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RISK ON-RISK OFF: A REGIME SWITCHING MODEL FOR ACTIVE PORTFOLIO MANAGEMENT

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Risk on-Risk off: A regime switching model for active portfolio management

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Abstract

Unlike passive management, where investors almost do not buy and sell securities, active management involves a set of trading rules that govern investment decisions regarding mainly market timing. In this paper, we take the basics of active management and the two fund separation approach, to exploit the fact that an investor can switch between the market portfolio and the risk free asset according to the perceived state of the nature. Our purpose is to evaluate if there is an *active management premium* by testing performance with our own non-conventional multifactor model, constructed with a Hidden Markov Model which depending on the market states signaled by the level of volatility spread. We have documented that effectively, there is present a premium for actively manage the strategies, giving evidence against the idea that "active managers" destroy capital. We then propose the volatility spread as the active management factor into the Carhart´s model used to evaluate trading strategies with respect to a benchmark portfolio.

JEL: C1, C3, N2, G11.

Key words: Regime switching, active investment, two fund separation, excess returns, hidden markov model, VIX.

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Introduction

Investors have two main sets of investment strategies that can be used to generate a return on their investment accounts: active portfolio management and passive portfolio management. These approaches differ in how the investor allocates securities held in the portfolio over time. One of the main objectives of investors has been historically to beat the market (though not always achieved), that is, to try to find ways to obtain excess returns against the market using different trading strategies that involve the purchase and sale of assets based on a set of rules. Several approaches have been addressed to do this. This behavior entitles what is called active portfolio management, given that investors actively buy and sell securities or asset classes in the aim of obtaining a plus return with respect to a benchmark portfolio. If investors knew when to switch between risky and risk free assets, that would be a great advantage.

In this paper, we build an “active management" factor by using a hidden Markov model (HMM). To do this, we follow a "two-portfolio separation" approcah, allocating the available funds to two assets; one risky and one risk-free.

As for the paper, the structure is the following: in section 1 we introduce the active and passive strategies and review the main contributions of the literature to the topic under analysis; in section 2 we describe thoroughly the implemented methodology; in section 3 we expose the obtained results. Finally, we discuss the main conclusions.

1 Review and past literature

The discussion of this paper has been matter of debate in the theory and practice of finance. There are many academics who claim that active investing, considering the high transaction costs involved, adds zero value or even destroys value for investors, so it is worthless to try to actively beat the market and becomes more efficient to passively hold a benchmark portfolio. There are different costs to consider, such as for example, transaction costs, management and performance fees, market impact and other implicit costs, among others (see, e.g., [French, 2008]).

Active portfolio management focuses on outperforming the market compared to a specific benchmark, while passive portfolio management aims to replicate the investment holdings of a particular index.

An actively-managed investment fund has an individual portfolio manager, co-managers or a team of managers actively making investment decisions for the fund.

The success of an actively-managed fund is dependent on combining in-depth research, market forecasting and the experience and expertise of the portfolio manager or management team and can be evaluated when compared to a benchmark. Investors committed to active investing pay close attention to market trends, shifts in the economy, changes to the political landscape and factors that may affect specific companies. This data is used to time the purchase or sale of investments in an effort to take advantage of irregularities. Active managers support the idea that this methodology may enhance the potential for greater returns than those achieved by simply mimicking the stocks or other securities listed on a particular index.

Since the objective of a portfolio manager in an actively-managed fund is to beat the market, he or she must take on additional market risk to obtain the returns necessary to achieve this end. Indexing eliminates this, as there is no risk of human error in terms of stock selection. Index funds are also traded less frequently, which means that they incur lower expense ratios and are more tax-efficient than actively-managed funds.

On the other hand, passive investors create portfolios that replicate a particular market index or benchmark as closely as possible. Managers select assets listed on an index and apply the same weighting, or alternatively, they invest in financial vehicles that follow an index (ETF like the SPY with respect to the SP 500). The purpose of passive portfolio management is to generate a return that is the same as the chosen index instead of outperforming it.

The real question is to what extent is worth to incur into de costs of actively investing when excess returns are not always guaranteed. Investors, depending on the specific characteristics of the strategy, pay considerable costs. An active strategy involves transaction costs and, as the frequency of the rebalancing increases, it seems that the costs too. This is the reason why transaction costs are one of the crucial points to consider when measuring the performance of active trading strategies. In many cases, the performance of active strategies, once adjusted for the costs involved, cannot outperform passive strategies, whose most attractive feature is the low transaction cost.

Under the assumption that markets are efficient, active investment should not be generating value, since the potential excess returns generated by these types of strategies are not sufficiently high as those generated by passive investment once the costs of transaction.

Different approaches have been employed to try to beat the market. The proliferation of the factor investment explains one of these, in which investors obtain a systematic exposure to determined factors with the idea that, in the long term, said exposure will generate higher risk-adjusted returns than passive approaches.

Other investors have been trying to beat the market using timing (and active) strategies. In a nutshell, this means beating the market by measuring “optimal” buying and selling points over time. In this regard, the best case scenario is to take long positions in risky assets when upward trends are near the beginning and bearish positions when the opposite occurs. However, empirical evidence has shown that, in the long term, this is very difficult.

On the other hand, we have the basic framework of two fund separation [Markowitz, 1952]. The approach shows that portfolios can be analyzed in a mean-variance framework, with every investor holding the portfolio with the lowest possible return variance consistent with that investor's chosen level of expected return (known as a minimum-variance portfolio). Under mean-variance analysis, it can be shown that every minimum-variance portfolio given a particular expected return (that is, every efficient portfolio) can be formed as a combination of any two efficient portfolios. If the investor's optimal portfolio has an expected return that is between the expected returns on two efficient benchmark portfolios, then that investor's portfolio can be characterized as consisting of positive quantities of the two benchmark portfolios.

Some strategies are aimed at detecting systematic patterns in data that, in the long term, generate excessive returns. This is widely known as “factor investing” (see, e.g., [Asness, 2017], [Gorton and Rouwenhorst, 2008], [Ung and Kang, 2015]).

At the same time, there are strategies whose objective is to timing the market. That is, to detect the “optimal" points of buying and selling risky assets in order to generate excess returns to the market (see, e.g., [Hull and Qiao, 2017], [Hull and Qiao, 2017a]).

So the sorcerer´s stone or the holy grail aimed by investor trying to find a way to obtain an excess return usually collapses with the reality of the market.

However, if we were given the chance of choosing a trading strategy that on the one hand it has minimum transactions costs, and on the other it guesses the direction of the market, that would be of much help. The active strategy may follow the basic recommendations of two fund separation, and it could work by switching between a stock index (profiting from the upside value inherent in stock) and a risk free asset (providing a hedge when the stock market goes down).

Such a strategy will try to infer whether the stock market is more likely to go up or down (two states of the nature) and have a two fund allocation switching between stocks market (if going up) and risk free asset (if going down). The only active part of the strategy would be the switching between the assets, and hence trying to capture the best of both states of the nature.

Our objective in this paper is to first test such a strategy and second to suggest a modification to the Carhart´s model by incorporating such a switch.

2 Data and methodology

Our purpose is to device a factor intended to capture the active management feature for a portfolio manager who switches between two funds, a stock fund and a risk free asset. To construct the active factor, we use a "latent" variable to generate the signals.

Empirical evidence suggests that "volatility premium", or the difference between implied and realized volatility, may work as an indicator of future equity returns. In this regard, we model and predict the volatility premium or gap using an HMM as in Dapena, Serur y Siri (2018) [1]. Most of the technology used si well described in that paper, where we sued the Baum-Welch algorithm to estimate the model, and, and the Viterbi algorithm to infer the most likely state of the nature.

When the most likely state is one with a low volatility spread, which means that the realized volatility is increasing more than the implied volatility, the strategy allocates the funds in short-term Treasuries, and the strategy becomes **"risk off"**; otherwise, the strategy allocates the funds in the S&P 500 Index (proxied by the SPY), where the strategy becomes **"risk on".**

In all cases, we use closing prices. In this regard, in order to avoid a *look ahead bias*, we set up all the positions during each rebalancing date one day after the signal was generated, that is, each signal is generated at time t and the transaction is executed at time t + 1. As for the trading periodicity, the strategy of 2 states changes on average 16 times a year, that is, it rebalances the portfolio every 22 days. As for the strategy of the 3 states, it changes 55 times per year on average, which means a rebalancing approximately every 7 days.

As mentioned above, we use a proprietary model, consisting on an HMM which model the volatility spread:

$$Spread_t = \mu_{z_i}(t) + \epsilon_{z_i}(t) \tag{1}$$

Where $\mu_{z_i}(t)$ and $\varepsilon_{z_i}(t)$ are the mean and the error term at time t, respectively. Both are conditional to the current regime z_i. Besides,

$$\varepsilon_t \sim N(0,\sigma_z) \tag{2}$$

[1] For more details, see, [Dapena, Serur and Siri, 2018].

Following the calculated spread, we set our trading rules. Depending on the current state dictated by the calibrated HMM, we defined the corresponding trading decisions:

- take short positions in SPY or

- allocate the total money available in short-term Treasury Bills.

In this way, we build a market factor model that considers the changes in the state of the nature of the market and, therefore, works as an active strategy (as opposed to the standard market factor, which is a passive strategy, i.e., buys and holds the market portfolio). When the subsequent risk perceived is high, the model acts as an "off risk" indicator and, therefore, all the money is allocated to low-risk assets. In the opposite scenario, the model acts as an indicator of "risk on", and therefore, the funds are allocated in high-risk assets.

The volatility spread is therefore used as the active factor signaling to switch between stocks and a risk free asset. The strategy aims to capture the upside of stock when the state of the nature us bullish, and to benefit from the hedge of treasuries when the state of the nature is bearish.

3 Main Results and extensions

When the most probable state was a calm market, characterized by a high volatility spread, we take long positions in equity ETFs (SPY), i.e., we gain exposure to high-risk assets. Opposite, during volatile markets, we switch the total available money to 7-10 years Treasury Bills, gaining exposure to low-risk assets.

On table 1, we can appreciate the performance of the S&P 500, i.e., a passive strategy that buys and holds the Index versus the performance of an active strategy built as explained before (see figure 3). The CAGRs were 8.48% and 11.36% with volatilities of 18.28% and 12.71% respectively, leading to Sharpe ratios of 0.46 and 0.89. At the same time, it is possible to appreciate the dramatic reduction in the maximum drawdown, decreasing from -55.18% for the case of the passive strategy to -25.95% for the case of the active strategy.

Then, we tested if our strategy were able to generate economically and statistically significant alphas against traditional multifactor models. Using the Fama-French three-factor model and Carhart four-factor model, we can appreciate (see table 2) positive and statistically significant alphas, leading us to conclude that an active strategy can actually generate excess returns against traditional factor models.

Conclusions

Market timing is the holy grail of active investors. If an investor could profit from stocks when they are going up (take the risk, or be in mode “risk on”), and switch to treasuries when the market goes down (switch to mode “risk off”), she may not require further sophistication in her investment allocations. However, market timing becomes very difficult. In this paper we use the basics of two fund separation and active management to propose an active factor aimed to capture the benefits from stocks in bull markets and the hedge of treasuries in a bear market. For that purpose we resort to a volatility spread model signaling the state of the nature by means of a HMM. By modeling the volatility spread (or the volatility premium) with an HMM, we can infer the most likely subsequent state and, therefore, use it to make decisions. However, here, instead of trading volatility, we buy the market portfolio when the subsequent perceived risk is low and Treasury bonds otherwise.

The active factor suggested thus becomes the level of volatility spread. We then test the results obtained by this simple and basic active strategy with respect to the Fama-French three-factor model and Carhart´s model, showing there is a statistically significant excess return.

Given that the tested model is simple, and can be achieved bay any algorithm, we suggest an additional factor labelled by us as the “active premium” to the Fama-French three-factor model and the Carhart´s model, aiming to capture the state of the nature and the simplicity of switching between portfolios.

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Graphs and tables

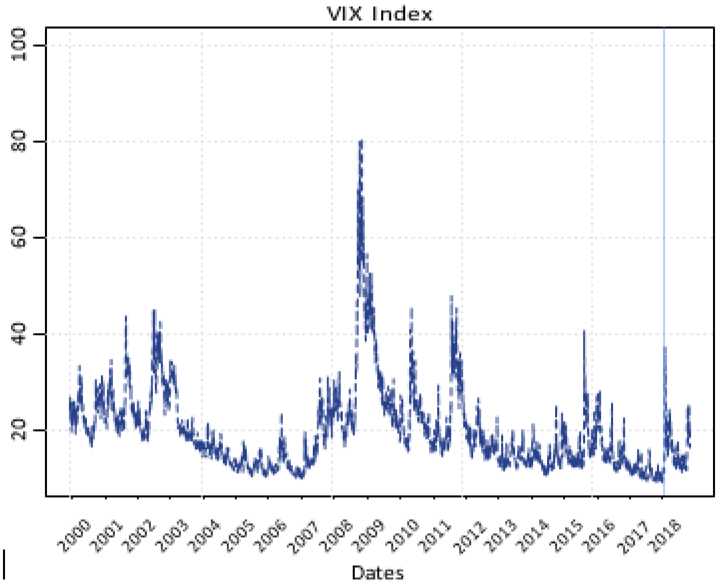

Figure 1: This plot presents the VIX Index from January 2000 to October 2018. The shaded area represents the "volatility event" under study on February 5.

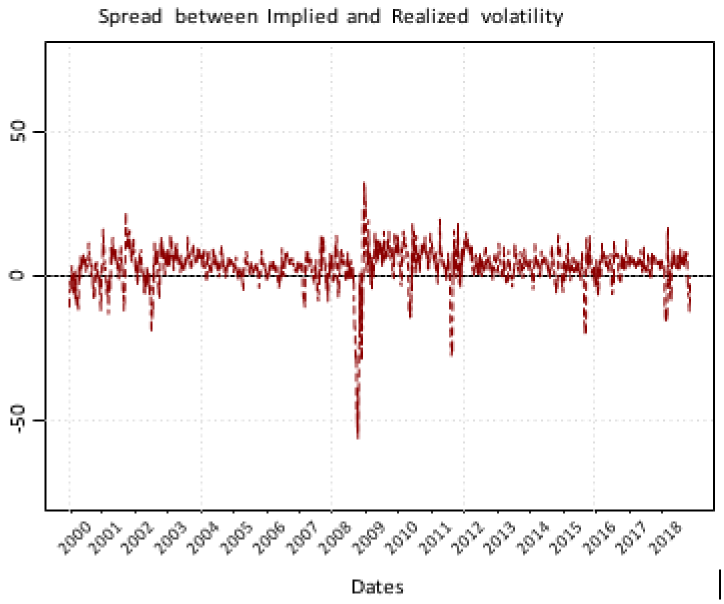

Figure 2: This plot presents the spread between the previous-month level of the VIX Index and the rolling 30-day close-to-close volatility from January 2000 to October 2018.

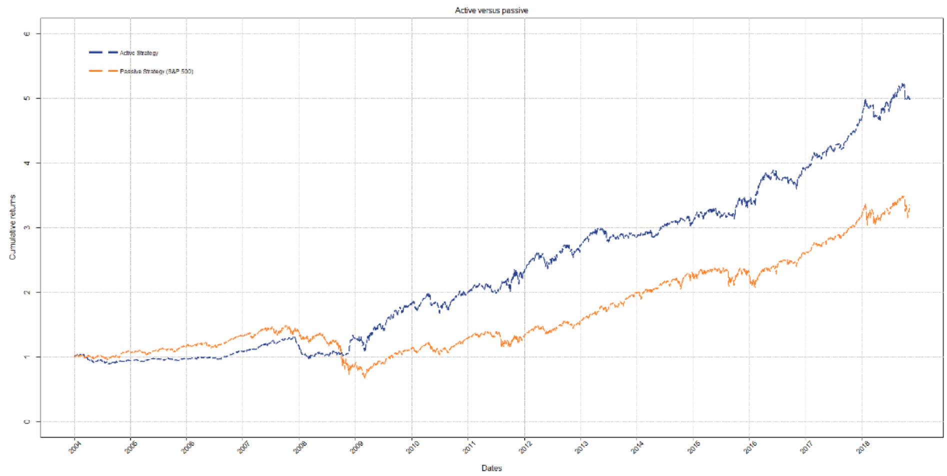

Figure 3: This plot presents the active strategy (blue equity curve) and the passive strategy (orange equity curve) during the period under analysis (2004 to 2018).

	S&P 500	Active S&P 500
CAGR	8.48%	11.36%
SD	18.28%	12.71%
Sharpe ratio	0.46	0.89
Skewness	0.15	0.26
Kurtosis	17.03	8.17
MaxDD	-55.18%	-25.95%
Calmar Ratio	0.15	0.44

Table 1: This table shows the descriptive statistics and ratios on annual basis of the S&P 500 Index and the Active S&P 500 strategy for the whole sample (from April 2004 to October 2018).

	Alpha	RMRF	SMB	HML	MOM	Adj.R2
FF Model	0.0003	0.332	0.148	0.149		0.31
	(3.12)	**(31.77)**	**(7.03)**	**(7.82)**		
Carhart Model	0.0003	0.324	0.145	0.109	-0.057	0. 32
	(3.19)	**(30.63)**	**(7.24)**	**(5.09)**	**(-4.04)**	

Table 2: This table shows the results of regressing the active strategies returns against different factor models: Three Fama-French Model and the Four Carhart model. Bolded t-stats are significant at 95% level.