness. I select a sub-set of variables that allows for in-sample explanation power (quality of fit) and hit ratio. I test not only for the explanation power of the raw variables Z_i, for i=1…11, but also for some transformations, such as difference $Z_{i,t} - Z_{i,t-1}$, lags $Z_{i,t-1}$, difference of logarithm $\log(Z_{i,t}) - \log(Z_{i,t-1})$, moving average on a quarterly basis $\frac{1}{3}Z_{i,t-1} + \frac{1}{3}Z_{i,t-2} + \frac{1}{3}Z_{i,t-3}$, and for a stochastically detrending variable of the form $Z_{i,t-1} - \frac{1}{12}(Z_{i,t-2} + Z_{i,t-3} + Z_{i,t-13})$. To avoid spurious regression problems, I test whether the independent and dependent variables are stationary, using the Dickey-Fuller (1979) test. At this stage, the explanation power is measured in terms of in-sample R2 and Akaike information criteria of the dependent variable on a sub-set of permutations (difference lagged, lags, moving average, etc) on one of the 11 aforementioned variables, and of out-of-sample hit ratio greater than 50%. This procedure is applied to find structural breaks and to have enough new data to restart the variable selection process.

Among the variables chosen, I compute the correlation matrix in order to check for multi-co-linearity problem. I run regressions with combination of those variables that have correlation smaller than 60%. In this way, I eliminate numbers of combinations that will not give us any information in terms of forecast.

Given the nature of my tactical asset allocation strategy, I employ a model to forecast the sign of equity returns over the LIBOR 1M interest rate rather than the magnitude of excess returns. There are many authors that employ OLS, but I believe as it is stated by more up-to-date papers that deviating from OLS procedure is appealing considering the observed non-normality in the return series. Thus, I use a non-linear model, basically a Logistic model[13]. Even though it uses less information than OLS, because the depend variable is transformed to 1 if excess returns are positive and 0 otherwise, it has better estimation and implementation given the fact that it makes a non-linear transformation of the input data, decreasing the influence of outliers, and that it gives probability estimation between 0 and 1 instead of numbers greater than 1 as in OLS.

In each of the Logit regressions, I implement the HAC Consistent Covariance (NeIy-west (1987)) as they propose a more general covariance estimator that is consistent in the presence of both heteroskedasticity and autocorrelation of unknown form.

Within this framework, the implementation of the ***dynamic econometric model*** is as follows:

1. I take 10 years of historical data, which is divided into two samples of data; one comprises of a six year period from 1994:8 to 2000:7 and the other comprises of 3.5 years from 2000:8 to 2003:12[14]. The first sample is separated into two other periods; the first one is used to run regressions and calibrate the parameters (calibration period) which will be used to obtain a one-step out-of-sample forecast of excess returns, and the second one is used to train and to chose models based on their performance during 24 months of out-of-sample testing (training period). Finally, the trading period is used to implement and back test the tactical asset allocation strategy using futures and a portfolio of options, based on the forecasting power of the other two periods.

2. I use the calibration and the training periods to choose variables and models, while testing for structural breaks and adjusting the window size in accordance with these results. If I see a change in the data generating process, I shorten the historical information considered to estimate parameters, otherwise I expand the window size with more observations up to a new structural break when I shorten the data again. This procedure allows us to incorporate only relevant historical information and not just more historical data, to run regressions and obtain less biased parameters, and to check whether there are new good variables to be considered or to be excluded in front of structural changes in the data generating process.

3. I chose my council of models based on the performance of the strategy in a 24-month out-of-sample training period subsequent to the in-sample estimation period. The selection criteria employed to obtain a set of models that will be used

[13] In the Appendix I add intuitive explanations upon the Logit Model.
[14] In Figure 3 in the Appendix it is attached a graphical representation of the recursive model.

to forecast excess returns 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-statistics and Schwartz Information Criterion (SIC). This information criterion has the characteristic that penalizes different models for the number of degrees of freedom more harshly than any other indicators. Indicators of type 2 are meant to represent the out-of-sample forecasting poIr measured in terms of hit ratio (accuracy of the direction in estimation).

4. The group of models chosen as good models will give the percentage probability that equity returns will out/under-perform that of risk free interest rate. As I probably will end up with more than one model, I compute the average and standard deviation of those estimation weights in equal proportions because all of them Ire chosen by the same process.

5. During the trading period, I execute the asset allocation strategy and realize investments using futures on the equity index and a money market account. The investment rule is based on mean and on standard deviation of my forecasts. If the mean of the estimation is greater than 50% I buy index futures, otherwise I sell them. The aggressiveness on the investment depends upon how far the mean is estimated from 50%. One or more standard deviation away from that level implies that I will invest with confidence, otherwise I constrain the investment by a certain percentage.

6. During this trading period I have a dynamic update of models, not only because models can change but also because variables can change.

7. I add variables that I call "momentum variables", which are chosen when t-statistics have been greater than 2 (significant at the 5% level) at least during the last quarter instead of the last year. As financial markets are dynamic, taking into account these variables I are able to capture models that carry dynamic information faster to make my forecasts. As I incorporate these new "momentum variables", they help us to obtain a large quantity of good models with more up-to-date information and to increase the confidence in my forecasts.

8. Models with certainty (forecast of 1 or 0) in their estimations are not considered.

5 Results of my Tactical Asset Allocation Strategy

5.1 Testing for Stability and Changing the Window Size

A first indication of possible breakdowns or structural changes in the return process comes from the rolling window estimates of the coefficients of the prediction model. However, as the council of models vary almost every month and it is composed of more than one model, it becomes difficult to carry out this test. Thus, I take as an approximation of it and run pair-wise regressions of excess returns with one month lagged level and difference for all the explanatory variables and plot the evolution of coefficients.

Figure 2 in Appendix displays the pair-wise regression coefficients. These numbers are obtained rolling over 48 months of historical data during the whole out-of-sample data period. It is apparent that almost none of the relations with the predictive variables are stable through time. In other words, it is likely that relations reverse, disappear or restore.

In order to gain practical back-testing results, I account for the dynamic predictive relationships that investors face in reality, which frequently causes them to review the "optimal" combination of predictive instruments with more recent data. Yet, the majority of research papers on this matter still assume a time-invariant joint significance of predictive relations, making the empirical results subject to data-snooping criticism.

The extent to which information about breaks improves my ability to predict excess returns depends of course on my success in identifying the break times and my ability to exploit such information in forecasting.

The key distinction between the approaches to determine window size lies in how much data is used to estimate the prediction model, the recursively determined window sizes associated with the Cusum tests. What Pesaran and Timmermann do at this stage is to show a sharp break in the regression model as a drop in the window size, followed by a smoothly increasing window size until a subsequent break is detected. They use as the smallest window size 20 observations. The window then expands until a new break when the observation falls again to 20 observations. When they see stability they expand the window with upcoming observations.

My primary interest lies in determining the precision of the recursive forecasts produced by conditional window selection methods. Throughout the sample, the conditional window based on Cusum tests tends to be shorter than the expanding window, so I would expect the forecasts arising from this method to have closer information and less biased predictions, even though they could have greater standard errors.

When I run the Cusum and Cusum Squared tests for excess returns for the whole period under analysis, I find that the variance of the distribution suffers structural changes during 1996 – 1998 and during 2001 – 2002, and that the mean of the distribution does the same at the beginning of year 2000 and at the last quarter of year 2002. I combine these structural changes in order to change the size of the window data using the process explained above.

5.2 Empirical Results

In this section, I outline the out-of-sample performance of the econometric model, during the trading period. Using Hit Ratio, I test the percentage of time that the model has good sign predictability. I also back test the model through the application of tactical asset allocation strategies trading futures and options.

The robust econometric approach highlighted above, gives us probability estimates based on a council of selected logit models chosen during the training period. Based on these estimations, I build the mean and standard deviation among them, which will be the parameters to be considered for executing the trading period.

The following table depicts the average and standard deviation for the council of models and its Hit Ratio, since 2000:8 to 2003:12.

	Average	Standard Deviation	Hit Ratio
Aug-00	***44.1%***	***47.7%***	***1***
Sep-00	21.3%	19.0%	0
Oct-00	8.7%	1.6%	1
Nov-00	4.9%	0.0%	0
Dec-00	27.5%	15.1%	1
Jan-01	***38.1%***	***19.8%***	***1***
Feb-01	18.0%	25.5%	1
Mar-01	17.9%	4.4%	1
Apr-01	***37.6%***	***26.5%***	***1***
May-01	12.4%	10.9%	0
Jun-01	16.2%	10.9%	1
Jul-01	30.9%	16.2%	1
Aug-01	***37.1%***	***29.0%***	***1***
Sep-01	23.6%	16.9%	1
Oct-01	16.1%	15.6%	1
Nov-01	15.3%	12.6%	0
Dec-01	28.6%	14.7%	0
Jan-02	26.5%	20.6%	1
Feb-02	16.0%	13.5%	1
Mar-02	***38.0%***	***20.2%***	***0***
Apr-02	17.5%	5.2%	1
May-02	54.0%	3.0%	0
Jun-02	25.2%	15.4%	1
Jul-02	***35.2%***	***20.6%***	***1***
Aug-02	28.3%	5.5%	1
Sep-02	***46.6%***	***30.2%***	***0***
Oct-02	18.8%	15.5%	1
Nov-02	59.8%	0.0%	1
Dec-02	85.1%	9.1%	1
Jan-03	11.1%	9.7%	1
Feb-03	15.1%	20.1%	1
Mar-03	19.2%	27.8%	1
Apr-03	46.6%	3.1%	0
May-03	95.1%	7.5%	1
Jun-03	75.3%	22.3%	1
Jul-03	***36.6%***	***34.6%***	***0***
Aug-03	78.5%	1.7%	0
Sep-03	78.1%	21.3%	1
Oct-03	91.2%	0.0%	0
Nov-03	91.2%	0.0%	1
Dec-03	59.1%	6.6%	1

Estimations in italics and boldfaced relate to cases when the average forecast probability is less than one standard deviation away from 50%.

For instance, in August 2000 I estimate a probability of 44.1% and a standard deviation of 44.7%. These numbers imply that I should expect an under-performance of the equity index over the risk free interest rate, but that this estimation has low confidence given that models show discrepancies in estimations.

The success of predictability is based on the percentage of time I estimate that equity over/under-performed risk free interest rate. This is measured through the hit ratio, which is 70% (significantly greater than 50% at the 2.5% confidence interval). If I compare this hit ratio to that of AMM, it is 4% greater thanks to the incorporation of a moving size window, the inclusion of dummy variables that help us to learn from the past and improve confidence, and the inclusion of momentum variables. Another characteristic is that standard deviations are much lower than those of AMM, also due to the reasons explained above. This characteristic will impact the way I trade futures and options given that confidence is important at the time when I allocate money to investments.

5.3 Tactical Asset Allocation Based on Futures

Given that I built and back-tested a complete and robust econometric model to forecast excess returns, I implement a tactical asset allocation strategy to generate alpha, during the trading period. Based on the directional forecast on excess returns, I build a dynamically shifting portfolio investing in two asset classes, equity (DJ Euro Stoxx 50 Index Future) and cash (money market account that pays Libor 1M).

I build three hedge fund portfolios consistent with a chosen benchmark, using two different degrees of risk aversion (less and more aggressive). TAA strategies will be applied in the following portfolios,

1. 100% Money market: is a portfolio whose benchmark is money market interest rate. The allocation of the HF will be money market and will be allowed to invest in equity taken leverage from the market. The allocation of equity will range from –50% to 50%.

2. 100% Index Future: is a portfolio whose benchmark is the DJ Euro Stoxx 50 Index. As I will trade futures on the index, I consider futures as the benchmark. The allocation to equity futures ranges from 100% - y% to 100% + y%.

3. 50% Money Market / 50% Index Future: is a portfolio whose benchmark will be half money market and half index future. The asset allocation to equity ranges from 50% - y% to 50% + y%

The variable y allows us to control the level of aggressiveness of the strategy depending upon the confidence level I have to take decisions on investments. As stated above, confidence in investments will be based on standard deviation on the estimated probability. The trading rule for the HF consisting of 100% Money market is as follows,

- ✓ If the average forecast is more than one standard deviation away from 50%, I interpret this as a signal of higher confidence in the prediction and I allocate equity equal to the mean of the estimation less 50% (mean – 50%). The remaining amount goes to the money market account (100% - (mean – 50%)).

- ✓ If the average forecast probability is less than one standard deviation away from 50%, I interpret this as a signal of lower confidence in the prediction and I allocate equity equal to half of the allocation described in the last point (mean – 50%)/2, and the remaining goes to the money market account 100% - (mean – 50%)/2.

For the other two HF Portfolios, the trading rule is the same but adding the percentage of equity considered as benchmark.

I test two levels of aggressiveness of this portfolio process, where the allocation to equity is equal to 2*(mean – 50%) and (mean – 50%), in the higher and lower confidence cases, respectively.

In the following table[15], I compute for the three HF Portfolios, different degrees of aggressiveness and for their benchmarks, the annualized expected return and standard deviation, Sharpe index, average and maximum level of leverage, and some performance indicators.

	HF Money Market			HF 100% Stocks			HF 50 Money Market - 50 Stocks		
	Benchmark	Less Aggressive	More Aggressive	Benchmark	Less Aggressive	More Aggressive	Benchmark	Less Aggressive	More Aggressive
Annualized Returns	4.43%	12.3%	21.7%	-16.90%	-14.4%	-3.9%	-6.23%	-0.6%	9.5%
Annualized Volatility	0.25%	6.0%	11.9%	25.61%	18.9%	15.4%	12.93%	7.7%	7.2%
Sharpe	na	2.06	1.82	na	na	na		na	1.33
Average Gross Leverage	na	1.23	1.45	na	1.88	1.76	na	1.38	1.26
Max Gross Leverage	na	1.45	1.90	na	2.45	2.90	na	1.95	2.40
Best Month	0.50%	6.1%	11.8%	16.17%	11.6%	11.2%	8.33%	5.7%	5.5%
Worst Month	0.28%	-3.2%	-6.7%	-18.98%	-15.8%	-9.9%	-9.35%	-4.8%	-3.8%
% Up month	100.00%	82.9%	78.0%	39.02%	41.5%	43.9%	69.51%	43.9%	65.9%
Average Gain	0.35%	1.4%	2.8%	5.64%	3.5%	3.4%	2.99%	1.8%	1.9%
% Down month	0.00%	17.1%	22.0%	60.98%	58.5%	56.1%	30.49%	56.1%	34.1%
Average Loss	na	-1.1%	-1.4%	-5.84%	-4.9%	-3.2%	-2.92%	-1.5%	-0.7%

The out-performance of the three HF Portfolios in comparison with their respective benchmarks can be seen. For instance, the less aggressive-HF Money Market Portfolio reaches an annualized return of 12.3% with standard deviation of 6%, showing an appealing combination of both for private banking investors. These results are obtained taking an average and maximum leverage of 1.23x and 1.45x, respectively. It is also clear that as its volatility is greater than its benchmark, it will have greater best and worst

[15] All these numbers take into account the cost of leverage, and interest rate earned in money market account over 90% of the NAV. The remained 10% is used to trade futures and to make deposits for margin accounts.

month results. I want to point out too that the percentage of up months is consistently high with good average gains.

HF consisting of 100% Index Future, also shows over-performance in terms of annualized returns and standard deviation. As expected, the level of leverage increases considerably. A lower volatility also means lower best returns but better worst returns. The percentage up months increases from 39% to 41 and 44%, respectively for level of aggressiveness, and the percentage down months decreases from 61% to 58% and 56%, respectively. This shows the value added of the TAA implemented.

During downward markets, investors change their positions more heavily using futures than spot instruments. This is because they need to rebalance and hedge their portfolios more often. Trading individual assets could take time and incur expensive transaction costs. Executing future instruments is cost effective and more efficient. For this reason, future prices are more sensitive to this kind of situation and react differently to spot prices. It can be shown that the correlation between these two indexes, which is not very high, is only 60%. This effect adds mistakes to the TAA because I predicted excess returns of spot prices over risk free interest rate.

5.4 Transaction Costs

In order to complete the last simulation, I include transaction costs every time the fund trades futures, and I incorporate administrative and management fees. Trading futures is cost effective (25 bp), for this reason this TAA makes sense. I considered as benchmark administrative and management fees, 120 bp all in cost. The following table shows the performance of funds including these costs,

	HF Money Market			HF 100% Stocks			HF 50 Money Market - 50 Stocks		
	Benchmark	Less Aggressive	More Aggressive	Benchmark	Less Aggressive	More Aggressive	Benchmark	Less Aggressive	More Aggressive
Annualized Returns	4.43%	10.4%	19.2%	-16.90%	-18.3%	-7.4%	-6.23%	-2.9%	7.2%
Annualized Volatility	0.25%	5.9%	11.9%	25.61%	18.9%	15.2%	12.93%	7.6%	7.1%
Sharpe	na	1.75	1.62	na	na	na		na	1.02
Average Gross Leverage	na	1.23	1.45	na	1.88	1.76	na	1.38	1.26
Max Gross Leverage	na	1.45	1.90	na	2.45	2.90	na	1.95	2.40
Best Month	0.50%	5.9%	11.6%	16.17%	11.2%	10.8%	8.33%	5.5%	5.1%
Worst Month	0.28%	-3.4%	-6.9%	-18.98%	-16.1%	-10.1%	-9.35%	-5.0%	-4.0%
% Up month	100.00%	75.6%	73.2%	39.02%	34.1%	39.0%	69.51%	43.9%	65.9%
Average Gain	0.35%	1.2%	2.6%	5.64%	3.1%	3.1%	2.99%	1.6%	1.7%
% Down month	0.00%	24.4%	26.8%	60.98%	65.9%	61.0%	30.49%	56.1%	34.1%
Average Loss	na	-1.3%	-1.6%	-5.84%	-5.2%	-3.5%	-2.92%	-1.7%	-0.9%

Transaction costs are not economically significant, except for those funds that take heavy leverage, as it is the case for HF 100% Index Future. Its average leverage is 1.76x, and when considering transaction costs this means that the expected returns change from –3.9% to –7.4%. In standard deviation terms, costs have no significant impact.

In the Appendix, I attach graphs for each HF. They include monthly returns and cumulative returns with and without transaction costs.

6 Portfolio of Options to Enhance TAA

I saw before that the econometric model gave us the estimated probability that excess returns on equity will out-perform that of interest rate, which allowed us to generate bets on market directions, getting sustainable alpha.

In this case, I will use an optimum portfolio of options in order to enhance the performance of HFs during those periods of time when directional bets are not clear. 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's 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 Ill-designed TAA strategy usually performs poorly (only slighter better than the risk-free rate) in periods of low volatility.

I 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 I examine the suitability of embedding option positions in a portfolio whose characteristics should achieve these desired objectives.

For the strategy to perform Ill 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 I 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:

$$C(t) = S_t N(d_1) - Ke^{-r(T-t)} N(d_2)$$

where d_1, d_2 are

$$d_1 = \frac{\log(\frac{S_t}{K}) + (r + \frac{\sigma^2}{2})(T - t)}{\sigma\sqrt{T - t}}$$

$$d_2 = \frac{\log(\frac{S_t}{K}) + (r - \frac{\sigma^2}{2})(T - t)}{\sigma\sqrt{T - t}}$$

The *N(x)* denotes the cumulative standard normal probability:

$$N(x) = \int_{-\infty}^{x} \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}u^2} du$$

In this formula, *C* is the call price, *S* the underlying asset price, *K* the strike price, *r* the risk free rate, *σ* the volatility and *T* the time to maturity.

I will need the following sensitivity parameters called the "Greeks", to establish my strategy. With Greeks I monitor the sensitivities of the option with respect to changes in the main variables:

$$Delta = \frac{\partial C}{\partial S_t} = N(d_1)$$

$$Gamma = \frac{\partial^2 C}{\partial S_t^{\ 2}} = \frac{1}{S_t \sigma \sqrt{T - t}} \left[\frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{\log(\frac{S}{K}) + (r + \frac{\sigma^2}{2})(T - t)}{\sigma\sqrt{T - t}} \right)^2} \right]$$

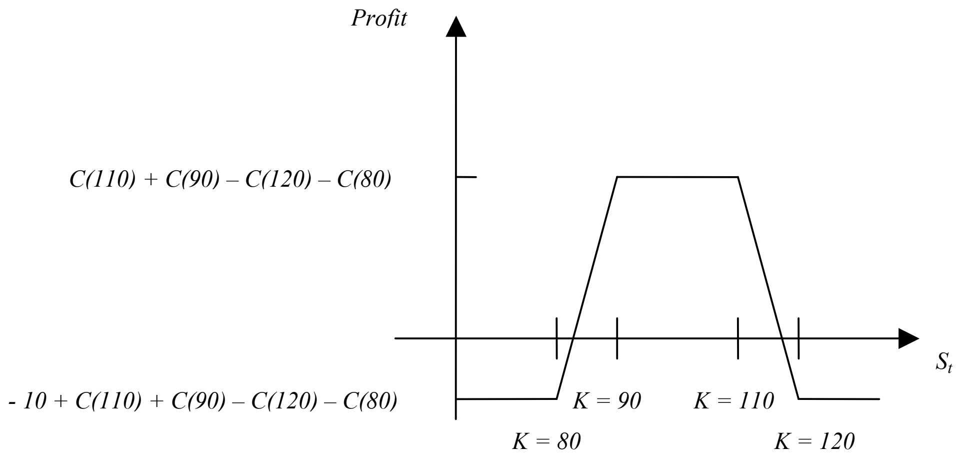
$$Theta = \frac{\partial C}{\partial t} = -\frac{S_t \sigma}{2\sqrt{T - t}} \left[\frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{\log(\frac{S}{K}) + (r + \frac{\sigma^2}{2})(T - t)}{\sigma\sqrt{T - t}} \right)^2} \right] - Kre^{-r(T-t)} N(d2)$$

Delta is the theoretical price change of the option, if the underlying asset price, S_t, moved by an infinitesimal amount. *Gamma* represents the rate of change of the delta as the underlying, S_t, changes. *Theta* is the theoretical price change of the option, if a small amount of time passes.

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. I 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 out-perform 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, I add long positions in further out-of the-money options. To get back to the previous example, I 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 my example. 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.

I 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.



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

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

In the case of delta neutral portfolio:

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

In the same way, another simulation that could have added value to HFs but which I do not include it is the truncation of excess returns probability density function, through the use of synthetic options. For instance, the Portfolio Manager could avoid having deep negative returns if she reverses her position when excess returns goes below a certain threshold. Of course, this strategy could also eliminate positive returns in these cases the market change signs.

6.1 Empirical Results with Transaction Costs

In what follows, I implement an option overlay strategy that is designed to meet these requirements.

I aim at implementing a short position in short-term out-of-the-money options (both calls and puts). I also add a long position in longer-term and further-out-of-the-money call and put options. Then, I 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 net initial value.

I need to build implied-volatility smiles through time, in function of different strikes, time to maturity and underlying asset prices[16]. As it is obvious, I could not acquire all of this information. To solve this problem, I make the assumption that the shape of the smile is constant through time[17]. I run a quadratic regression to obtain its shape. Given the fact that I had ATM Implied Vol for different strikes, maturities and underlying values, I use the shape of the smile to obtain all the option values. From these data, I back test the strategy.

For instance, in August 2001 I apply a portfolio of options assuming a NAV for the fund of USD 10 MM. In the table below, it can be seen that I cash in $ 418 (per net option) in the first day of the strategy as the portfolio optimization is done by selling more options than buying options; theta is maximized with delta-neutral and very low gamma. I also compute the amount of money moved through options premium ($100,753), in order to subtract transaction costs ($ 1611). After a month, given the new volatility of the market and the underlying value, which increases slightly, I end up having a capital gain of $6,629 given the fact that sold options are unexercised and I hold valuable options; I cash in $41,841 and I pay transaction costs of $1,611. As a result, I gain $ 46,859, representing a return of 0.36% on an annualized basis.

Aug-01

NAV	10,000,000
Ann Returns	0.36%

S0 *5100*

			Strike	quantity	price	delta	theta	gamma	vega	Contract %
BUY	CALL	130	6120	22	13.39	0.061	-103.13	0.000227	366.88	17.7%
BUY	PUT	130	4080	0	22.48	-0.059	-122.39	0.000143	360.12	0.0%
SELL	CALL	30	5610	52	-8.44	-0.065	249.24	-0.000420	-186.05	41.9%
SELL	PUT	30	4590	50	-5.48	0.041	163.40	-0.000269	-127.87	40.3%
				124	-418	-0.0185	18861.3	-0.0303	-7996.4	-0.0002

	$	100,753
Tcosts	**1.5%**	**1610.7**

Sep-01

S1 *5200*

			Strike	quantity	price	delta	theta	gamma	vega	Contract %
SELL	CALL	100	6120	22	3.01	-0.022	41.39	-0.000137	-142.30	17.7%
SELL	PUT	100	4080	0	5.13	0.020	54.27	-0.000073	-132.41	0.0%
	CALL	1	5610	52	0.00	0.000	0.00	0.000000	0.00	41.9%
	PUT	1	4590	50	0.00	0.000	0.00	0.000000	0.00	40.3%
				124	66	-0.4820	910.6231	-0.0030		0.0000

Capital gains	6,629
Cash out	41,841
Trans Costs	-1,611
Total	46,859

[16] I make the assumption of constant interest rate.
[17] I take the shape of the smile in the first day of August 2004.

Applying this optimized option portfolio I are able to enhance the portfolio's performance by adding value when the market has no clear direction. Based on risk tolerance, which is expressed and managed by the amount of Gamma that the portfolio manager wants to add, one can show different scenarios. In my case, I target a very low gamma given the fact that I include transaction costs and aim at avoiding rebalancing. The impact of this overlay strategy on the HF 100% Money Market portfolio is as follows,

	HF Money Market		
	Benchmark	Less Aggressive	More Aggressive
Annualized Returns	4.43%	13.2%	22.8%
Annualized Volatility	0.25%	5.97%	11.8%
Sharpe	na	2.06	1.82
Average Gross Leverage	na	1.23	1.45
Max Gross Leverage	na	1.45	1.90
Best Month	0.50%	6.3%	12.1%
Worst Month	0.28%	-3.0%	-6.1%
% Up month	100.00%	83.0%	78.4%
Average Gain	0.35%	1.5%	3.1%
% Down month	0.00%	17.0%	21.6%
Average Loss	na	-1.0%	-1.1%

7 Conclusion

In this master thesis I implement a quantitative approach to build hedge fund portfolios. The main idea of this robust, dynamic and complete process is to obtain the data generating process of excess returns and to understand how investors take investment decisions in order to apply tactical asset allocation strategies using futures and portfolio of options.

I use financial and not macroeconomics factors to explain future probability of equity returns over risk free interest rate returns mainly because macro data is usually adjusted after the first release and because financial data is more up-to-date. I also deal with a group of models instead of the best model, obtaining more robust results in my estimations. Financial time series are likely to undergo sudden, large changes reflecting institutional changes, regime switches or breakdowns in market mechanisms as observed during financial crises. Forecasting such series poses a difficult problem, particularly if one is interested in the sign of the variables as is frequently the case in financial applications. I implement a two-stage approach that estimates the time of structural breaks and then I change the window size of input data to run my estimations. This process adds value and gives higher hit ratio in my out-of-sample estimations.

With a high percentage of right estimations of future probabilities, I could implement tactical asset allocation strategies to obtain alpha and beta drivers. I trade futures for directional bets based on my quantitative model and optimized portfolio of options for no directional bets. In this way, I build three different hedge fund portfolios (Money market, equity and a combination of both) and I demonstrate that my approach adds value during downward and upward markets. I also include transaction costs in order to obtain results as close as possible to real market conditions.

Avoiding noisy decision-making processes to execute my investments, I prove that my dynamic, robust and complete quantitative approach is an efficient procedure to gain better risk-adjusted returns compared with benchmarks.

Appendices

Logit Model:

Assume that I have a regression model

$$y_i^* = \beta_0 + \sum_{j=1}^{k} \beta_j x_{ij} + u_i \tag{1}$$

where y_i^* is not observed. It is commonly called a “latent” variable. What I observe is a dummy variable y_i defined by

$$y_i = \begin{cases} 1 & \text{if } y_i^* > 0 \\ 0 & \text{otherwise} \end{cases} \tag{2}$$

In equation (1) I assume the existence of an underlying latent variable for which I observe a dichotomous realization. For instance, if the observed dummy variable is whether or not a person is employed, y_i^* would be defined as “propensity or ability to find employment”. Similarly, if the observed dummy variable is whether or not a person has bought a car, then y_i^* would be defined as “desire or ability to buy a car”. Note that in both the examples I have given, there is “desire” and “ability” involved. Thus the explanatory variables in (1) would contain variables that explain both the elements.

Note from system (2) that multiplying y_i^* by any positive constant does not change y_i. Hence if I observed y_i, I can estimate β’s in (1) only up to a positive multiple. Hence it is customary to assume var(u_i) = 1. This fixes the scale of y_i^*. From the relationship (1) and (2) I obtain

$$P_i = \text{Prob}(y_i = 1) = \text{Prob}\left[u_i < -\left(\beta_0 + \sum_{j=1}^{k} \beta_j x_{ij}\right)\right]$$

$$= 1 - F\left[-\left(\beta_0 + \sum_{j=1}^{k} \beta_j x_{ij}\right)\right]$$

where F is the cumulative distribution function of u.

If the distribution of u is symmetric, since $1 - F(-Z) = F(Z)$, I can write

$$P_i = F\left(\beta_0 + \sum_{j=1}^{k} \beta_j x_{ij}\right) \tag{3}$$

Since the observed y_i are just realization of a binomial process with probabilities given by equation (3) and varying from trial to trial (depending on x_{ij}), I can write the likelihood function as

$$L = \prod_{y_i=1} P_i \prod_{y_i=0} (1 - P_i) \qquad (4)$$

The functional form for F in equation (3) will depend on the assumption made about the error term u. If the cumulative distribution of u_i is logistic I have what is known as the *logit* model. In this case

$$F(Z_i) = \frac{\exp(Z_i)}{1 + \exp(Z_i)} \qquad (5)$$

Hence

$$\log \frac{F(Z_i)}{1 - F(Z_i)} = Z_i$$

Note that for the logit model

$$\log \frac{P_i}{1 - P_i} = \beta_0 + \sum_{j=1}^{k} \beta_j x_{ij}$$

The left hand side of this equation is called the *log-odds ratio*. Thus the log-odds ratio is a linear function of the explanatory variables.

Maximization of the likelihood function (4) for the logit model is accomplished by nonlinear estimation methods. There are now several computer programs available for the logit analysis, and these programs are very inexpensive to run.

Table 1 - Effect of explanatory variables over excess returns

S&P 500 Index - Returns	Low		Medium		High		Unconditional Values
	Min	Max	Min	Max	Min	Max	
Difference between conditional and unconditional values	-13.0%	-0.6%	-0.6%	3.5%	3.7%	17.5%	
	Mean		***Mean***		***Mean***		***Mean***
Excess returns	-0.70%		0.53%		0.09%		0.61%

Currency Index - Returns	Low		Medium		High		Unconditional Values
	Min	Max	Min	Max	Min	Max	
Difference between conditional and unconditional values	-5.3%	-0.9%	-0.9%	0.9%	1.0%	4.5%	
	Mean		***Mean***		***Mean***		***Mean***
Excess returns	-0.02%		-0.06%		0.09%		0.61%

Commodity Index - Returns	Low		Medium		High		Unconditional Values
	Min	Max	Min	Max	Min	Max	
Difference between conditional and unconditional values	-23.1%	-2.2%	-2.1%	2.9%	2.9%	14.7%	
	Mean		***Mean***		***Mean***		***Mean***
Excess returns	-1.18%		-0.32%		1.55%		0.61%

Euro Dividend Yield	Low		Medium		High		Unconditional Values
	Min	Max	Min	Max	Min	Max	
Difference between conditional and unconditional values	1.33	1.84	1.85	2.62	2.62	4.09	
	Mean		***Mean***		***Mean***		***Mean***
Excess returns	1.36%		-0.06%		-1.29%		0.61%

US spread - %	Low		Medium		High		Unconditional Values
	Min	Max	Min	Max	Min	Max	
Difference between conditional and unconditional values	0.43	0.69	0.70	1.65	1.66	3.74	
	Mean		***Mean***		***Mean***		***Mean***
Excess returns	1.67%		0.56%		-2.32%		0.61%

Level of Euribor 3M	Low		Medium		High		Unconditional Values
	Min	Max	Min	Max	Min	Max	
Difference between conditional and unconditional values	2.03	3.43	3.45	4.72	4.76	7.36	
	Mean		***Mean***		***Mean***		***Mean***
Excess returns	0.10%		0.22%		-0.35%		0.61%

Table 1* - Effect of explanatory variables over excess returns

US Term Slope	Low		Medium		High		Unconditional Values
	Min	Max	Min	Max	Min	Max	
Difference between conditional and unconditional values	-0.79	0.78	0.88	2.39	2.42	3.72	
	Mean		***Mean***		***Mean***		***Mean***
Excess returns	0.62%		0.52%		-1.22%		0.61%

Euro Term Slope	Low		Medium		High		Unconditional Values
	Min	Max	Min	Max	Min	Max	
Difference between conditional and unconditional values	-3.30	-0.52	-0.49	0.91	1.02	3.43	
	Mean		***Mean***		***Mean***		***Mean***
Excess returns	0.91%		-0.82%		0.03%		0.61%

Levels of Implied Volatility	Low		Medium		High		Unconditional Values
	Min	Max	Min	Max	Min	Max	
Difference between conditional and unconditional values	10.63	18.31	18.55	24.22	24.42	44.28	
	Mean		***Mean***		***Mean***		***Mean***
Excess returns	0.16%		0.27%		-0.47%		0.61%

** We organize time series in ascending order and stratify them into three equal groups, the first is the average of low numbers, the second is the average of the medium numbers and the third is the average of higher numbers. In this way, we will be able to obtain the intuition of the effect in different scenarios of the explanatory variables onto excess returns.*

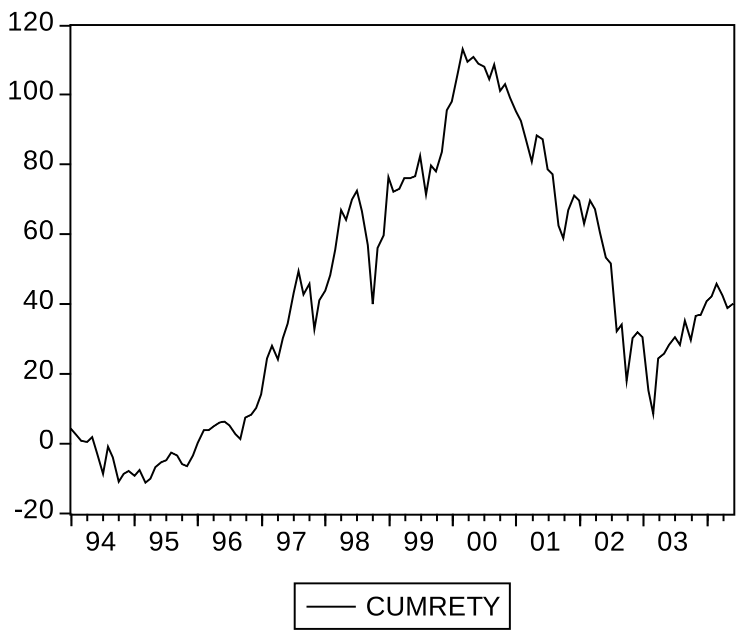
When the credit spread of US corporate bonds increases (high scenario), the excess returns in the Euro Zone are negative by 2.32% on average on a monthly basis, in excess of the unconditional mean. On the contrary, when the credit spread decreases, equity returns out-performs the LIBOR 1M interest rate by 1.67% on average on monthly bases, in excess of the unconditional mean. This intuition confirms the idea that when there is high credit spread in the US, as a proxy for price of risk, equity returns under-perform the interest rate returns.

Table 2 - Out of sample estimation using simple regression

	Excess returns	Estimation	Hit ratio
			63.4%
Aug-00	-3.82%	10.01	0
Sep-00	4.02%	12.74	1
Oct-00	-7.68%	13.24	0
Nov-00	1.67%	10.12	1
Dec-00	-4.18%	(11.47)	1
Jan-01	-4.10%	(26.51)	1
Feb-01	-2.81%	(24.23)	1
Mar-01	-5.46%	(24.87)	1
Apr-01	-6.73%	(21.85)	1
May-01	7.41%	(17.61)	0
Jun-01	-1.30%	(15.83)	1
Jul-01	-9.02%	(26.14)	1
Aug-01	-1.45%	(15.80)	1
Sep-01	-15.08%	(16.18)	1
Oct-01	-3.72%	(2.50)	1
Nov-01	7.98%	(41.03)	0
Dec-01	3.91%	(75.12)	0
Jan-02	-1.49%	(69.05)	1
Feb-02	-6.72%	(65.72)	1
Mar-02	6.54%	(72.91)	0
Apr-02	-2.84%	(75.30)	1
May-02	-6.58%	(61.40)	1
Jun-02	-7.50%	(96.43)	1
Jul-02	-1.87%	(40.85)	1
Aug-02	-19.44%	(72.84)	1
Sep-02	1.62%	(80.72)	0
Oct-02	-16.15%	(66.06)	1
Nov-02	12.13%	(33.56)	0
Dec-02	1.38%	(53.76)	0
Jan-03	-1.53%	(25.66)	1
Feb-03	-15.30%	(16.42)	1
Mar-03	-7.06%	33.35	0
Apr-03	15.73%	36.80	1
May-03	1.41%	(7.57)	0
Jun-03	2.32%	(0.60)	0
Jul-03	2.20%	(0.05)	0
Aug-03	-2.44%	(4.65)	1
Sep-03	6.93%	(18.23)	0
Oct-03	-5.72%	(22.80)	1
Nov-03	6.87%	0.44	1
Dec-03	0.09%	(8.59)	0

** Taking input data from stationary periods and low volatility, where the data doesn't show spikes, we run simple regressions using as factors our set of explanatory variables. Once we get a parsimonious model based on R2, t-stats, ACF and heterocedasticity problems, we take those parameters to make forecasts for the next 3,5 years. Then, we calculte Hit Ratio (% of time our estimation coincide with the markets) for out-of-sample data. Surprisingly, this naïve model predict excess returns well 63% of the time.*

Figure 1 - Cumulative month-to-month excess returns

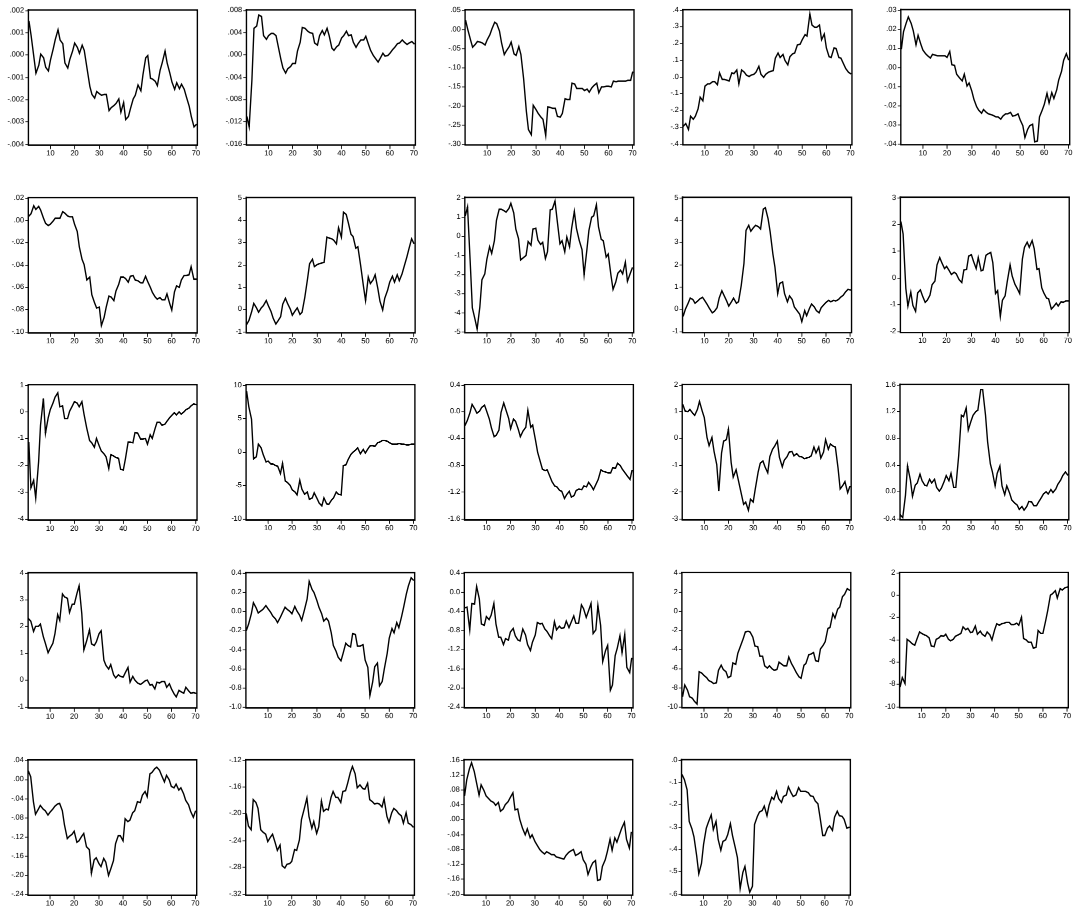


	Excess Returns
Mean	0.316984
Median	0.885
Maximum	16.64
Minimum	-19.3
Std. Dev.	6.406692
Skewness	-0.316408
Kurtosis	3.941694
Jarque-Bera	6.758035
Probability	0.034081

Values are expressed in percentage on a monthly basis.

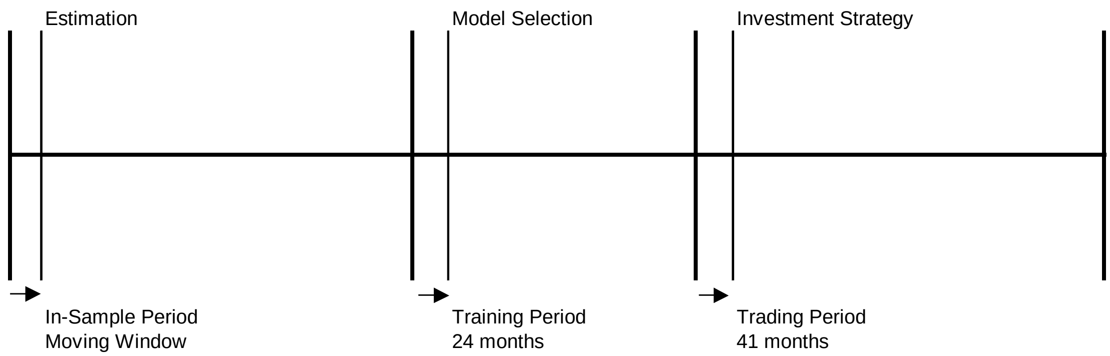
** The plot shows the cummulative exess returns during the whole period. The table shows standard descriptive statistics of exess returns.*
Test of normality based on Jarque-Bera statistic evidences that the probability density function is close but not normally distributed.

Figure 2: First indication of structural breaks in the data process



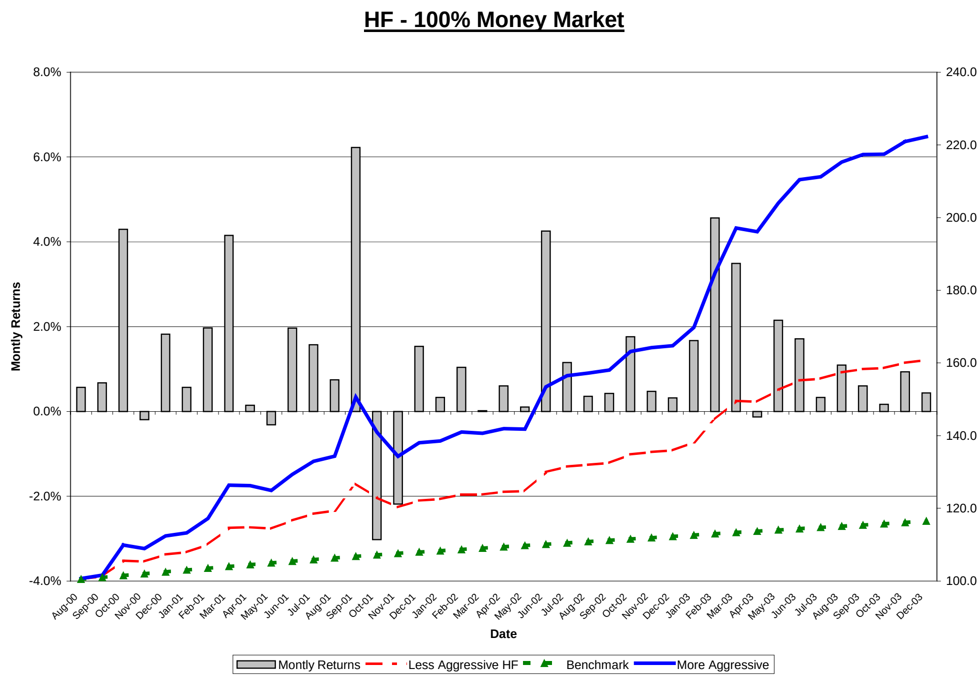
** As an indication of possible breakdowns or structural change in the data generating process, we run pairwise regressions of depend variables onto all explanatory factors that we use.*
It is clear that coeficients throught time shows some indication of breakdowns in the data.
These numbers are obtained rolling over 48 months of historical data during the whole out-of-sample data period. It is apparent that almost none of the relations with the predictive variables are stable through time. In other words, it is likely that relations reverse, disappear or restore.

Figure 3 - Graphical representation of recursive modeling approach



** We take 10 years of historical data, which is divided into two samples of data; one comprises of a six year period from 1994:8 to 2000:7 and the other comprises of 3.5 years from 2000:8 to 2003:12 . The first sample is separated into two other periods; the first one is used to run regressions and calibrate the parameters (calibration period) which will be used to obtain a one-step out-of-sample forecast of excess returns, and the second one is used to train and to chose models based on their performance during 24 months of out-of-sample testing (training period). Finally, the trading period is used to implement and back test the tactical asset allocation strategy using futures and a portfolio of options, based on the forecasting power of the other two periods.*

Figure 4: 100% Money Market Hedge Fund without and with transaction costs.



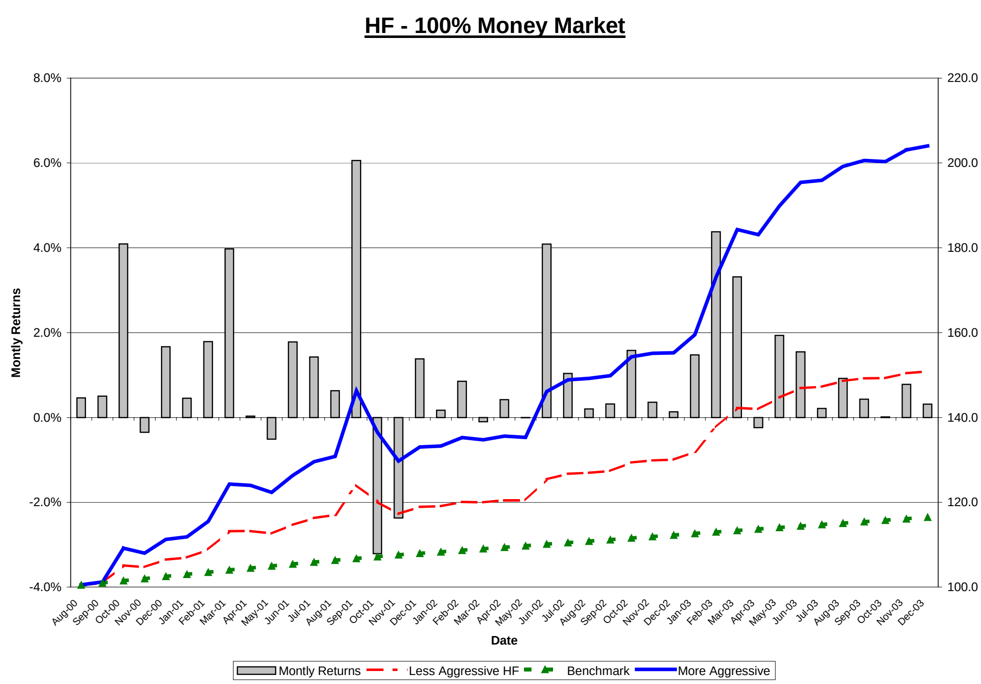
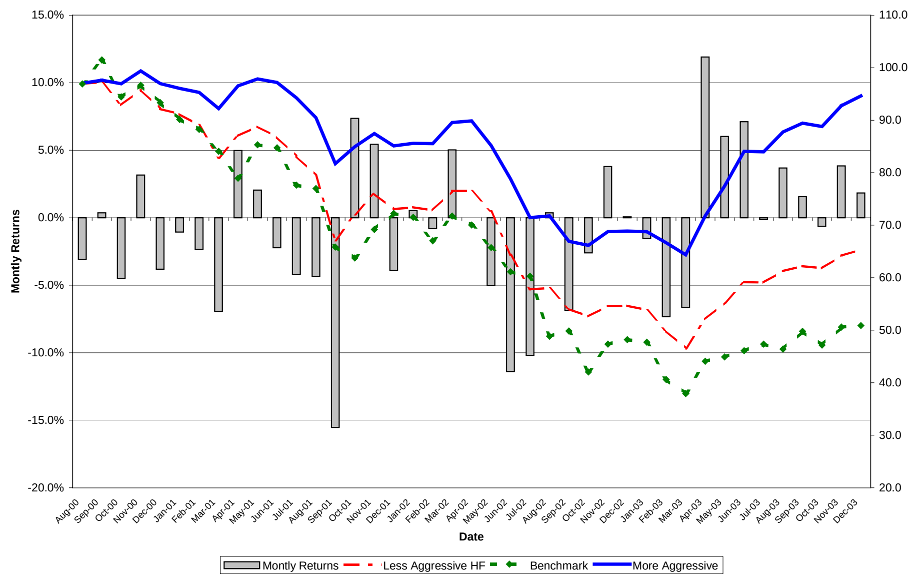


Figure 5: 100% Index Future Hedge Fund without and with transaction costs.

HF - 100% Future Index



HF - 100% Future Index

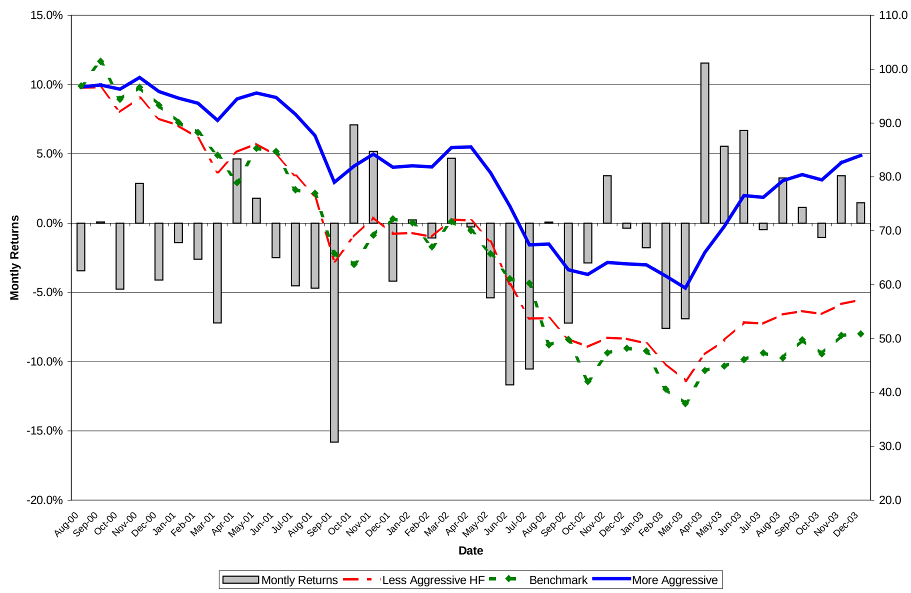
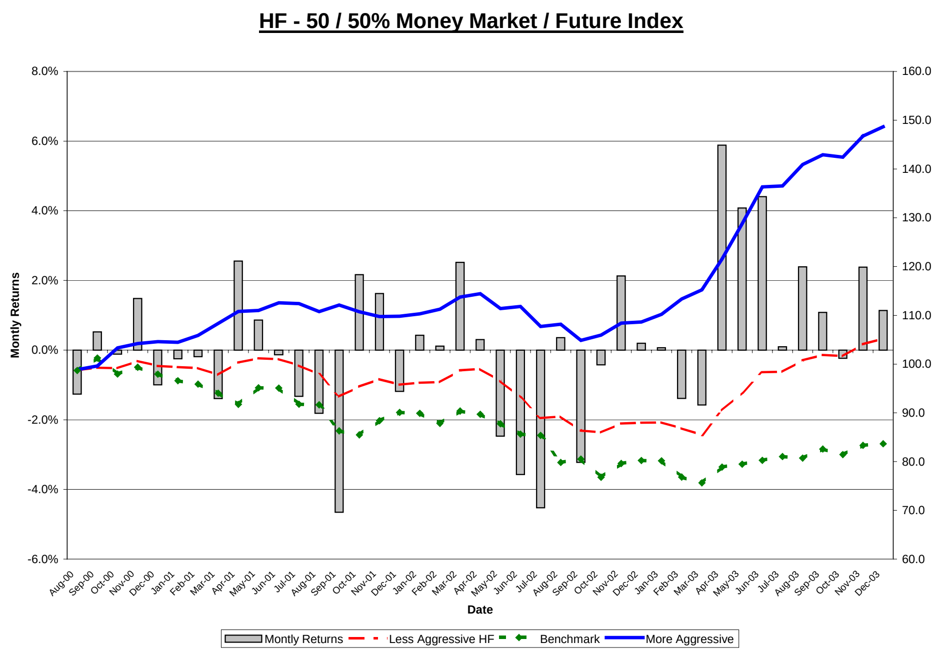
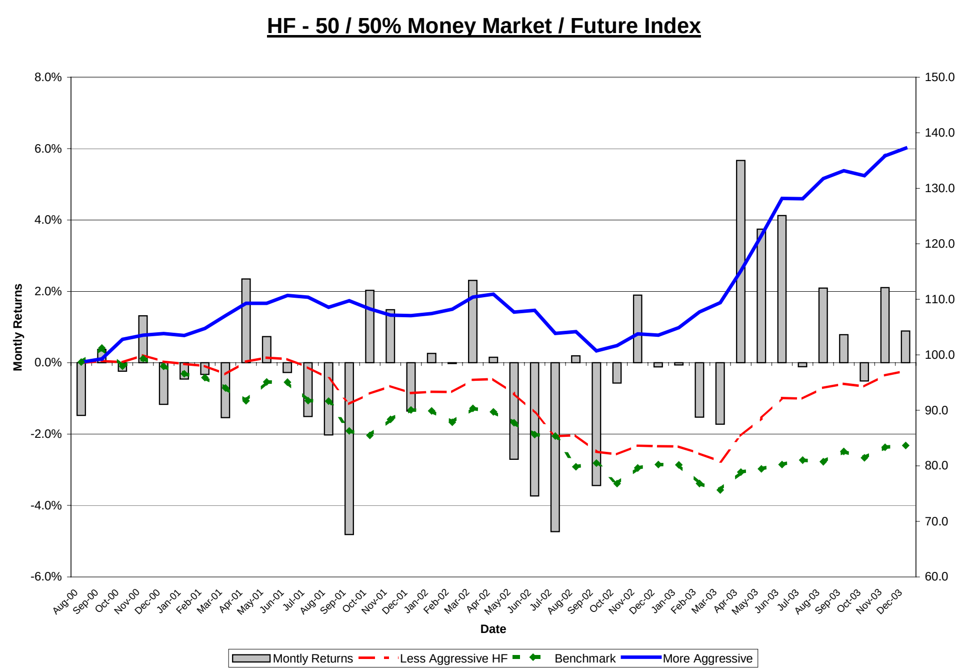


Figure 6: 50 / 50% Money Market - Index Future Hedge Fund without and with transaction costs.





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