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A UPSIDE/DOWNSIDE PERSPECTIVE TO MOMENTUM STRATEGIES IN THE S&P 500

The Development of a Novel Volatility Model for Stock Selection

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ABSTRACT

The analysis brings forward a novel empirical model that accounts for upside-downside beta and introduces VIX as a measure of market volatility with the intention of improving the flaws of momentum strategies through a different stock selection process. The study focuses on the constituents of the S&P500 in the period 1985-2016. The study reveals that this strategy displays low volatility and other relative advantages in comparison to the market and to the classical price momentum; however it is significantly not profitable. The unprofitability of the latter is a stimulus to investigate a related stock selection based only on the excess returns generated by the individual assets prior to the investment period.

Key Words: Momentum, Upside Beta, Downside Beta, Volatility

INTRODUCTION

"Big Mo is investors' guilty little secret. You can rely on momentum. But it makes many people feel uncomfortable" (Financial Times, John Authers, 2014)

Jegadesh and Titman (1993) have been the pioneers of what it is called momentum investing. They state and prove that buying recent winners and short selling recent losers creates abnormal returns in a presumably efficient financial market. Particularly, they prove that these abnormal returns are not a direct cause of systematic risk or slow price adjustment to firm's specific information as was initially believed. Since their study, momentum strategies have been a hot topic on the lips of academics, professionals and economic journals. Still, even though momentum was found across different asset classes ranging from commodities, credits, currencies, equity indices and cross assets environments, there has not yet been an agreement with regards to the sources of this phenomenon.[1] Classic literature points towards behavioral and price reaction justifications while recent work develops, on top of that, a risk based approach that does not necessarily explain momentum, but rather filters differently the selection of stocks to include in the portfolio with the purpose of creating a more profitable and stable investment strategy.

Regardless of the reasons, momentum proves to generate excess and generally stable returns but also has major flaws which make investors feel uncomfortable, such as the specific volatility of the strategy. The significant losses that can be experienced in times of panic and volatility are the cause of sleepless nights for investors, who feel as if they were sitting on a ticking bomb. The latter sensation is well expressed by the initial quote and is the main

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[1] See Asness, Liew, and Stevens (1997) for country stock indices. Okunev and White (2003) and Menkhof, Sarno, Schmeling, and Schrimpf (2012) for currency markets. Moskowitz and Grinblatt (1999) for industry portfolios. Erb and Harvey (2006) for commodities, and Asness, Moskowitz, and Pederson (2013) for momentum across asset classes.

inspiration of this study, which aims at exploring a novel empirical model of stock selection with the scope of selecting profitable stocks in times of high market turmoil. In this model, the difference between the upside beta and downside beta is exploited together with a forward looking measure of market volatility in order to compute stocks' individual expected returns, which ultimately will be used to rank and select stocks that will enter the WML (Winner Mins Loser) portfolio. In the next pages, a short summary of existing literature useful for the understanding of the topic is brought forward, followed by an analysis of the methodology and data used. A brief paragraph will explain the implementation of the methodology, resulting in the outcomes of this study. Lastly, possible reasons for flaws in the result will be covered and conclusions will be drawn.

LITERATURE REVIEW

Momentum has proven to generate excess returns and alphas. For instance, between 1927 and 2011, the strategy of buying recent winners and selling losers produced on average a 1.75% monthly excess return over the market after controlling for Fama-French factors (Barroso, Santa-Clara, 2014). [2] This is just one example of the many back tests carried out in the industry, all displaying similar results through the use of different sample periods, especially after WWII. What are still to be defined are the reasons that cause these abnormal returns. Literature such as Frazzini (2006), Grinblatt and Han (2005), Barberis, Shleifer, Hong and Stein (1999), Vishny (1998) and Daniel, Hirshleifer and Subrahmanyam (1998, 2001) attempt to infer to behavioral finance and price adjustment theories, but there is still no unique agreement. The aim of this

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[2] The abnormal performance has led researchers to add Momentum as a risk factor in the asset pricing world (Carhart, 1997)

paper is not to add further effort in analyzing the underlying reasons of momentum, but rather to build on what is already known with the singularity of developing a novel approach to stocks selection based on a simple empirical model.

On the other hand, returns of momentum strategies have proven to be particularly negatively skewed, meaning that the positive Sharpe ratios are knocked out by occasional strong reversal, or in a more simplistic term, "crashes". It has been observed that momentum strategies lose value in times of panic, defined as times of stress, in particular when the market has fallen significantly and forward looking measures of volatility are high (Daniel, Moskowits, 2013). As an example: the winner-minus-loser (WML) portfolio lost 91.59% and 73.42% in a couple of months in 1932 and 2009 respectively (Barroso, Santa-Clara, 2014). Adding to the previous argument, momentum strategies suffer especially in rebound markets, when returns are high following a severe crush. This is in line with the fact that WML portfolios have a negative beta following bear markets (Grundy and Martin, 2001). Indeed, it is a direct cause of the sorting process in the formation period: during crisis the strategy will short high beta stocks and long low beta stocks, which will perform better. The problem for momentum strategies arises when the market rebounds as the portfolio is exposed to negative beta and, instead of being long high beta stocks, the portfolio will short them for the same duration of the length of the formation period is.

Having realized the pitfalls of momentum, academics started to find ways to improve and to hedge the performance. One of the first attempts was explored by Grundy and Martin (2001), whose study concluded that investing in momentum strategies involves a non-trivial bet on momentum in the factor exposures of returns. Those stocks that were exposed to well performing factors during the formation period are more likely to be in the WML portfolio. Thus, by hedging the WML portfolio's exposures to the market and size factor, they were able to achieve stable

returns with a 78.6% decrease in the variability of monthly returns.   Later on, Daniel and Moskowits (2012) focused their effort in mitigating the time varying systematic risk of momentum by using real time betas. However, this does not prevent crashes to happen and creates forward looking biases. Furthermore, Pedro and Santaclara (2015) highlight the importance of aggregate momentum-specific volatility in determining momentum performance. They prove that targeting a constant volatility level by scaling the portfolio with six months realized volatility brings significant economic gains to the momentum strategy. This risk based approach improves excess kurtosis from 18.24 to 2.68 and negative skewness is reduced from -2.47 to -.42. They argue that this method is superior to using time varying betas for hedging as market risk accounts only for 23% of total risk. Instead, they focus on predicting strategy specific risk which is more persistent and predictable than the market component.

An equally important financial concept to be mentioned for the understanding of the rationale behind this study and the proposed innovative stock selection model is downside risk. At this point in time, academics have agreed that investors are differently sensible to downside losses and upside gains, giving more weight to the adverse scenario (Roy, 1952). Since then, the focus has been on introducing new measures of risk, such as semi-variance (Markowits, 1959) and new ways of giving heavier weight to downside risks in investors utility functions: Kahneman and Tversky's (1979) loss aversion preferences and Gul's(1991) axiomatic approach to disappointment aversion preferences.[3] Further studies have tried to exploit the previous findings to achieve acceptable returns: Ang et al (2005) conclude that stocks that significantly co-vary with down moments in the market, display high average returns. They determine that the cross sectional premium required to bear downside beta is approximately 6% per year. They also

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[3] Semi-variance measures downside losses rather than upside losses

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conclude that past downside beta predicts future covariation in future market downturns, unless the stock is very volatile by nature. Our study tries to merge the above mentioned concepts: it aims at an improvement of the standard price momentum strategy through a model of stock selection based on the asymmetric nature of beta and on market volatility.

A successful attempt in tying momentum returns with downside and upside risks is brought forward by Dobrynskaya (2015). In this study it is shown that traditional beta has no explanatory power in explaining momentum returns. Contrarily, using relative downside beta for measuring the extra downside risk seems to be significant in explaining returns of the momentum portfolios. In other words, the exposure to downside risks and the hedge against upside risk is obviously unattractive for investors and thus this asymmetric risk profile carries a premium. [4]

A last aspect that I would like to touch to conclude this academic introductory section regards CAPM. Even if it is still used in the academic world, professionals soon started to deviate from the actual efficiency of this model for asset pricing purpose. A first view completely rejects the model when index returns are used as proxy for market returns. [5] Another view, instead, argues that beta is not the only factor but rather size, value and momentum should be added to the model (Fama French, 1993/1996). Another line of thought, as Bawa and Lindenberg (1977) advocate, is an extension of CAPM such that it takes into consideration the asymmetric exposure to downside and upside risk (beta). Further convincing evidence that the latter extended version of CAPM has better explanatory power in currency, bonds, commodity and equity markets is brought forward by Lettau et al. (2014) and Dobrynskaya (2014), who show that the commonly asset returns are greatly explained by the exposure to downside risk. This version of CAPM will serve as prompt to our empirical model.

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[4] Relative downside beta is measured by subtracting downside beta from the "normal" beta

[5] Roll (1977) and Ross (1977) argue that the market portfolio is not observable.

METHODOLOGY

The momentum strategy developed by Jegadesh and Titman in 1993 selects stocks based on their cumulative performance over a prior formation period, somehow challenging the efficient market hypothesis stating that past performance is not a good predictor of future performance. The WML Portfolio is composed by long positions in the top decile of stocks that have performed well over the formation period and by short positions in the bottom decile of stocks that have performed the worst over that same period.[6] It is important to introduce the classic momentum strategy as this will be used as terms of comparison to the one being developed in this paper.

The strategy that we bring forward applies the same principles of the classic price momentum strategy but brings innovation in the way stocks are selected based on their expected return, rather than past performance.[7] As previously expressed, the empirical asset pricing model that is used is an altered derivation of the traditional equilibrium CAPM model, with the peculiarity of the separation between upside and downside beta. Therefore, the equation that can be used to describe the empirical relationship that is hypothesized and which investors use as a forecasting tool when building an optimal portfolio, is the following:

$$r_{i,t} = \alpha_i + \beta_i^+ r_{m,t}^+ + \beta_i^- r_{m,t}^- + \varepsilon_{i,t} \qquad (1)$$

Given

$$r_{m,t}^+ = \max(0, r_{m,t}) \qquad \text{and} \qquad r_{m,t}^- = \min(0, r_{m,t})$$

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[6] The formation period can be of any length. However it has been proved that a formation period of 11 or 12 months is the length that enhances the most the effect of momentum strategies.

[7] A formation period, an investment/holding period, rebalancing at each interval.

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Where $r_{i,t}$ is the daily asset return, $r_{m,t}^+$ and $r_{m,t}^-$ are the market positive and negative market daily excess returns (respectively) and β_i^+ and β_i^- are the upside and downside daily betas.

A first assumption must be drawn here: market returns are normal and have a mean of zero and a standard deviation equal to the market volatility σ_m. Normality of market returns is known not to be true. However, it is very common in financial literature to assume normality for the simplification and development of models and derivations that could not be done in a non-normality setting. [8] I will follow the literature and will assume returns to be normal for two further reasons. Firstly, the strategy is developed for short holding periods resulting in a small number of observations in the investment period which lets us safely conclude that there is no much loss of generality in assuming market returns with mean zero. Secondly, the stocks selected at the rebalance date are independent from the ones that were in the portfolio previously.[9] Thus, assuming normality and taking expectations we have that (1) becomes:

$$E[r_{i,t}] = \alpha_i + \beta_i^+ E[r_{m,t}^+] + \beta_i^- E[r_{m,t}^-] \qquad (2)$$

A well-known statistical result about the conditional expectation of normal random variables allows the derivation of the following:

$$E[r_{i,t}] = \alpha_i + (\beta_i^+ - \beta_i^-)\sqrt{\frac{2}{\pi}}\sigma_m \qquad (3)$$

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[8] In practice, contrary to literature, financial management firms, funds, hedge funds, investment banks and many other financial institutions work with the non-normality of returns

[9] In other words: A stock could remain in the portfolio for one month, but also for two or more depending on the expected return it generates, but the allocation of stocks to be included in the portfolio is independent from the previous allocation. Therefore the same principle expressed previously can be applied.

Where σ_m is the market's volatility. The portfolio construction will be then based on the ranking and sorting of different assets dependent on the value of the daily $E[r_{i,t}]$. The main motivation driving this empirical model is that an investor should be able to select profitable stocks even in times of high volatility. In this setting, stocks with high downside betas might have low or even negative expected returns in times of high market volatility. A more precise and detailed explanation is provided in the "Key Hypothesis" section later on. A last remark before introducing the sample data and the implementation of the model is about holding periods. As previously stated, the main focus is to use short term holding periods. However, holding periods of six months and one year are reported both with the intent of confirming that momentum benefits disappear with longer investment periods, but also as a measure of comparison of performance.

DATA

The sample of this study includes all the constituents stocks of the S&P 500 Index for the past thirty years, from 1/1/1985 to 1/1/2016. As eleven months of observations are used for the formation period and the desired outcome is to represent the back tested performance of the various strategies in the past thirty years, data in 1985 is used only to accommodate the formation period calculation. Moreover, it makes sense to use data from the most recent thirty years as it is a way to observe if momentum is dead or not, since most trading strategies are profitable only until they are not vastly known.[10]

There are several reasons for which the S&P500 members were used in this research rather than the whole US equity world. Firstly, the performance of these stocks is closely monitored by all institutional and individual investors, providing a good proxy of sector and

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[10] Momentum now is a well-known strategy among investors.

market performance. This monitoring ensures high trading volumes on average, guaranteeing a cheaper price in terms of Bid Ask spreads. Especially in strategies such as momentum where there is a high turnover of positions due to the frequent rebalancing, trading costs can have a huge and significant effect, possibly wiping out any gains that the strategy has created in the first place. Therefore, limiting the sample to stocks that display higher market liquidity and guarantee a smaller Bid-Ask spread, allows a better representation of the cost implications of executing trading strategies.

Daily prices from January 1985 to January 2016 were obtained through *Datastream* together with an updated constituent list of the index per year. It is important to account for member changes in order not to incur in a survivorship bias. The figure below gives a detailed representation of the member's turnover within the Index over time.

Figure 1. S&P500 New Companies per Year
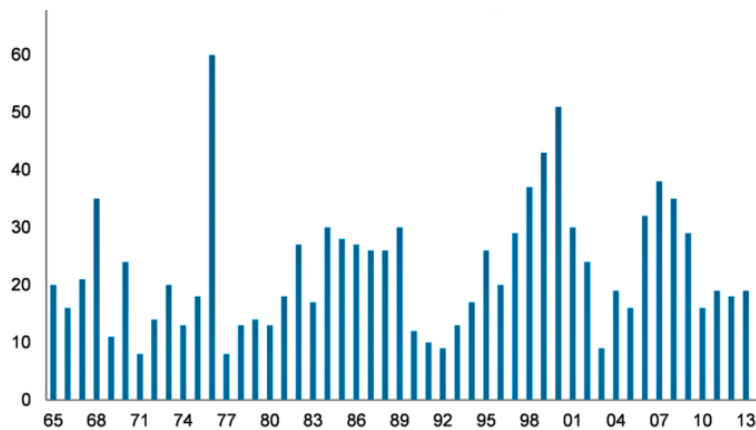
<div align="right">Source: Thomson Reuters, Morgan Stanley Research</div>

As per the market return, the most natural choice is to use the S&P500 Index returns, which are often considered as a good proxy of the US market performance. Clearly the market portfolio cannot be replicated, consequentially most academics and professionals use this Index

as benchmark for back testing trading strategies.[11] Daily index closing bid prices were also obtained from *Datastream* as well.

The variable that brings innovation in the strategy and in the way stocks are ranked is market volatility (σ_m), which is used to estimate $E[r_{i,t}]$. An indicator that is closely watched by financial institutions and investors is the VIX index, also known as the CBOE Volatility Index, which it used for the variable σ_m. This measure, calculated by the Chicago Board Options Exchange, represents the implied volatility of options that have, as underling value, the performance of the S&P 500 and is often referred as the *fear index*. In practical terms, the VIX Index is a forward looking measure that represents the market´s expectation of US equity market volatility within the next 30 days. Two main adjustments have to be made to this measure. As the VIX Index was firstly quoted only in 1990 and in light of avoiding losing five years (1985-1990) of observations, an estimate of VIX values prior to 1990 was used.[12] Generally the VIX Index overestimates the actual realized volatility in the subsequent months, therefore σ_m in (3) is adjusted. An analysis of VIX levels and the realized volatility in the subsequent month has been carried out, leading to the conclusion that during the period 1985-2016, on average, the VIX overstated realized volatility by 146.8%, making the adjustment necessary in order to have a realistic estimation of $E[r_{i,t}]$.

IMPLEMENTATION

The ultimate goal of this approach is to create reliable trading signals which, implemented in back-testing scenarios, will provide returns of the strategies. For the classical price momentum strategy the daily signals were created by ranking cumulative performance at any point in time

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[11] Or similar variations such as ETFs replicating the S&P500 as the index cannot be traded on itself.

[12] See Appendix

computed over the previous eleven months. On the other hand, the daily trading signals for our strategy were created by ranking daily expected returns estimated from (3). [13]

In order to estimate $E[r_{i,t}]$ through (2), it is necessary to estimate first α_i, β_i^+, β_i^-. These are computed with an OLS rolling window regression for every individual asset with an eleven months window and daily step.[14] The outcome of this regression will provide an estimate of daily alpha, daily upside and daily downside beta for all the stocks present in the S&P500 at that point in time. Upside betas are estimated by regressing stocks' daily returns only when the market shows positive returns and the exact opposite principle applies to downside beta. After these estimates are produced, an expectation of daily return per each asset is formulated through (3), including the adjustment of volatility overestimation mentioned in the previous section. The next step is to rank daily $E[r_{i,t}]$ and create daily trading signals would allow to go long the top decile (50 stocks) and go short the bottom decile, accounting for different holding periods. These signals multiplied by the according daily returns allow deriving strategies' returns.[15] The assumed portfolio construction is that of an equal weighted portfolio that is long and short fifty stocks, and whose daily return is the average of the individual assets´ returns that enter the portfolio.

Both strategies follow the results of previous literature suggesting that a formation period of eleven months is the time frame that creates the most advantages for momentum strategies. Furthermore, both strategies share a waiting period of one month between the formation period

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[13] Stocks that ranked in top decile receive trading signal 1 (long position) and those that ranked in the bottom decile receives -1 (short position), otherwise 0 meaning no position taken in that stock in that particular day.

[14] This allows to have daily observations of Alpha, Upside and Downside Beta.
[15] The signals created at T are multiplied by the daily returs at T+22 to account the one month waiting period before the investment period.

and the investment period. In other words, the investment decision at any certain point in time is dependent on the trading signals created during the previous month on the basis of data from twelve up to one month prior to investment period or rebalancing date. This is done in order to avoid short term reversal that has been documented by Jegadeesh (1990). In his study, Jegadeesh brings forward the argument that over the period 1934-1987 the strategy that buys and sells stocks based on their previous month performance and holds them for the subsequent month is able to generate on average a monthly excess return of 2%, thus explaining the avoidance of such short term reversal period that is damaging for momentum strategies.

A last aspect that has a significant effect on the cumulative returns of the various strategies is the holding period. Holding periods of ten days up to one, three, six and twelve months will be analyzed here. Again, long holding periods of six months and one year have the mere function of measure for comparison, since it is known already that longer holding periods diminish momentum performance.

KEY HYPOTHESIS

The key hypothesis is that in times of high volatility one can still find winners whose future expected performance is relatively independent from volatility. The Beta strategy aims at the exploiting the following scenarios:

- If $\beta_i^+ > \beta_i^-$ and volatility is high, it will generate a high estimate of $E[r_{i,t}]$ meaning that it is more likely to be inserted in the long top decile portfolio. Being long these stocks, the position would have a smaller loss when the market declines and have a bigger gain when the market rebounds, especially after a period of high volatility. The idea is therefore to exploit the higher upside Beta for when the market has a positive return.

- If $\beta_i^+ < \beta_i^-$ and volatility is high, $E[r_{i,t}]$ the expected return will be negative. This is will cause these stocks to be in the low decile portfolio, which will hold a short position. These positions are taken in order to take advantage of the high volatility and the negative performance of equities in such periods. In these cases, the gain of a short position would be greater than the loss in case the market return is positive.

- If $\beta_i^+ < \beta_i^-$, $\beta_i^+ > \beta_i^-$ but the volatility is low, the same concept applies and the strategy aims at taking advantage of the differences in upside and downside beta. In fact, forward looking volatility is used to scale and boost the difference between upside and downside beta.

It is the case that in bearish markets, especially when volatility in the market is high, the downside betas of past losers (in terms of price performance) are low, while the upside betas are very large. This phenomenon does not seem to be priced and, therefore, when the market rebounds there are a lot of potential gains. The strategy proposed tries to capture this trend in a systematic way.

RESULTS

In this section the strategy under scrutiny is referred as "Beta" Strategy as opposed to the classical momentum strategy.[16] Beta Strategy refers to the process described until now, where stocks are ranked based on their $E[r_{i,t}]$ coming from equation (3). The current analysis takes into consideration holding periods of ten days and of one, three, six and twelve months and assumes 22 trading days per month. The outcome is an analysis of the cumulative performance of the Beta

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[16] Naming the strategy will help not making confusion later in the paper when another strategy is analyzed

Strategy and the classical price momentum as compared to the market.[17] A Graphical representation of each strategy per holding period is displayed below.

Figure 2. Cumulative Performance for Different Holding Periods

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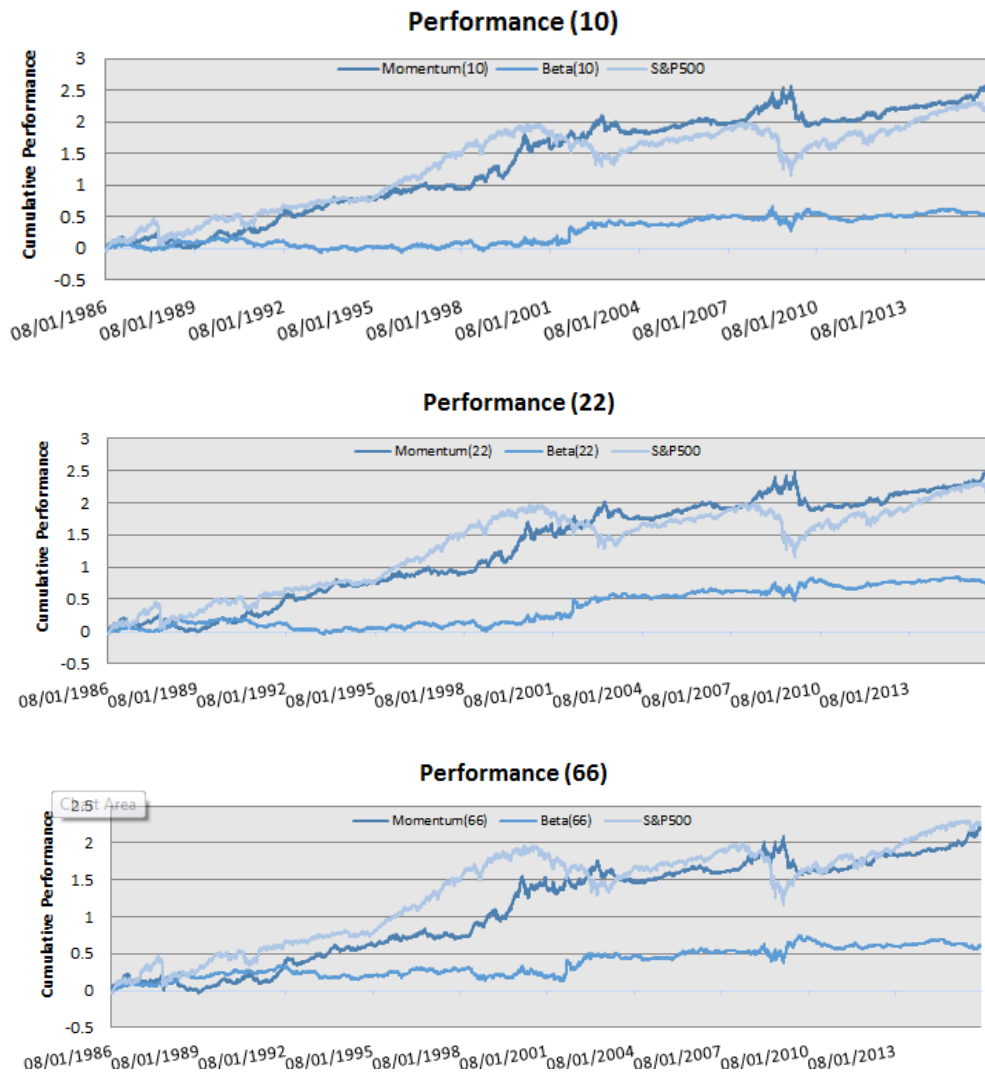
[17] 10 for ten days, 22 for one month, 66 for three months, 132 for six months, 264 for twelve months.

Performance (132)

Performance (264)
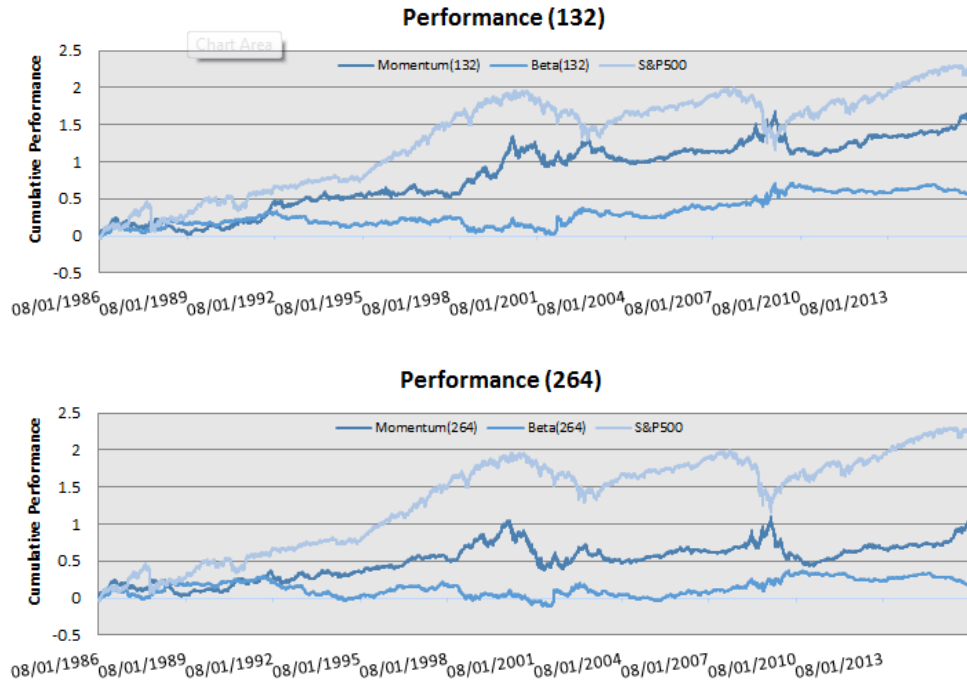
From the graphs above is possible to draw some initial conclusions. In the past thirty years momentum did not perform better than the market in terms of cumulative returns, especially with holding periods higher than one month. In addition, is possible to see that momentum performs the worst in times of market rebound after a crisis. This is in line with the discovery of Grundy and Martin (2001) that prove that WML portfolios have a negative beta following bear markets, caused by the sorting process in the formation period: during financial crisis the strategy will short high beta stocks and go long low beta stocks, resulting in a better performance than the market. However, when the market rebounds, the portfolio is exposed with negative beta. A further thing that can be noticed is that the Beta Strategy is not a losing strategy but it is an unprofitable one. Even if less volatile than the momentum strategy and the market, it underperforms them significantly. Before presenting performance statistics the strategies, it is interesting to see that a longer holding period has damaging effects to both approaches, as previously mentioned. The results are displayed below:

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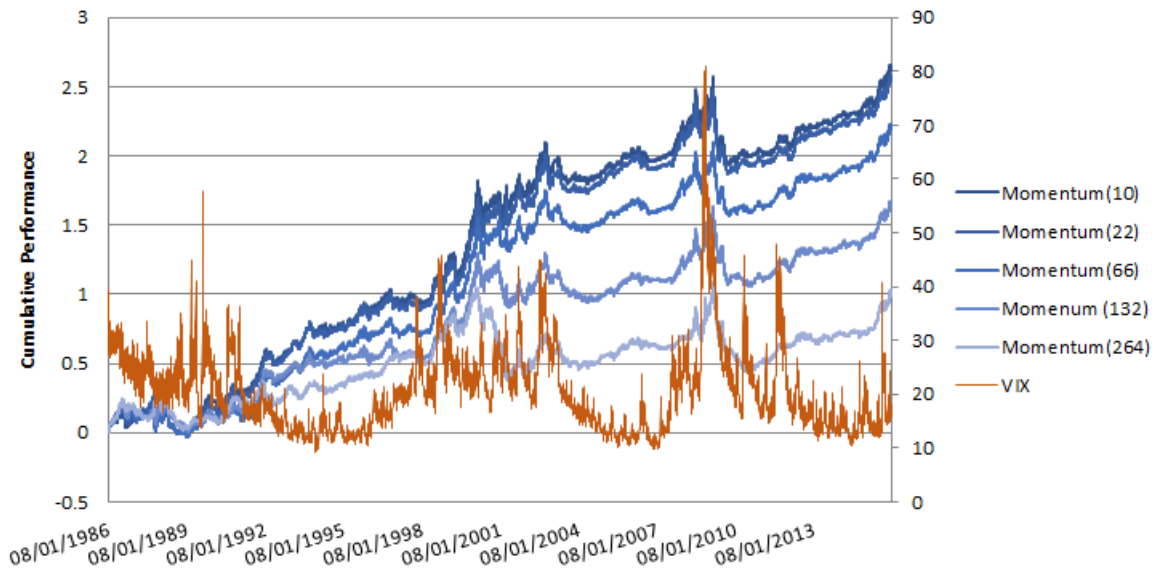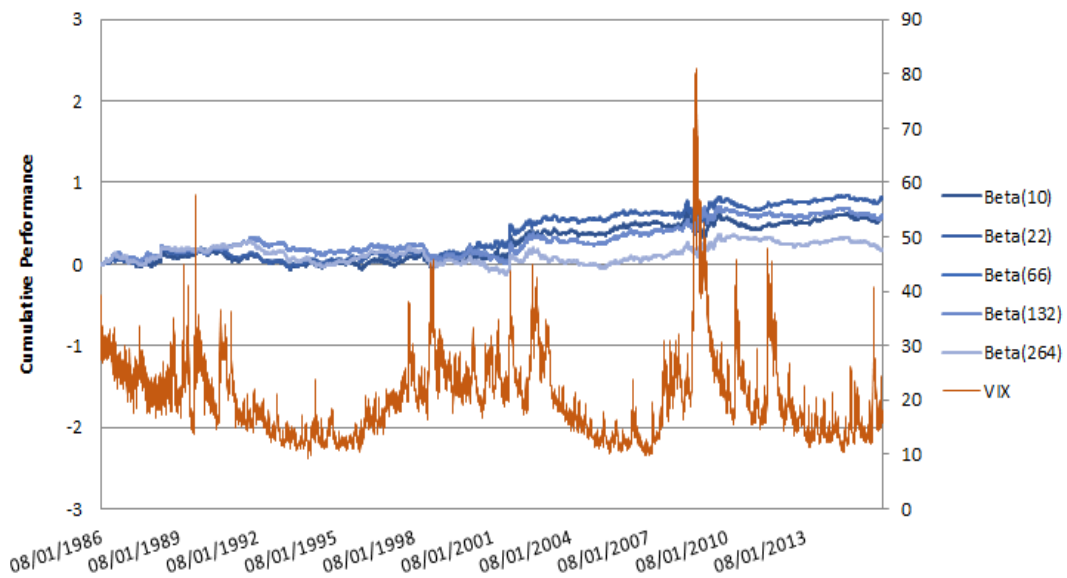**Figure 3. Momentum with Different Holding Periods**

Figure 4. Beta Strategy with Different Holding Periods

In terms of volatilities both strategies seem stable and experience some slight volatility in all different holding period scenarios when the VIX reaches high levels such as 40. What follows is a more detailed table with performance statistics that allow a better interpretation of the results.

Table 1. Performance Statistics: Beta, Momentum and Market

STRATEGY	S&P500	10 days		22 days		66 days		132 days		264 days	
		Momentum	Beta	Momentum	Beta	Momentum	Beta	Momentum	Beta	Momentum	Beta
Average Annual Return	7.503%	8.750%	1.891%	8.482%	2.689%	7.331%	1.987%	5.475%	1.926%	3.330%	0.576%
Standard Deviation	18.482%	12.733%	9.578%	12.679%	9.438%	12.230%	9.403%	11.572%	9.026%	11.606%	8.628%
Info Sharpe	0.406	0.687	0.197	0.669	0.285	0.599	0.211	0.473	0.213	0.287	0.067
Positive Days	53.75%	53.88%	51.36%	53.93%	51.06%	53.97%	51.03%	52.70%	50.55%	52.36%	49.95%
Daily Skew	-1.290	-0.667	2.065	-0.596	2.317	-0.571	2.321	-0.478	2.963	-0.416	3.287
Daily Kurt	28.560	9.799	68.774	9.161	71.569	8.993	73.622	8.279	85.015	9.548	97.921
Daily Max	0.1096	6.335%	12.533%	6.579%	15.400%	6.908%	15.400%	6.415%	15.400%	6.579%	15.400%
Q3	0.0055	0.412%	0.274%	0.405%	0.272%	0.425%	0.274%	0.360%	0.266%	0.341%	0.265%
Med	0.0003	0.034%	0.000%	0.032%	0.000%	0.033%	0.000%	0.013%	0.000%	0.010%	0.000%
Q1	-0.0043	-0.315%	-0.248%	-0.315%	-0.250%	-0.331%	-0.247%	-0.300%	-0.245%	-0.292%	-0.247%
Daily Min	-0.2290	-8.974%	-5.530%	-8.475%	-5.253%	-8.898%	-5.253%	-8.319%	-4.939%	-8.532%	-3.929%

Clearly the Beta Strategy is not a profitable one, but still something can be said about it. The one month holding period scenario is the one that provides the highest yearly average return of 2.689% and a standard deviation of 9.438%, having a Sharpe ratio of 0.285. Despite the poor performance the strategy provides a yearly volatility of around 9%, half of the market volatility in the past thirty years and on average 3% lower than the momentum strategy. Another problem that in this specific case "plays in favor" of this strategy, is the extremely high daily kurtosis and the high positive skewness. In practical terms this means that the strategy experiences small returns on average but has frequent big gains such as 15.4%. Leveraging up the strategy could be one solution to increase the expected average yearly return, but leverage also increases the risk and therefore the volatility of the strategy, with the result of not improving the Sharpe ratios. Speaking briefly about momentum, it is possible to confirm the excess average annual return of about 1.25% over the market and a much better risk return profile, displaying a 0.687 Sharpe ratio compared to 0.406 of the Beta Strategy. Due to different number of assets in the sample, it

can be observed that momentum has indeed lost value during the financial crisis of 2009, but not of 73.42% as previous literature suggested. A last thing that can be seen is that the maximum daily loss experienced in the past thirty years is of -5.253% compared to the -8.475% of price momentum and the -22.9% of the market, further demonstrating the lower risk of this trading idea.

Before analyzing pitfalls of the Beta Strategy, another interesting and more satisfying alternative that can also be derived from this same model below is analyzed.

$$E[r_{i,t}] = \alpha_i + (\beta_i^+ - \beta_i^-)\sqrt{\frac{2}{\pi}}\sigma_m$$

A better performing strategy can be constructed by using the daily alphas (α_i) estimated through the same rolling regressions as a basis to create new rankings and new trading signals. Therefore, this variation would go long (Short) short the top (bottom) decile of stocks that have experienced better (worst) daily alphas in the eleven months from T-12 to T-1, estimated through the above model. This is more commonly known as alpha momentum and will be referred as Alpha Strategy. The two strategies are not so different from each other and it can be stated that the Alpha Strategy is a variation of the Beta Strategy. In fact, the Beta Strategy ranks the stocks based on their $E[r_{i,t}]$, which by definition of the empirical model used, includes also daily alphas (α_i), while the Alpha Strategy ranks stocks based only on this latter measure. This separation is thrived by the breakdown of the Beta Strategy for the purpose of understanding the flaws that cause it to be unprofitable. Below, the graphical cumulative performance of the Alpha Strategy with regard to VIX and the market is displayed.

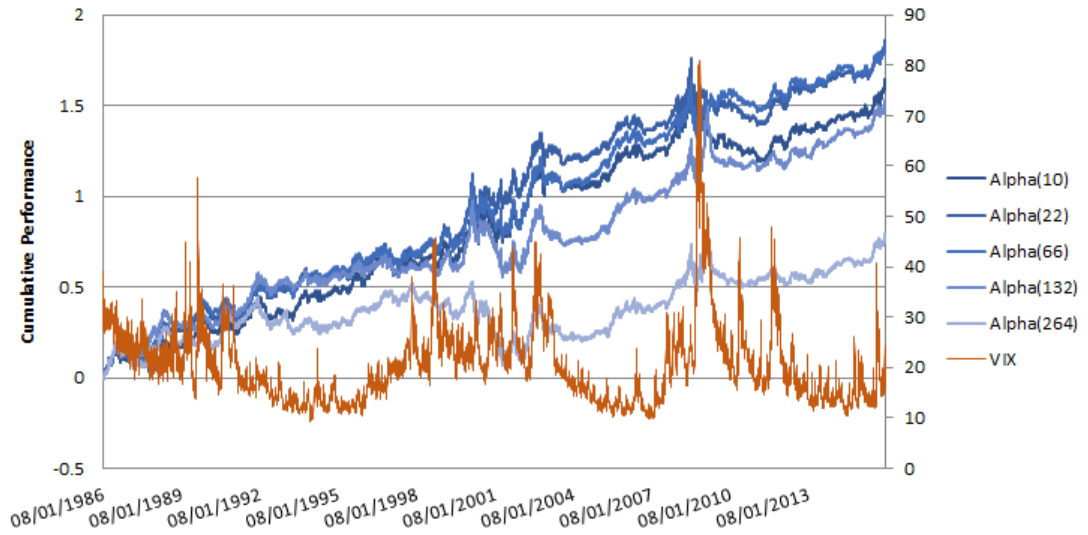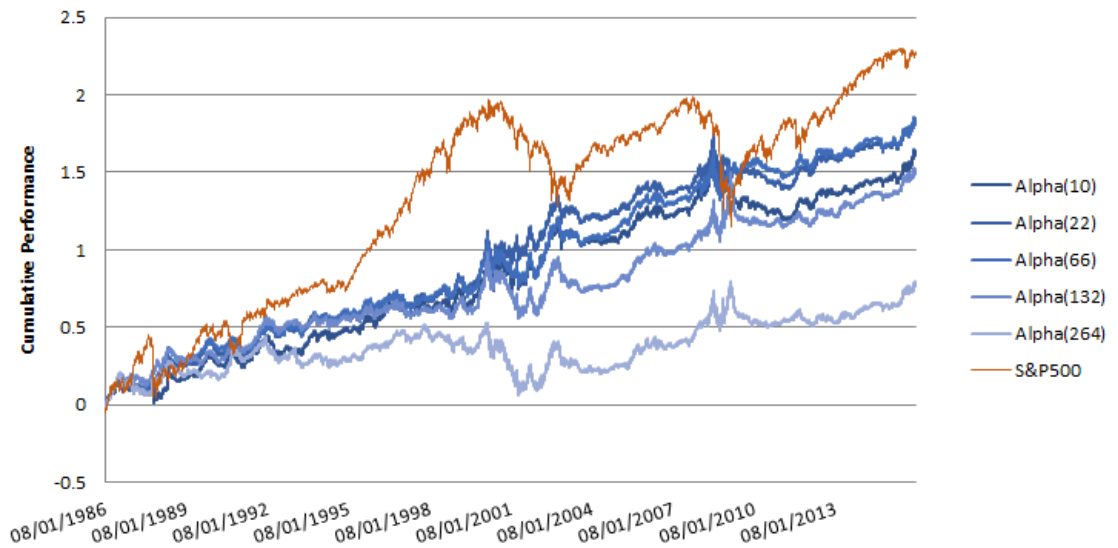**Figure 5. Alpha Strategy with Different Holding Periods**

Figure 6. Alpha Strategy Perforormance vs the Market

As the graphs above display, the Alpha Strategy seems superior to the Beta Strategy. It is relevant and interesting to notice that the first performs quite well in times of market declines, which correspond to times of increasing volatility. The separation of the upside and downside beta and the scaling with volatility levels allows for a good estimation of alphas, resulting in a

valid strategy. Furthermore, the latter seems to be inferior to the market only in terms of cumulative performance but as it is possible to note from the below table, it displays higher Sharpe ratios.

Table 2. Performance Statistics: Alpha, Momentum and Market

		10 days		22 days		66 days		132 days		264 days	
STRATEGY	S&P500	Momentum	Alpha	Momentum	Alpha	Momentum	Alpha	Momentum	Alpha	Momentum	Alpha
Average Annual Return	7.503%	8.750%	5.396%	8.482%	6.096%	7.331%	6.057%	5.475%	5.000%	3.330%	2.585%
Standard Deviation	18.482%	12.733%	10.852%	12.679%	10.783%	12.230%	10.733%	11.572%	10.418%	11.606%	10.094%
Info Sharpe	0.406	0.687	0.497	0.669	0.565	0.599	0.564	0.473	0.480	0.287	0.256
Positive Days	53.75%	53.88%	53.37%	53.93%	53.50%	53.97%	53.67%	52.70%	52.47%	52.36%	51.99%
Daily Skew	-1.290	-0.667	-0.410	-0.596	-0.417	-0.571	-0.398	-0.478	-0.385	-0.416	-0.512
Daily Kurt	28.560	9.799	12.689	9.161	11.835	8.993	12.177	8.279	8.483	9.548	7.473
Daily Max	0.1096	6.335%	8.859%	6.579%	8.500%	6.908%	8.500%	6.415%	5.096%	6.579%	4.822%
Q3	0.0055	0.412%	0.345%	0.405%	0.360%	0.425%	0.351%	0.360%	0.328%	0.341%	0.313%
Med	0.0003	0.034%	0.022%	0.032%	0.021%	0.033%	0.022%	0.013%	0.010%	0.010%	0.003%
Q1	-0.0043	-0.315%	-0.276%	-0.315%	-0.278%	-0.331%	-0.278%	-0.300%	-0.269%	-0.292%	-0.269%
Daily Min	-0.2290	-8.974%	-6.726%	-8.475%	-6.692%	-8.898%	-6.692%	-8.319%	-4.948%	-8.532%	-4.948%

The Alpha Strategy is not superior to price momentum, expect with six months between rebalancing dates, but it is always superior to the market in terms of Sharpe ratio. Both price momentum and alpha momentum fail to perform better than the market when the holding period is twelve months and in absolute terms the second displays a lower annual standard deviation. Moreover, the Alpha strategy shares the same trend with regard to holding periods: in general the longer the investment period, the worst the performance. The alpha approach also displays a third of Kurtosis and Skewness with respect to the market, being on average around 10-11 and -.4 respectively.

ROBUSTNESS AND PITFALL

As seen until now, the Beta Strategy failed to deliver acceptable performance, while the Alpha Strategy performs better than the market but slightly worse than the classical momentum strategy. Since the individual asset's daily alphas are calculated with the same rolling regression as for the upside and downside betas, and, given the fact that the Alpha Strategy performs well, it must be then that the component of the empirical model that cause it to be unprofitable is $(\beta_i^+ - \beta_i^-)\sqrt{\frac{2}{\pi}}\sigma_m$. Since volatility has already been adjusted to respect realized volatility, unprofitability can be caused by the estimation of upside beta and downside beta. To test if this is the case, the correlation between the beta estimated through the regression and the realized beta in the following two months is analyzed. This allows to test how precise the estimation of upside and downside beta out of sample is. As a matter of fact, it turns out that the correlation ranges on average between 0.03 and 0.05, a quite low and not significant value. This result must be interpreted carefully, however. First, the realized upside and downside beta was estimated through rolling regressions of 44 days to represent the realized beta in the waiting period and one month holding period, therefore too few observations. On the other hand, the betas estimated through eleven months might be slightly biased depending on the market health. For instance, if from any point in time until the following eleven months the market saw major gains, then the upside beta at the end of the period will be better estimated than the downside beta. This is simply due to the higher number of positive market return observations. On the other hand, in a period of crisis and recession, the market will display a higher number of negative days, therefore increasing the precision of the downside beta estimate at the end of the period. This is to say that it is likely that the expression above $(\beta_i^+ - \beta_i^-)$ will reflect some bias in the estimation, affecting $E[r_{i,t}]$,

CONCLUSIONS

Momentum is a phenomenon that has been studied for the past two decades and still there is no correct agreed rationale behind it. This paper as few others attempts to complement the Jegadesh and Titman's strategy of buying recent winners and short selling recent with a model that would prevent to avoid momentums major pitfalls. The introduction of an empirical model, which finds its roots in an equilibrium model such as CAPM, permitted the analysis of a strategy that attempts to use VIX and the gap between upside and downside beta to produce estimates of expected returns, used consequentially as criteria for ranking and selecting stocks of the S&P500. The Beta Strategy proposed does not seem to be a profitable one, especially if we take into account trading costs, but still some takeaways can be taken from this study. It has been confirmed that alpha momentum exists and is profitable while the estimation of betas does not have a strong predictive power for the following months. However, both Alpha and Beta strategies prove to have lower volatility and lower downside risk than the classical price momentum scenario. In my opinion, a further attempt in trying to derive a better model for the estimation of upside and downside beta that show predictive power over the subsequent months could be the solution to the unprofitability of the Beta Strategy.

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APPENDIX

1. MOMENTUM STRATEGY CODE

```
%calculation of daily log returns from prices.
for jj= 1:(size(Prices,2));
for ii= 2:size(Prices,1);
Daily_ret(ii-1,jj)=log(Prices(ii,jj)/Prices(ii-1,jj));
end
end

%takes out the NaN and substitutes them with 0 from daily returns.
Daily_ret(isnan(Daily_ret))=0;

%calculation of rolling comulative returns over the previous 11 months.
%Assumptions: Formation period equal to 11 months(242)days.
%            Trading days in a month is equal to 22
formation_period = 242;
Comu_ret = conv2(ones(formation_period,1),1,Daily_ret(:,:));
Comu_ret = Comu_ret(formation_period:end-formation_period+1,:);

%Need to tranform the zeros to NaN so that when you rank, we make sure to
%rank only those stocks trading at certain time period
Comu_ret(Comu_ret == 0) = NaN;

%ranks each components of each row excluding those NaN values
for i=1:size(Comu_ret,1);
    Rank2(i,:)= tiedrank(Comu_ret(i,:));
end

%creates a matrix where it repeats the rank every 22 days
rankfull2 = repelem(Rank2(1:22:end, :), 22, 1);

%removes last rows of matrix so that Rank1 and rankfull1 are of the same size
rankfull2= rankfull2(1:end-(size(rankfull2,1)-size(Rank2,1)),:);

decile2= 0.1;% which top and bottom percentile to go Long/Short

for iii=1:size(rankfull2,1)
for jjj= 1: size(rankfull2(1,:),2)
    if rankfull2(iii,jjj) < (decile2 *sum(~isnan(Comu_ret(iii,:)),2));
      signals2(iii,jjj)= -1;
    elseif rankfull2(iii,jjj) > ((1-decile2)* sum(~isnan(Comu_ret(iii,:)),2));
      signals2(iii,jjj)= 1;
    else signals2(iii,jjj)= 0;
    end
end
end

Position_imbalances = (sum(signals2 == 1,2))- (sum(signals2 == -1,2));

%eliminates the last month of signals as it will not be useful since future
%returns are not known

signals2= signals2(1:end-23,:);

%creates a matrix where the trading daily signal is multiplied to the daily
%return.
Sig_ret2= signals2(1:end-1,:).*Daily_ret(265+1:end,:);

%Calculates the daily average returns of the strategy. NaN substituted with
%zeros. NaN caused by non trading days.
stgy_daily2= sum(Sig_ret2,2)./(sum(Sig_ret2~=0,2));
stgy_daily2(isnan(stgy_daily2))=0;

%calculates the cumulative return of the strategy.
stgy_cum2= cumsum(stgy_daily2);
```

2 . *BETA / ALPHA STRATEGY CODE*

```matlab
for u= 1:(size(mkt_prices,2));
for uu= 2:size(mkt_prices,1);
mktretu(uu-1,u)=log(mkt_prices(uu,u)/mkt_prices(uu-1,u));
end
end


% the following loop creates 2 vectors with positive market returns and one
% with negative market returns (otherwise 0)

for x= 1:size(mktretu,1);
if mktretu(x,1)>0
MKTpos(x,1)= mktretu(x,1);
else MKTpos(x,1)= 0;
end
if mktretu(x,1)<0
MKTneg(x,1)=mktretu(x,1);
else
MKTneg(x,1)=0;
end
end
% the indipendent va riables in the regression should be a matrix
MKT=[MKTpos MKTneg];

%rolling regression
Y=Daily_ret;
X=MKT;
steps=size(Y,1); % this function gives you the size of the colume vector
window=242;%this is discrete window length
p=2; %number of regressors
adjustment=(window-1)/(window-p-1); % regressor adjustment for multiple regression
increment=1; %increment level
for k=1:assets;
for nn=1:increment:steps-window;
    b =regress(Y(nn:241+nn,k),[ones(242,1),X(nn:241+nn,:)]);
    Alpha1(nn,k)=b(1); %creates vector of rolling alphas
    Bp1(nn,k)=b(2);% upside beta
    Bn1(nn,k)=b(3);%downside beta

end
end

%ceates a matrix of the differences in upside downside rolling betas
Betadiff1=[Bp1-Bn1];

% calculates expected return.
Exp_ret1= Alpha1 +((bsxfun(@times,VIX(244:end,:),Betadiff1))*sqrt(2/pi)*(1/1.468));

%if Expected Return is 0 then it is substitited with NaN so for
%accomodating ranking
Exp_ret1(Exp_ret1 == 0) = NaN;


for nn=1:size(Exp_ret1,1);
Rank1(nn,:)=tiedrank(Exp_ret1(nn,:));
end

rankfull1 = repelem(Rank1(1:22:end, :), 22, 1); %creates a matrix where it repeats the rank every
22 days
rankfull1= rankfull1(1:end-(size(rankfull1,1)-size(Rank1,1)),:); %removes last rows of matrix so
that Rank1 and rankfull1 are of the same size


decile1= 0.1;% which top and bottom percentile to go Long/Short

for xx=1:size(rankfull1,1)
```

```
for yy= 1: size(rankfull1(1,:),2)
    if rankfull1(xx,yy) < (decile1* sum(~isnan(Exp_ret1(xx,:)),2));
    signals1(xx,yy)= -1;
    elseif rankfull1(xx,yy) >((1-decile1)* sum(~isnan(Exp_ret1(xx,:)),2));
    signals1(xx,yy)= 1;
    else signals1(xx,yy)= 0;
    end
end
end

%Calculates the position imbalance between the long and the short positions
Position_imb1 = (sum(signals1 == 1,2))- (sum(signals1 == -1,2));

%Takes out the last month signals as these will only be useful in the one
%month time
signals1= signals1(1:end-23,:);

%Creates a matrix by multiplying the return times the signals
Sig_ret1= signals1(1:end-1,:).*Daily_ret(265+2:end,:);

%Daily return of the strategy´
stgy_daily1= sum(Sig_ret1,2)./(sum(Sig_ret1~=0,2));
stgy_daily1(isnan(stgy_daily1))=0;

%cumulative returns
stgy_cum1= cumsum(stgy_daily1);
```
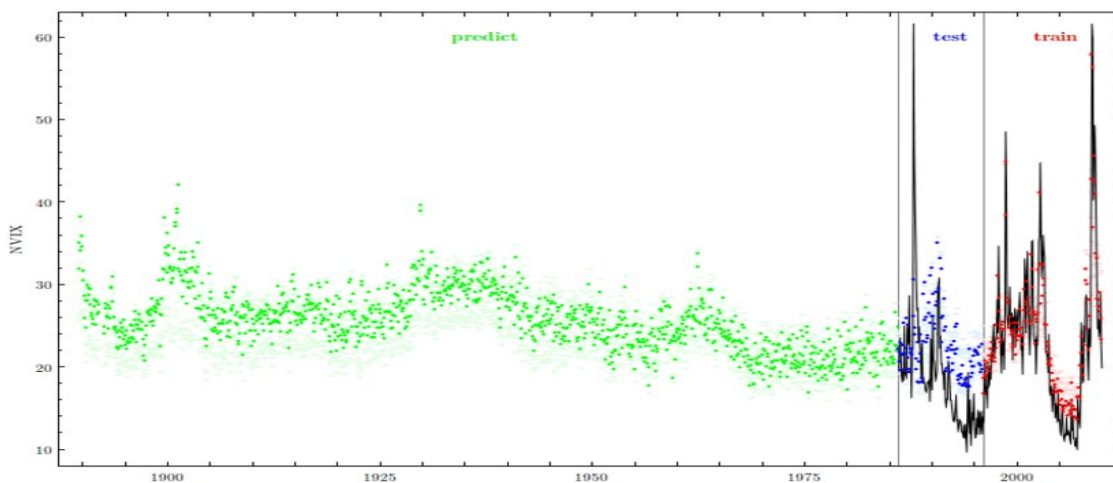
3. NVIX- NEWS IMPLIED VOLATILITY AND DISTASTER CONCERNS

In my analysis I used estimates of VIX for the period 1985-1990 as this volatility Index only started trading in 1990. The study carried out by Asaf Manela was a great discovery. They were able to construct a measure of uncertainty by analyzing words and phrases from front-page articles of the Wall Street Journal since 1890. Their measure, called News implied volatility (NVIX) reached high levels in times of market crashes, policy uncertainty, financial crisis and wars. Below is a representation of their data.