UNIVERSITY OF GOTHENBURG
SCHOOL OF BUSINESS, ECONOMICS AND LAW

Graduate School

Master Thesis

Quantitative tactical asset allocation: Using the VIX to exploit bull and bear market movements in a Mean-Variance portfolio

Christian Persson

Robin Williams

Contact information:

Christian Persson: guschrispe@student.gu.se

Robin Williams: gusrobiwi@student.gu.se

Thesis supervisor:

Charles Nadeau

Master Thesis, Spring 2020

School of Business, Economics, and Law at the University of Gothenburg

Abstract

The Chicago Board Options Exchange (CBOE) Volatility Index (VIX) is known as being an indicator of fear, often referred to as the *fear index*. Low volatility indicates tranquility in the market, whereas high volatility indicates distress. We aim to use the level of the VIX as an indicator for stock market movements and incorporate it into an investment strategy within a Markowitz (1952) mean-variance (MV) setting. By using Kenneth French's 12 industry assets over a 30-year window, we calculate the sensitivity between VIX and the assets. Further, by incorporating transaction costs, and testing for different input variables for the strategy, we build upon earlier papers by Copeland and Copeland (1999), and Cloutier, Djatej, and Kiefer (2017). The VIX strategy is tested against a simple moving average (SMA) strategy suggested by Faber (2013). We find evidence in suggesting that our VIX strategy, using MV as the outset portfolio, outperform the buy-and-hold strategy as well as the SMA strategy. Additionally, after introducing an equally weighted outset portfolio, the strategy is able to outperform the S&P 500 over the 30-years.

Keywords: *VIX, strategy, mean-variance, simple moving average, volatility, transaction costs, bull market, bear market*

Acknowledgements

We want to thank our supervisor Charles Nadeau for his guidance and crucial input to our thesis. We would also like to give our thanks to anyone who has supported us over the years.

Contents

1 Introduction **1**

2 Literature Review **3**

2.1 The History of Volatility Estimation in Portfolio Selection 3

2.2 Tactical Asset Allocation 5

2.3 Alpha and Factor Models 8

3 Data **8**

4 Method **10**

4.1 Constructing the Buy-and-Hold Outset Portfolio 10

4.2 VIX Sensitivity and Market State Thresholds 11

4.3 Tactical Asset Allocation 12

4.3.1 Difference 15

4.4 Transaction Costs 15

5 Results and Analysis **16**

5.1 Input Variables 16

5.1.1 VIX Correlation Window 17

5.1.2 Sensitivity 18

5.1.3 Lag Size 19

5.1.4 VIX Bounds 20

5.2 Return Period 22

5.3 Equal-Weighted Portfolio 25

5.3.1 Equal-Weighted Main Results 26

5.4 Bull Limit Test 27

5.4.1 Equal-Weighted Test 27

5.4.2 Mean-Variance Test 29

5.5 Best Outcome 31

5.6 Extended Data Set 33

6 Conclusion **35**

References **38**

Appendix **42**

List of Tables

1 Varrying Correlation Window . . . 17
2 Varying Asset Sensitivity . . . 18
3 Varying Lag Size . . . 19
4 Varying Upper Bound . . . 21
5 Varying VIX Thresholds Upper Bound . . . 26
6 Equal Weights Outset Portfolio . . . 28
7 Mean-Variance Outset Portfolio . . . 30
8 Optimal Solution . . . 33
9 Asset Descriptions . . . 42
10 Asset's Corresponding SIC-codes . . . 42
11 Bid-Ask Spread Cost per Asset Class . . . 43
12 Varying Upper Bound MV Setting . . . 43
13 Main Regressions Results . . . 44
14 Main Regressions Results Cost Adjusted . . . 45
15 Varying Upper Bound EW Setting . . . 46
16 Mean-Variance Outset Portfolio . . . 47
17 Equal Weights Outset Portfolio . . . 48
18 Varying Correlation Window . . . 49
19 Varying Asset Sensitivity . . . 49
20 Varying Lag Size . . . 49
21 Max and Min Weights Allocated for each Outset Portfolio . . . 50
22 Main Regressions Results Best Outcome . . . 50
23 Main Regressions Results Best Outcome Cost Adjusted . . . 51
24 Optimal Solution Extended . . . 51
25 Main Regressions Results Extended . . . 52
26 Main Regressions Results Extended Cost Adjusted . . . 53

List of Figures

1 Cumulative Daily Returns . . . 23
2 VIX Strategy Performance . . . 24
3 VIX_c vs. S&P 500 . . . 25
4 Different VIX Strategies with EW Outset . . . 32
5 Extended Data Set . . . 34

1 Introduction

During the 2007-2008 financial crisis, and the stock market crash of 2020, the rapid sell-off caused simple buy-and-hold portfolios to lose many years of accumulated gains. During both crises, the market observed record-level increases in volatility, which reflected in record-high levels in the volatility index (VIX). The VIX was first introduced by Brenner and Galai (1989), where the VIX, as we know it today, was created by CBOE and had its inception in 1993. From there on, the average market return and the level of the VIX have had a clear negative correlation. Whaley (2009) explores the actual interpretation of the VIX and argues that the VIX represents the expected future market volatility over the next 30 calendar days. Since the VIX has been argued to show the expected future volatility, several financial papers have explored the subject of forecasting volatility over the years, using the VIX as a market-timing tool.

In this paper, we build upon the subject of market timing strategies using the VIX. Earlier papers by Copeland and Copeland (1999), and Cloutier, Djatej, and Kiefer (2017), apply tactical asset allocation (TAA) strategies that exploit the level of the VIX in order to time the market. The main reason for using a TAA strategy is to reduce investor bias. Cloutier et al. (2017) conclude that investor anxiety increases during times with elevated levels of the VIX, which in turn leads to an emotionally biased investment strategy. However, if a tactical asset allocation strategy were applied instead of letting an investor control the divestment, such erratic behavior would be limited. The main reason for using a TAA strategy that specifically exploits movements in the VIX is to have an unbiased indicator that forecasts future bull and bear markets. In a practical sense, a TAA using the VIX reallocates a chosen number of portfolio weights using the VIX-level as an indicator for when this should happen. For example, our method is closer to Cloutier et al. (2017), which looks at the current level of the VIX, while Copeland and Copeland (1999) look at relative changes in the VIX-level.

However, one major area that is lacking in research looking into the subject of TAA is that papers often ignore, or only briefly, consider transaction costs. By not including transaction costs, the results by Copeland and Copeland (1999), and Cloutier et al. (2017), are inflated. In this paper, we aim to include rudimentary transaction costs and view them as a crucial part of the investment strategy. Therefore, a commission fee, a short-selling fee, and the bid-ask spread, are used to account for the cost of trading appropriately. The costs are derived from the papers by D'Avolio (2002), Do and Faff (2012), Abdi and Ranaldo (2017), and Engelberg, Reed, and Ringgenberg (2018).

Further, when developing an investment strategy that utilizes the level of the VIX for a bull- and bear strategy, it is crucial to test its performance against other investment strategies. A rather simple TAA strategy suggested by Faber (2013), uses a simple moving average (SMA) of asset prices, with monthly rebalancing. They find that their simple strategy performs well over a longer time-frame and sets a good baseline for how a rather simple unbiased TAA strategy can improve the performance of a portfolio. However, as is the case with the other mentioned papers, Faber does not include transaction costs. Nonetheless, our suggested VIX strategy is compared with the SMA strategy side-by-side during the whole sample period to see which strategy performs better.

What should be noted is that a TAA strategy builds upon an already existing portfolio, and in terms of alpha, a TAA strategy is profoundly affected by the initial portfolio allocations. In order to test an investment strategy that exploits implied volatility derived from options, DeMiguel, Plyakha, Uppal, and Vilkov (2013) use different minimum-variance and mean-variance (MV) portfolios, as well as an equally weighted (EW) portfolio. To shed light on how a TAA strategy is affected by the underlying buy-and-hold portfolio, we replicate the classic MV strategy first described by Markowitz (1952), the SMA strategy by Faber (2013), as well as the EW portfolio as described by DeMiguel, Garlappi, and Uppal (2009).

If we assume that TAA reduces investor bias as suggested by Cloutier et al. (2017), our paper shows that our TAA strategy, not only, reduces investor bias, but also increases portfolio returns with relatively lower volatility. When extending the data to the last economic crisis of 2020, we can also show that we produce a significant positive alpha. The alpha is higher than both the underlying buy-and-hold portfolio and the SMA strategy.

The remainder of this paper is structured as follows. Section 2 discusses previous relevant academic research. Section 3 describes the data used. Further, section 4 describes the methodology of the investment strategies. Section 5 depicts the results, which are then thoroughly analyzed and discussed. Lastly, section 6 summarizes our findings and suggests for future research.

2 Literature Review

2.1 The History of Volatility Estimation in Portfolio Selection

One of the most well-known portfolio selection methods that use volatility as a part of the investment strategy is the MV portfolio selection process. First introduced by Markowitz (1952), it is a method in which a portfolio is selected based on expected returns (means) and the volatility (variance) of different portfolio combinations with a chosen number of assets. Markowitz shows that the solutions from the MV selection process result in more efficient and diversified portfolios than any particular undiversified portfolio. However, today it is well-known that many alternatives outperform the MV portfolio selection suggested by Markovitz.

To further develop and improve on Markowitz's findings, investors and researchers have spent many years trying to predict movements and exploit forecast models to develop better portfolio allocation strategies. Many of these improvements have focused on estimating volatility and incorporating it into the strategy. One such famous estimation model is the ARCH model, autoregressive conditional heteroskedasticity process, proposed by Engle (1982). The ARCH process utilizes past volatility (variance) to forecast future volatility, Engle shows that future volatility conditional on past volatility is not constant, but rather that it depends on past volatility. This was later expanded upon by Bollerslev (1986), who introduced the GARCH process, generalized autoregressive conditional heteroskedasticity process.

During this time, research on the need of a volatility-based index, which could give insight into current market volatility started to arise. Brenner and Galai (1989) first proposed such an index, where the authors argue that investors were exposed to changes in volatility and should, therefore, have an alternative to hedge that risk. They mention that a volatility index should be introduced with the purpose of being the underlying asset for volatility futures and options. From this came the VIX which was inaugurated four years later in 1993, however, it would take until 2004 before futures contracts were introduced in this market. First, the VIX was based on options on the S&P 100 (OEX), this later changed from 2003 onwards to options on the S&P 500 (SPX) according to Zhang, Shu, and Brenner (2010). However, the two different approaches in calculating the VIX have a 98% correlation. As it would turn out in later years, the VIX in itself is sometimes misunderstood, according to Whaley (2009). During the 2007-2008 financial crisis, the VIX was said to cause volatility in the stock markets, whereas, in reality, it shows the forward-looking expect, the purposes of the VIX are:

(i) The index should be a benchmark for short-term volatility

(ii) The VIX should be the underlying for derivative products such as futures and options

It is further argued that the VIX "is implied by the current prices of S&P 500 index options and represents expected future market volatility over the next 30 calendar days" Whaley (2009, p. 2), hence it does not measure realized volatility.

History has shown that the relationship between volatility and market effect is strong. As research on the area of volatility grew, and the VIX was introduced, papers started to look into using the VIX as a suitable method of predicting the volatility and using it in a portfolio allocation setting. Fleming, Ostdiek, and Whaley (1995) show that it is possible to use the VIX to forecast volatility. They find that there exists a negative correlation between the VIX, and returns on the S&P 100. The authors also find that the stock market's positive moves have a lower impact on the VIX compared to when the stock market goes down, in which case the impact on the VIX is more substantial, in absolute values. French, Schwert, and Stambaugh (1987) builds upon the subject of expected returns and volatility by statistically testing the exploratory paper of Merton (1980). The authors conclude that unexpected negative returns are negatively related to unexpected increases in volatility. They find that an unpredictable positive change in volatility has a positive effect on expected risk premiums and lowers the current stock price. It indicates that a market-timing approach, based on volatility, could be beneficial for a portfolio allocations strategy.

Fleming, Kirby, and Ostdiek (2001), try to confirm the merit of timing the market using volatility. They find that there is indeed an economically significant reason for timing the market using volatility modeling. Thus, trying to exploit market movements with predictions of volatility does indeed have its benefits. Further, Fleming, Kirby, and Ostdiek (2003) build upon this subject by comparing the realized volatility estimates with the famous estimation model GARCH. They conclude that realized volatility, instead of volatility estimation with GARCH or similar, has a higher economic value. In the paper, they test three primary rolling estimation methods of estimating the volatility for their portfolio optimization, daily, realized, and GARCH estimation. They find that using the realized volatility approach indicates that investors would be willing to pay for switching between "daily-returns-based estimator for the conditional covariance matrix to an estimator based on realized volatility." Fleming et al. (2003, p. 508). It means that the economic significance of better volatility estimations for market timing purposes exists, further cementing the importance of volatility as a market-timing tool.

2.2 Tactical Asset Allocation

Stemming from the papers focusing on only estimating the volatility, and then newer papers predicting market movements using volatility, research on the area of using the VIX as a tool for producing higher returns started to arise. Copeland and Copeland (1999) build upon the findings by French et al. (1987), and introduce a method of timing market movements using the VIX within a tactical asset allocation (TAA) strategy. They look into whether the VIX has a relationship with size and style portfolios, finding statistical significance of the relationship between the portfolios and the VIX. By changing the portfolio's allocation of the size and style factors and testing their strategy against a simple buy-and-hold portfolio, they can statistically prove that their strategy outperforms for any given variation in the VIX. Their findings show that a TAA strategy using the VIX as a market-timing tool is a viable option. Another paper by Cloutier, Djatej, and Kiefer (2017) uses a well-diversified portfolio within a TAA strategy, which takes the level of the VIX into account. If the VIX is above, or below, a certain bound, the portfolio reallocates. Thus, the authors' strategy tries to utilize the level of the VIX to predict bull- and bear market movements. Their TAA strategy manages to achieve higher returns than a simple buy-and-hold portfolio. However, both of these papers do not consider transaction costs to any significant degree.

Wells Fargo first used TAA in the early 1970s, where assets were shifting between bonds and stocks according to a set excess return threshold of stocks, according to Lee (2000). TAA has therefore been in use for many years before research on the area caught up. After TAA having outperformed the stock market during the crash of 1987, TAA as an investment strategy grew tremendously in the coming years, from $48 billion in 1994 estimated by Philips, Rogers, and Capaldi (1996) to $100 billion in 1999 by Lee

(2000). However, being practically applied for many years without distinct research on the area of what TAA is, meant TAA was not clearly defined. Lee (2000) tries to combat this issue by trying to explain that TAA has developed since its inception, but a general interpretation is an investment strategy, including stocks, bonds, and cash where the weights are predetermined as well as lower and upper bounds of the percentual allocation to these assets. The portfolio is then tactically rebalanced according to the manager's strategy. Dahlquist and Harvey (2001) take this a step further and distinguish between three different levels of asset allocation. The first level is the tracking of a benchmark, *e.g.*, the MSCI World Index[1], the second level being a strategic five-year asset allocation with annual updates, and the last one is TAA, with monthly and, or, quarterly bets. According to the authors, transaction costs in the TAA strategy is of high importance, with re-allocations done more frequently, which should lead TAA managers wanting to minimize the transaction costs.

What should be noted is that research on the area of TAA has not only focused on simply predicting volatility in markets, but instead timing the market in general. To see how well a VIX market timing approach performs, it is, therefore, relevant to test it against another simple market-timing approach. A paper by Faber (2013) explores a simple moving average (SMA) TAA strategy. Faber shows that using their TAA strategy; a well-diversified portfolio can achieve similar returns to that of equities, while having a volatility similar to bonds. By timing the asset reallocation to specific predetermined characteristics, Faber shows that, over 110 years, the specific TAA model applied outperforms the S&P 500 with a higher return, lower volatility, and a higher Sharpe ratio.

Another factor affecting the TAA strategy performance is, of course, the underlying portfolio. Beyond the strategy's implementation, the returns are only as good as the portfolio from which the TAA strategy deviates. Papers on different portfolios are numerous, one such paper is DeMiguel, Plyakha, Uppal, and Vilkov (2013), where they test several portfolio allocations focusing specifically on volatility. The authors use information retained from options, including implied volatility, to reduce the volatility of different minimum-variance and mean-variance portfolios. They conclude that using option-implied volatility can improve the volatility of a portfolio. After adding transaction costs, they still manage to improve the Sharpe ratio compared to not consider-

[1]Morgan Stanley Capital International (MSCI) World Index, includes 1644 mid- and large-cap stocks from 23 developed countries

ing option-implied volatility. In addition to testing volatility based portfolio allocations, they also test an equal-weighted (1/N) portfolio, the argument stemming from DeMiguel, Garlappi, and Uppal (2009), which concludes that although not relying on any specific optimization, the 1/N portfolio performs well.

The papers by Copeland and Copeland (1999), Faber (2013), and Cloutier et al. (2017) do not consider costs, while Dahlquist and Harvey (2001) argue that transaction costs in a TAA strategy is of high importance. Since reallocations are done more frequently than the previously stated strategies, TAA managers need to minimize transaction costs. DeMiguel et al. (2013) follow the same path by showing that transaction costs have a significant impact if the portfolio is allowed to reallocate daily compared to a fortnightly reallocation. It is, therefore, essential to expand the mentioned papers by adding transaction costs.

As noted, a common problem while looking at portfolio performance and asset allocation strategies, is that transaction costs, have to be estimated and included to yield realistic portfolio performances. According to Yoshimoto (1996), transaction costs are necessary to achieve efficient portfolios. Damodaran (2020) acknowledges four costs of trading, namely the following; *brokerage cost* (going further, we will address it as *commission fee*), *bid-ask spread*, *price impact*, and *opportunity cost.* Woodside-Oriakhi, Lucas, and Beasley (2013) describe the costs associated with the reallocation of assets in an MV setting as being a penalty that is paid in order to reallocate the assets. When looking at TAA, it is important to consider the cost of being long-short or only long in a portfolio. This subject is explored in a paper by Frazzini, Israel, and Moskowitz (2012), where the authors use real trading data from a large institutional investor. A long-short portfolio is said to experience lower trading costs than a simple long portfolio, the first having transaction costs of 10 basis points and the latter having transaction costs of 16 basis points. However, they conclude that after value-weighting, the long-short portfolio has slightly higher transaction costs than the long-only portfolio. As reported by Do and Faff (2012), the commission fees have been declining since the 1970s, e.g., in 1990 they were 20 basis points (bps) compared to 8 bps in 2008 and further falling to 3.2 bps in 2019[2]. Regarding the cost of short-selling, D'Avolio (2002) mentions that 91% of US stocks can be shorted at an annual fee of 1%. Do and Faff (2012) also use a 1% annual short-selling

[2]https://www.virtu.com/uploads/documents/Global-Cost-Review-2019Q4.pdf

fee, according to the authors, 84% of US-listed stocks can be shorted, and they cover 99% of the US stock market capitalization. In contrast, Engelberg, Reed, and Ringgenberg (2018) show that the median short-selling fee is only 11 bps per annum, with some significant outliers. Abdi and Ranaldo (2017) research the subject of the bid-ask spread cost, derived from the intra-daily high and low prices, as well as the daily closing price if quote data is not at hand. They report the bid-ask spread as a round-trip cost, *i.e.*, both buying and selling the stock, as one unit of the bid-ask spread cost.

2.3 Alpha and Factor Models

There have been many suggestions over the years concerning how to test the performance of a portfolio statistically. One of the most famous is Jensen (1968), which examines fund managers' performance by looking at the intercept (α) of the famous capital asset pricing model (CAPM), which would later become known as "Jensen's Alpha." He concludes that a positive α suggests that the fund manager manages to achieve an excess return regarding the market portfolio.

In later years, Fama and French (1993) would expand the CAPM by adding market factors that can better explain a portfolio's return. The authors identify risk factors on stocks, the three factors on stocks are; a market excess return factor (Rm-Rf), a factor concerning a firm's size (SMB), and a factor related to a firm's book-to-market equity (HML). The paper pre-beta sorts on size, to overcome the issue that betas and size are almost perfectly correlated. Using Fama-MacBeth regressions, the paper finds that the additional factors added, help explain the relationship of cross-sectional expected stock returns. Fama and French (2015) extend their three-factor model to a five-factor model, where the factors RMW and CMA are added, where RMW corresponds to Robust minus Weak (high minus low operating profitability) and CMA corresponds to conservative minus aggressive (regarding the firm's investment strategies).

3 Data

Our daily and monthly data represent the U.S. equity market. Also, we use the U.S. one month Treasury Bill. The U.S equity market data, as well as the risk-free rate, stem from French's data library[3], which in turn uses the Center for Research in Security Prices (CRSP). From the data library, we use French's 12 assets, which comprise all U.S. listed stocks. The description of the 12 assets are in Appendix Table 9. The VIX data and the S&P 500 data were extracted from Bloomberg. Due to the limited time since the VIX's inception, our data set corresponds to 30 years, starting in January 1990, and ending in December 2019. The VIX-spike in March 2020 that was caused by the Covid-19 pandemic resulted in adding data for the first three months in section 5.6. Note that the first year is used for backtracing correlation calculations and so forth, as outlined in section 4. Therefore, the starting date from when we start investing and calculate returns is January 1991. We use the daily closing prices of French's industry asset classes, S&P 500, and the VIX daily close level to calculate the corresponding daily returns, asset correlations, and additional metrics used in the strategies outlined in Section 4. For the outset portfolio, we use 80 months before the starting day of January 1991 to calculate variance-covariance matrices for the MV portfolio. The regressions are calculated on the daily data and returns from January 1991 onwards.

We obtained the commission fee from Do and Faff (2012), in combination with data retrieved from the ITG (Investment Technology Group)[4].

Their data set ends in 2009. Thus, we add the years through 2019. The commission fees add up to an average of 7.52 bps per trade. The short-selling fee was obtained by using an average of the papers by D'Avolio (2002), Do and Faff (2012), and Engelberg et al. (2018), which constitutes 55 bps per annum. Regarding the bid-ask spread, it was derived from Abdi's database[5] in combination with data from CRSP.

In stock price data, autocorrelation, or serial correlation, is a recurring issue that has to be taken into consideration. Autocorrelation is the correlation between an asset and any of the asset's lagged values. By implementing the Newey-West estimator in the regression analysis, the potential problem with autocorrelation is dealt with appropriately.

[3] https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

[4] https://www.virtu.com/uploads/2019/02/ITG-Global-Cost-Review-4Q18.pdf, https://www.virtu.com/uploads/documents/Global-Cost-Review-2019Q4.pdf

[5] https://www.farshidabdi.net/data/index.html

4 Method

This paper aims to increase the Sharpe ratio for an underlying buy-and-hold portfolio by using the TAA strategy outlined in section 4.2 through 4.4. Further, we aim to produce a significant positive alpha using the Fama-French five-factor model that is higher than the comparable portfolios. In addition, several versions of the strategy will be tested to shed light on the input variables that affect the strategy the most.

4.1 Constructing the Buy-and-Hold Outset Portfolio

For an efficient portfolio outset, we will use two different portfolios. The reason for using two portfolios is to analyze the potential effect that the outset portfolio may have on a TAA strategy. The first method is the mean-variance (MV) portfolio, as replicated from Markowitz (1952). The method is well known, and the derivation of it can be seen in Appendix 6.

By constructing the outset portfolio in this manner, the portfolio has an efficient outset, and after that, we apply TAA to the chosen portfolio. In this paper, we derive the neutral portfolio solution from minimizing the portfolio variance for a set number of returns[6]. Further, we reallocate the MV portfolio quarterly. Since both means and covariances change over time, it would not be reasonable to assume that the optimal portfolio allocation does not change over roughly 30 years. Additionally, we define the optimal neutral portfolio as the one with the highest Sharpe ratio. Formally stated as:

$$Sharpe\,ratio = \frac{R_p - R_f}{\sigma_p} \tag{1}$$

Where R_p is the portfolio returns, R_f is the risk-free rate, and σ_p denotes the standard deviation of the portfolio returns.

The second method for the outset portfolio is an equal-weighted buy-and-hold portfolio, similar to Copeland and Copeland (1999) and Cloutier et al. (2017). This portfolio allocates an equal amount into each asset at day one, and is not adjusted for any relative changes in an assets weight over the period. The reason for testing this method is that it is used by earlier papers, such as DeMiguel et al. (2009), and will eliminate any

[6]The portfolios are solved by constructing 1000 different portfolios by combining assets using a variance-covariance matrix calculated on monthly data in an 80-month moving window, moving backward from the month the MV-portfolio is reallocated.

estimation errors that may come as a consequence of the MV outset portfolio.

4.2 VIX Sensitivity and Market State Thresholds

The reason for using the VIX as an instrument for the expected volatility comes from the way the VIX is calculated. Since the VIX is calculated by using implied volatilities from the S&P 500, calculated on "... near- and next-term put and call options with more than 23 days and less than 37 days to expiration" CBOE (2019, p. 5). The general formula for calculating the VIX, stated by CBOE, is the following:

$$\sigma^2 = \frac{2}{T}\sum_i \frac{\Delta K_i}{K_i^2} e^{R_f T} Q(K_i) - \frac{1}{T}\left[\frac{F}{K_0} - 1\right]^2 \tag{2}$$

Where σ is the implied volatility, T is the time to expiration, F is the forward index level derived from index option prices, K_0 is the first strike below the forward index level, K_i is the strike price of the out-of-the-money option; a call if $K_i > K_0$, and a put if $K_i < K_0$; both put and call if $K_i = K_0$. Further, $\Delta K_i = \frac{K_{i+1} - K_{i-1}}{2}$ is the interval between strike prices, half of the difference between strikes on either side of K_i, R_f is the risk-free interest rate to expiration, and $Q(K_i)$ is the midpoint of the bid-ask spread for each option with strike K_i.

To use the VIX as a market timing indicator for the tactical asset allocation strategy, the sensitivity of an asset and the level of the VIX will be the two key factors when deciding whether to sell or buy an asset. The sensitivity will be estimated as follows.

For each considered asset, the correlation between the percentage change of the daily VIX-level and the percentage change of the asset's price will be calculated. The delta-VIX percentage change, or $\Delta VIXpct_t$, is calculated as:

$$\Delta VIXpct_t = \frac{VIX_t - VIX_{t-1}}{VIX_{t-1}} \tag{3}$$

Where VIX_t is the VIX closing level at day t. Further, the price percentage change for the assets are calculated as, $\Delta Ppct_i$, defined as:

$$\Delta Ppct_i = \frac{P_{i,t} - P_{i,t-1}}{P_{i,t-1}} \tag{4}$$

Where $P_{i,t}$ is the price of asset i at time t.

To measure the asset-sensitivity, we rank assets as either high or low sensitivity, depending on the correlation between $\Delta VIXpct_t$ and $\Delta Ppct_{i,t}$. The implications of whether the correlation is positive or negative is further discussed in section 4.3. The correlation is calculated in a rolling window, where we test different windows to find the optimal correlation window. High correlation is defined as above $|X|$, and is regarded as high sensitivity, while low correlation is defined as below $|X|$, and is regarded as low sensitivity. Different levels of the sensitivity bounds are tested in order to find the optimal sensitivity bound. Following this, assets are bought or sold depending on two major factors. The first is whether the VIX is at a high or low level, indicating a bear or bull market. The second factor is that we take into account the sensitivity of the assets.

4.3 Tactical Asset Allocation

The two tactical asset allocation portfolios are the simple moving average (SMA) portfolio and the VIX portfolio, from now on called the VIX strategy. The baseline "neutral" portfolio, in this paper defined as, the MV or the EW portfolio, is the outset portfolio for the two TAA strategies, meaning that the TAA strategies will deviate from the MV or EW portfolio during intervals where the window for TAA is triggered. For the VIX strategy, this is defined as above or below a certain threshold, while the SMA portfolio is triggered depending on its 200-day moving average and the asset's price, as outlined below. To summarize, the MV portfolio is used to keep the underlying outset portfolio clearly methodically defined and efficient, while the TAA portfolio re-allocations react to market movements.

When the VIX is above the upper bound, the assets which are sensitive to the VIX and have a negative correlation are sold, and excess is put into risk-free. Conversely, if the VIX is below the lower bound, the market is deemed as a bull market. The VIX strategy can leverage its position for all of the assets and put the excess into risk-free to gain the upside from a low volatility market. In practice, this means that when the VIX is above its upper bound, or below its lower bound, two things will happen. If the VIX is above its upper bound, the VIX strategy will change any positive weight allocated in an asset to negative, *i.e.* shorting the asset and then allocate the difference to risk-free. If the VIX is below its lower bound, the VIX strategy will leverage any position it has by twice and borrowing the difference from risk-free.

The MV portfolio, which is rebalanced quarterly, is used when the TAA-window has not been triggered. If the VIX is in a TAA-window, and the underlying outset portfolio is reallocated, the VIX strategy weights will also be reallocated based on the changes in the outset portfolio. For the TAA-window, the bounds that define either a bull or a bear market were replicated from Cloutier, Djatej, and Kiefer (2017), but will be iterated over several values to analyze the effect the input variable has. The bounds determine what is considered high or low volatility and, therefore, depict *bull* and *bear* stock market movements. Low volatility, and, consequently, a low level of the VIX, indicates periods of stability, while high levels of the VIX indicate periods of higher uncertainty.

Further, within the TAA strategy, an n-day average is applied to calculate when the VIX is above or below its bounds, where n is the number of lag-days used when calculating the average. Using n-day averages instead of fixed values lets us test for the optimal input for the VIX strategy and see if we enter or exit the positions too early. The TAA strategy is in use until the n-day average VIX between the upper and lower threshold; at this point, the mean-variance portfolio is re-implemented. The TAA-window thresholds are formally defined as:

$$VIXAverage = \frac{1}{n} \sum_{t=k-n+1}^{k} VIX_t \geq [Upper\ Bound] \tag{5}$$

or

$$VIXAverage = \frac{1}{n} \sum_{t=k-n+1}^{k} VIX_t \leq [Lower\ Bound] \tag{6}$$

While the TAA strategy is only triggered by the pre-determined levels of the VIX, we continuously run the TAA_{BEAR} and TAA_{BULL} portfolios. Where TAA_{BEAR} corresponds to a $VIX_{Average} \geq [Upper\ Bound]$, and TAA_{BULL} corresponds to a $VIX_{Average} \leq [Lower\ Bound]$.

The paper also tests different trading limits in addition to correlation windows, sensitivity limit, VIX average lag size, and upper and lower bounds. The trading limit works as a percentage limit of the percentage that would have changed for an asset in a TAA-window. For example, if the strategy is in a bull market and wants to change an asset's weight from 50% to 100% by borrowing the risk-free, the limit will only allow a movement from 50% to 75% if the trading limit is set at 50%.

The SMA portfolio is replicated from Faber (2013) and is reallocated monthly, with the difference being that instead of either buying when the moving average is lower than the current price or selling when the moving average is higher than the current price, moving the excess into risk-free, we apply the same method as for the VIX strategy. This means that when the moving average is lower than the current price, the SMA strategy leverages its position by borrowing risk-free to gain potential upside. Following this, the SMA strategy changes its positive positions to short positions and allocates the difference to risk-free. Further, the window size used is a 200-day moving window. We calculate the moving average as follows.

$$SMA_n = \frac{1}{n} \sum_{t=k-n+1}^{k} P_{i,t} \tag{7}$$

Where $P_{i,t}$ is the price of asset i at time t, where t is a function of k where i is the current date at which the SMA counts back from, and n is the number of lagged days, which is 200 in this paper.

After constructing the portfolio weights, we calculate the returns as the cumulative daily returns throughout the data set, given the weights allocated into each asset. The two TAA-strategies SMA and VIX, and the neutral optimized MV portfolio, are examined for portfolio performance by testing for a statistically significant alpha in each of the portfolios using the Fama-French five-factor model (Fama and French (2015)). Formally stated as:

$$\mu_p = \alpha_i + \beta_1(R_{M,t} - R_{f,t}) + \beta_2(SMB_t) + \beta_3(HML_t) + \beta_4(RMW_t) + \beta_5(CMA_t) + \epsilon_{i,t} \tag{8}$$

Further, by using the Fama-French five-factor model, a comparison between the different strategies' characteristics can be made. This means that statistically significant different betas for each factor in the portfolios can give further information regarding the characteristics that each portfolio creates. We use this to see whether there are any similarities concerning how the different strategies invest, but will not focus too much on this in the paper. We will primarily employ this model to find a significant alpha. However, the benefit of using the Fama-French five-factor model is that the model explains the portfolios' returns in a better way, and less omitted variable bias affects the alpha.

4.3.1 Difference

In the paper by Copeland and Copeland (1999), the authors conduct difference regressions, which we implement by using the following formulas:

$$VIX_r - SMA_r = \alpha + \beta \Delta VIX + \epsilon_{i,t} \tag{9}$$

$$VIX_r - MV_r = \alpha + \beta \Delta VIX + \epsilon_{i,t} \tag{10}$$

$$SMA_r - MV_r = \alpha + \beta \Delta VIX + \epsilon_{i,t} \tag{11}$$

Where VIX_r, SMA_r, and MV_r are the cumulative returns for the respective investment strategy. α is the intercept, β is the slope, ΔVIX is the daily change in the VIX, and ϵ_{i_t} is the error term. The focus of the regressions is to see how the TAA strategies perform compared to each other, and additionally, how they perform compared to the outset portfolio.

4.4 Transaction Costs

Without accounting for transaction costs, the different asset allocation strategies will show inflated returns simply because there are no trading restrictions. However, as was discussed in the literature review, having to make a trade penalizes the portfolio manager with a transaction fee. Copeland and Copeland (1999), and Cloutier et al. (2017), do not incorporate any transaction costs, leading strictly to theoretical assumptions about the over performance of their respective VIX-based investment strategies.

Included in the transaction costs, $tc_{i,t}$, are commission fees, short-selling fees, and the bid-ask spread costs. We do not include any price impact costs or opportunity costs, that is beyond the scope of this paper. The transaction costs are calculated as:

$$tc_{i,t} = (w_{i,t} - w_{i,t-1})cf_{i,t} + Short* \mid -w_{i,t} \mid sf_{i,t} + (w_{i,t} - w_{i,t-1})0.5 * ba_{i,t} \tag{12}$$

Where $cf_{i,t}$ is the commission fee of asset i at time t, and $sf_{i,t}$ is the annual short-selling fee of asset i at time t, and $0.5 * ba_{i,t}$ is the one-way bid-ask spread cost of asset i at time t. The $w_{i,t}$ corresponds to the weight allocated in asset i at time t, where the change in weights for each asset between t and *t-1* is the total amount that is traded. Short is a scalar value of 1 or 0, triggered when the value for the weight is negative, and adding a short-selling fee to the allocated weight for each day that the short position is held. The commission fee is set at 7.52 basis points per trade, as was mentioned in section 3. The annual short-selling fee is set at 55 bps per year, as outlined in section 3. The daily short-selling fee is the annual fee divided by 252 (the number of trading days per year). Regarding the bid-ask spread cost, we compute the appropriate cost for the twelve industry assets, using CRSP's permanent id-number of (security) PERMNO in combination with their corresponding Standard Industrial Classification (SIC) code, and the data provided by Abdi[7]. The data attainable from Abdi's database extends from before our starting point in January 1991 but ends in December 2016. The bid-ask-spread does not vary dramatically during that 25-year time-span; we, therefore, use the average bid-ask spread over the whole period. The calculated average bid-ask spreads for the twelve assets are shown in Appendix Table 11.

5 Results and Analysis

5.1 Input Variables

In the following sections, the specific inputs for the VIX strategy are, unless varied in the individual sections, as follows:

1. VIX correlation window: 70
2. Sensitivity: 0.75
3. Lag size: 4
4. VIX upper bound: 40
5. VIX lower bound: 0
6. Trading limit bear market: 0%
7. Trading limit bull market: 0%

The VIX correlation window is the window in which the asset-correlations to the VIX are calculated. The sensitivity is the absolute value of the correlation for when an asset is deemed sensitive to the VIX. Lag size is the value of the lag, used when calculating the average VIX-level that triggers the VIX strategy. The VIX upper and lower bounds control when the VIX strategy is triggered. The trading limits control the amount that is

[7]https://www.farshidabdi.net/data/index.html

allowed to be reallocated from the outset weights. A 100% trading limit would result in zero deviation from the outset weights, while 0% allows for full reallocation of the outset weights. Further, each following section discusses the effects of changing each input variable. The inputs above represent the optimal choice given an MV outset portfolio, unless stated otherwise, and thus, each variable's effect will be compared with these inputs. This optimal choice is derived from single variable optimization tests, where the best combination was found by testing all of the different combinations of the input variables.

5.1.1 VIX Correlation Window

Table 1: Varrying Correlation Window

Summary Statistics

STATS	**30**	**40**	**50**	**60**	**70**	**80**	**90**	**100**
Return	339.4761	313.5659	334.1361	367.4154	415.1045	383.0584	365.1968	363.1868
Return_c	253.418	237.511	248.4613	276.2	323.5275	295.9078	283.3075	285.4001
No. of trades	668	647	659	645	611	610	608	585
μ	0.3806	0.3575	0.379	0.404	0.4405	0.4182	0.4046	0.4021
μ_c	0.2952	0.2764	0.2918	0.3197	0.3667	0.342	0.3293	0.3307
σ	2.405	2.3932	2.5366	2.4392	2.4909	2.5291	2.5343	2.4997
σ_c	2.3526	2.3422	2.4478	2.3427	2.4014	2.4469	2.4392	2.4093
Sharpe	0.1582	0.1494	0.1494	0.1656	0.1768	0.1653	0.1596	0.1609
Sharpe_c	0.1255	0.118	0.1192	0.1365	0.1527	0.1398	0.135	0.1373

Table 1 shows the summary statistics when varying the VIX correlation windows. The Return is the cumulative daily excess return in the period 1991.01.03-2019.12.31. No. of trades is calculated as the summary of changes in weights over the period, where one trade is defined as any change in any asset's weight from one day to the next. μ is the daily mean return in percent during the period. σ is the daily standard deviation in percent of the portfolio. Sharpe is the daily Sharpe ratio for each iteration of correlation window size. The cost-adjusted statistics are denoted with c; these include commission fees, short-selling fees, and the bid-ask spread.

As seen in Table 1, by changing the VIX correlation window, we can see there is a large increase in return moving from 40 to 70, and after that, an increase in window size yields lower returns both before and after costs. Changing the window limit has two potential merits. Firstly, by decreasing the window size, the correlation is calculated on newer data and should better reflect the correlation between assets in a shorter time-frame. Secondly, increasing the window size has the opposite effect of incorporating older data by taking a longer time-frame, giving a long-term view of the correlation of each asset over time. Therefore, the risk of taking too short of a correlation window may result in inaccurate correlations due to a small sample size. On the other end, increasing the correlation window could incorporate correlation data no longer relevant for when the VIX strategy should be implemented. Interestingly, the 100-day window slightly increases returns from the 90-day window. Indicating that there is no consistency in terms of a large or small window resulting in higher returns.

5.1.2 Sensitivity

Table 2: Varying Asset Sensitivity

Summary Statistics

STATS	**0.5**	**0.55**	**0.6**	**0.65**	**0.70**	**0.75**	**0.80**	**0.85**
Return	392.5202	395.2974	395.0475	382.8411	375.1322	415.1045	288.9511	229.1871
Return_c	284.7092	290.6448	291.0705	284.3616	281.6165	323.5275	237.9063	204.6833
No. of trades	663	652	647	642	628	611	567	465
μ	0.4253	0.4272	0.427	0.4173	0.4111	0.4405	0.3323	0.2687
μ_c	0.3308	0.3366	0.337	0.3296	0.3265	0.3667	0.2767	0.2361
σ	2.5325	2.5282	2.5284	2.5005	2.4849	2.4909	2.3245	2.447
σ_c	2.4436	2.4359	2.435	2.4078	2.3972	2.4014	2.3402	2.4465
Sharpe	0.1679	0.169	0.1689	0.1669	0.1654	0.1768	0.143	0.1098
Sharpe_c	0.1354	0.1382	0.1384	0.1369	0.1362	0.1527	0.1183	0.0965

Table 2 shows the summary statistics when varying the asset's sensitivity limits. The Return is the cumulative daily excess return in the period 1991.01.03-2019.12.31. No. of trades is calculated as the summary of changes in weights over the period, where one trade is defined as any change in any asset's weight from one day to the next. μ is the daily mean return in percent during the period. σ is the daily standard deviation in percent of the portfolio. Sharpe is the daily Sharpe ratio for each iteration of sensitivity limit. The cost-adjusted statistics are denoted with c; these include commission fees, short-selling fees, and the bid-ask spread.

In Table 2, the returns do not show a clear pattern, as the correlation approaches $|1|$. However, the number of transactions show a clear pattern, where they decrease substantially. With a lower number of transactions, the method is not as penalized by the transaction costs. The reason behind the lower amount of trades is simple. The strategy uses asset correlations to decide whether the asset is sensitive or not, and from there, it decides on whether the assets should be traded or not given the level of the VIX. In a TAA window, reducing the number of sensitive assets will reduce the number of potential trades that are available.

Our results indicate that increasing the sensitivity and limiting the number of trades yield higher returns, up until sensitivity limit 0.75. This pattern may arise from trading the wrong assets with the sensitivity limit too low. For example, if the VIX moves up sharply, indicating a bear market, and the wrong asset (given a $|0.5|$ sensitivity limit) trades, the following error could occur. In the TAA window, the strategy is shorting the asset; however, its return during this period is positive. This results in money lost on the trade. Since the optimal sensitivity limit is $|0.75|>$, this indicates that there is a trade-off between a high sensitivity limit and a low sensitivity limit. However, note that there are large variations in the level of return when the sensitivity limit is low, indicating that it is not a linear trade-off.

5.1.3 Lag Size

Table 3: Varying Lag Size

Summary Statistics

STATS	3	4	5	6	7	8	9	10
Return	436.0230	415.1045	405.7001	369.8205	366.2317	349.9331	346.5937	333.375
Return$_c$	315.8576	323.5275	311.7854	297.8552	294.9671	285.2499	282.5251	271.6493
No. of trades	707	611	628	574	574	564	564	564
μ	0.4549	0.4405	0.4341	0.407	0.4041	0.3916	0.3889	0.377
μ_c	0.3605	0.3667	0.3561	0.3428	0.34	0.3308	0.328	0.3163
σ	2.498	2.4909	2.4976	2.4816	2.4802	2.5053	2.505	2.4776
σ_c	2.4311	2.4014	2.405	2.4003	2.4011	2.416	2.4179	2.3992
Sharpe	0.1821	0.1768	0.1738	0.164	0.1629	0.1563	0.1552	0.1522
Sharpe$_c$	0.1483	0.1527	0.1481	0.1428	0.1416	0.1369	0.1357	0.1318

Table 3 shows the summary statistics when varying the VIX average lag size. The Return is the cumulative daily excess return in the period 1991.01.03-2019.12.31. No. of trades is calculated as the summary of changes in weights over the period, where one trade is defined as any change in any asset's weight from one day to the next. μ is the daily mean return in percent during the period. σ is the daily standard deviation in percent of the portfolio. Sharpe is the daily Sharpe ratio for each iteration of lag size. The cost-adjusted statistics are denoted with c; these include commission fees, short-selling fees, and the bid-ask spread.

Varying the lag size will affect how fast or slow we trigger the VIX strategy. As can be seen in Table 3, the returns show that there is a clear pattern in the trade-off between a shorter or longer lag size window. This may be connected to transaction costs and missing out on potential profits. For example, having the lag size window too narrow, results in the number of trades being higher, leaving the strategy vulnerable to noise in the VIX and therefore increasing costs without increasing returns. However, for every additional day that is part of the lag, the probability increases that the strategy is not triggered fast enough, thus missing out on potential profits. Therefore, a one-day lag size would be nonsensical, since the strategy would be triggered too many times and be profoundly affected by short-term spikes in the VIX. Copeland and Copeland (1999) employ a 75-day simple moving average (SMA) compared to the daily level of the VIX, the motivation being that a 75-day SMA of the VIX reduces the noise in the data. Our application is different and instead uses a moving average over a small period, which triggers the strategy when it is over a specific upper and lower bound. By testing different lag sizes, we can shed light on the effect of decreasing or increasing the amount of noise in the VIX. The authors do not investigate the relevance of this window, but our results indicate that there is an optimal solution to the trade-off between having the window too small or too large. In our case, the optimal solution is the four-day lag size, yielding the highest Sharpe$_c$ ratio of 0.1527 as well as the highest mean (μ_c). The four-day lag produces the highest returns, both including and excluding costs. From six and above, there is no significant effect on the number of trades, and there is a downward trend in the returns.

5.1.4 VIX Bounds

The summary statistics and regression results are depicted in Table 4, for different levels of the upper bound along with the SMA and MV strategies. The table includes only the alphas from the regressions, for full regression results of the optimal solution, see Appendix Tables 13 and 14. The returns are generated with the input variables from section 5.1, except for the varying upper bound.

At which upper bound, the VIX strategy is triggered is important. Copeland and Copeland (1999), find that triggering their strategy at different percentage changes of the VIX can yield negative and positive returns. Although our VIX strategy uses another type of limit as a trigger, the bounds serve the same purpose as the authors' percentage changes of the VIX. In Table 4, we can see that there is a clear trade-off between decreasing or increasing the upper bound. This upper bound sets the limit for what constitutes a bear market for the strategy. Naturally, it follows that this can yield lower returns if triggered often. For example, a VIX-level of 20 does not indicate a potential bear market. The poor performance of the VIX strategy at upper bound 20 reflects this. These results are consistent with Copeland and Copeland (1999), who find that triggering their strategy at 10% changes in the VIX yield negative returns. This indicates that no matter the TAA strategy, triggering it too soon will yield significantly lower returns due to the increase in transaction costs. An example of this is that after the introduction of transaction costs, the investor is better off by using upper bound 40. Not accounting for transaction costs would result in the investor picking upper bound 25. Therefore, we can conclude that even rudimentary costs have a significant impact on the strategy's performance, which is consistent with Dahlquist and Harvey (2001). Additionally and, most importantly, it also changes what constitutes the optimal solution.

Table 4: Varying Upper Bound

Summary Statistics and Regressions Results

STATS	**20**	**25**	**30**	**35**	**40**	**45**	**SMA**	**MV**
Return	440.2212	465.3267	449.5513	388.8763	415.1045	311.7862	392.3947	219.5394
Return_c	134.5022	172.5663	251.2019	259.2105	323.5275	262.0611	146.2378	202.7941
No. of trades	1,936	1,597	1,038	788	611	526	1,226	390
μ	0.4521	0.4716	0.461	0.4204	0.4405	0.3579	0.5326	0.2569
μ_c	0.1135	0.1868	0.2945	0.3048	0.3667	0.3079	0.2522	0.2341
σ	2.2548	2.3991	2.3709	2.4141	2.4909	2.4876	5.2342	2.4724
σ_c	2.3735	2.4353	2.4184	2.4572	2.4014	2.4860	5.2979	2.4722
Sharpe	0.2005	0.1966	0.1944	0.1741	0.1768	0.1439	0.1017	0.1039
Sharpe_c	0.0478	0.0767	0.1218	0.1241	0.1527	0.1238	0.0476	0.0947
FF5								
α	0.0002***	0.0001**	0.0001*	0.0001	0.0001	0.0000	0.0000	-0.0001**
p	0.006	0.025	0.060	0.235	0.276	0.826	0.785	0.001
R^2	0.022	0.072	0.125	0.228	0.315	0.385	0.241	0.765
α_c	0.0000	0.0000	0.0000	0.0000	0.0000	-0.0000	-0.0002	-0.0001***
p_c	0.866	0.876	0.526	0.759	0.600	0.834	0.187	0.000
R^2_c	0.023	0.072	0.129	0.228	0.318	0.388	0.238	0.765

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4 shows the main regression results and summary statistics when varying the VIX upper bounds, and the SMA as well as the mean-variance strategy. The Return is the cumulative daily excess return in the period 1991.01.03-2019.12.31. No. of trades is calculated as the summary of changes in weights over the period, where one trade is defined as any change in any asset's weight from one day to the next. μ is the daily mean return in percent during the period. σ is the daily standard deviation in percent of the portfolio. Sharpe is the daily Sharpe ratio calculated on daily mean and daily volatility. The cost-adjusted statistics are denoted with c; these include commission fees, short-selling fees, and the bid-ask spread. FF5 corresponds to the main regression, where the α is Jensen's alpha from the Fama-French five-factor model. p is the p-value for the regression, derived from Newey-West standard errors to overcome the issue of heteroskedastic and autocorrelated standard errors. R^2 is the r-squared for the model.

The same story applies to the mean (μ), adjusted for costs; it is the highest at the 40 bound. μ is positive over the whole sample before and after accounting for transaction costs for all the different threshold levels. Compared to Copeland and Copeland (1999), our strategy does not seem to produce negative returns, as is the case with their lowest threshold. One reason behind our consistent positive returns may connect to how we trigger the strategy. While their method triggers on relative changes in the VIX compared to a 75-day SMA, our strategy triggers simply on the actual level of the VIX. Therefore, our method will be triggered when the market is deemed as distressed, while their method runs the risk of triggering when there is no distress in the market.

The Sharpe ratio is at its highest at bound 25, while adjusting for transaction costs it the highest at bound 40. Cloutier et al. (2017) achieve a Sharpe ratio of 0.7021; their data set expands over the years 2002-2014; however, they do not include transaction costs, leading to inflated values. Similar to their strategy, our VIX strategy produces a higher Sharpe ratio than the outset neutral portfolio. Besides, it also outperforms the

SMA strategy. We can, therefore, conclude that we achieved the goal of increasing the returns while reducing the portfolio's volatility. As mentioned, Cloutier et al. (2017) do not consider costs; by including them, we can see that costs have a large impact on the TAA strategy. It is not the case that the costs simply lower the return of the VIX strategy; the fact is, they completely change what the optimal implementation of the strategy is. Further cementing the findings by Dahlquist and Harvey (2001).

Under "FF5", the regression output in Table 4 shows that when excluding transaction costs, the alphas with statistical significance for the VIX-strategy are all positive. Only the MV strategy has a statistically significant alpha, after the introduction of transaction costs. As a form or robustness test, the ΔVIX is added to the Fama-French five-factor model (see Appendix Table 12, 13 and 14), adding this variable to the regression increases the R_c^2, while also decreasing the p-value of the constant. Adding ΔVIX does not make it possible to draw any new conclusions concerning alphas. However, it shows that there may be an omitted variable bias not accounted for in the main model, including the variable yields significant alphas on all regressions, except for the SMA strategy, including costs. The second model used is suggested by Copeland and Copeland (1999), and the corresponding results can be seen in Table 12 in the Appendix. The regressions yield no positive statistically significant alphas; therefore, we can not conclude any differences in returns between the portfolios for any given percentage change in the VIX.

It is important to note that when the VIX strategy moves towards its optimal upper bound (40), the alphas in the difference regressions are almost zero against both the MV outset portfolio and the SMA strategy. One reason behind this poor performance may connect to the number of trades. As the VIX strategy moves its upper bound upwards, the number of trades goes down. This, in turn, means that over the whole sample period, the daily differences are small, albeit higher for the VIX strategy in the long-run. This leads to the daily differences not being significant. Our results are not in line with Copeland and Copeland (1999).

5.2 Return Period

As can be seen in Figure 1, we observe the most dramatic decrease in the SMA strategy after the introduction of transaction costs. During the first ten years of the period, until the end of the dot-com bubble, the volatility and the sell-off was not high enough for the VIX strategy to be able to utilize its short-selling strategy in any meaningful way. It is apparent where the VIX strategy starts to exploit a high volatility throughout and after the 2007-2009 financial crisis. During that period, the VIX strategy starts to deviate from its outset MV portfolio and begins to outperform it, as can be seen in Figure 2. The higher volatility of the SMA strategy is reflected by higher up-and-down movements in Figure 1, which can also be seen in Table 4.

Figure 1: Cumulative Daily Returns

Figure 1 shows the excess returns of the three different investment strategies, VIX, MV, and SMA. The period depicted is 1991.01.03-2019.12.31., included in the graph are both outputs excluding and including transaction costs. The Y-axis is denoted in hundreds of percent, meaning 1 on the axis corresponds to 100%.

Faber (2013) manages to achieve higher returns for their SMA strategy compared to a simple buy-and-hold portfolio. However, their strategy lets the invested funds leave and re-enter the market by using the risk-free; they do not incorporate the ability to short any assets. Additionally, they do not consider transaction costs. Faber's strategy reallocates monthly, as does our SMA; however, there are some significant differences. First, the author's strategy does not allow for a higher allocation than 60% in risky assets, and the rest in risk-free, whereas we have no limitations. Second, the underlying assets are different, where Faber includes commodities, foreign stocks, and real estate. Also of importance is the fact that our SMA strategy uses the MV strategy as its outset portfolio, which significantly affects the performance of the SMA strategy, as can be seen in section 5.3.1.

Figure 2: VIX Strategy Performance

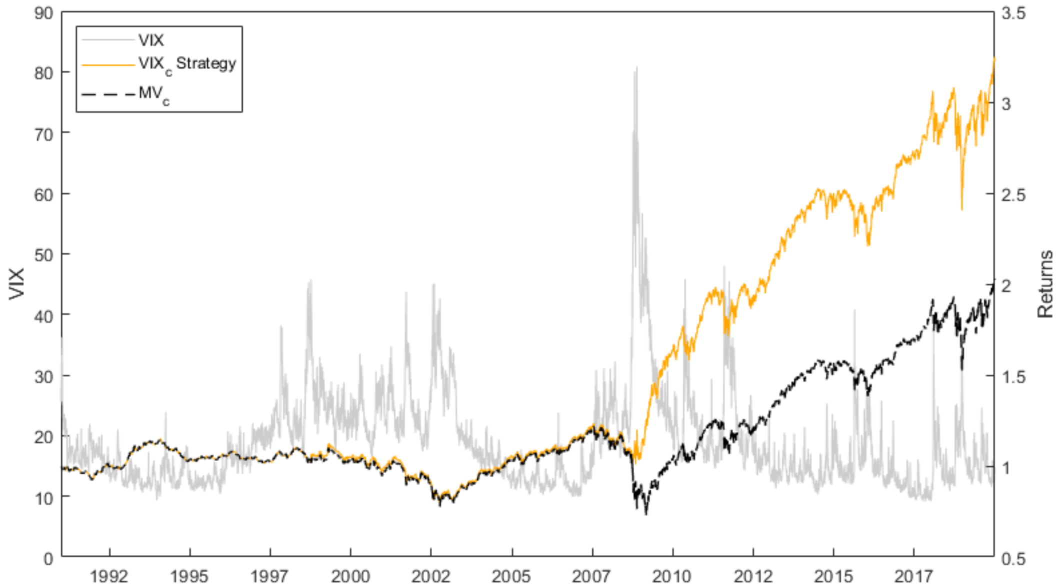

Figure 2 shows the excess returns of the VIX and MV strategies. The period depicted is 1991.01.03-2019.12.31. The grey line (left Y-axis) is the VIX-level, in 2008 the VIX peaked at a level above 80. The right Y-axis is denoted in hundreds of percent, meaning 1 on the axis corresponds to 100%.

Over the years from 1997 until 2002, the VIX had a period of elevated volatility; however, there were just short intervals where the VIX was above 30, let alone above 40, leading the strategy to simply follow the outset portfolio's trend. From Figure 2, especially the spike in the VIX in 2008 is exploited by the VIX strategy, resulting in it outperforming the MV strategy. In Figure 3, the performance of the strategy and the importance of it acknowledging a bear market makes it perform closer to the S&P 500 index from late 2008 until 2015. The key take away from the graphs is that the ability to use the VIX as an indicator for a bear market yields higher returns during a rapid and broad market sell-off. However, the strategy does not seem to be able to use the short-selling tactic in order to generate any abnormal returns, though it does reduce the level of the decline during the financial crisis compared to the MV strategy.

The market sell-off during low volatility periods leads to the VIX strategy not being triggered. It is seen during the end of 2018 in Figure 3, where the S&P 500 fell roughly 20% from the September highs to the December lows. With a threshold set at 40, the bear strategy never triggered, since the VIX reached a high of 36 on December 24. A lower threshold would have triggered the strategy; however, the VIX was only above 30 for a mere three days. It was thus leading the bear strategy to be unexploited during a low volatility market sell-off. Worth noting is the underperformance during the first 18 years, as seen in Figure 3; this is, of course, without exploiting the potential upside with implementing the lower bull market indicator. Overall, by looking at the performance of the VIX portfolio in Figure 3, the question arises whether other outset portfolios would be better suited for a combination with the VIX strategy.

Figure 3: VIX_c vs. S&P 500

Figure 3 shows the excess return of the VIX strategy and the excess return of a buy-and-hold S&P 500 portfolio. The period depicted is 1991.01.03-2019.12.31. The Y-axis is denoted in hundreds of percent, meaning 1 on the axis corresponds to 100%.

5.3 Equal-Weighted Portfolio

As was shown in the preceding sections, using the MV approach as the outset portfolio does not render any significant excess returns over thirty years, the investor would be better off by buying a broad market index, like the S&P 500. To isolate whether the returns are lower due to the outset portfolio rather than the strategy in itself, we take inspiration from DeMiguel et al. (2009) by testing the MV outset portfolio against an equal-weighted (EW) portfolio. It is known that MV optimization can suffer from estimation errors over more extended periods and produce inferior results to other alternatives; therefore, an EW portfolio removes the possibility of estimation errors in the outset portfolio. In addition, it lets us test the impact an outset portfolio has on a TAA strategy.

5.3.1 Equal-Weighted Main Results

Across the board, reiterating the same tests as in section 5.1 (see Appendix Tables 18, 19, and 20) produces the same results, *e.g.*, the optimal asset sensitivity is still 0.75, the optimal correlation window is still 70 and so forth. Therefore, the input variables in this section are the same as in 5.1.

Table 5: Varying VIX Thresholds Upper Bound

Summary Statistics and Regressions Results

STATS	20	25	30	35	40	45	SMA	EW
Return	1,337.1576	1,857.7141	1,837.5725	1,678.9793	1,810.4707	1,362.4181	5,616.9229	798.8899
Return_c	362.0435	598.5943	1,005.8976	1,140.529	1,458.9412	1,176.6485	1,921.2081	793.8085
No. of trades	1,559	1,232	661	411	234	149	942	13
μ	0.7919	0.8937	0.893	0.8738	0.8983	0.8189	1.472	0.6654
μ_c	0.4177	0.5677	0.7204	0.7654	0.8319	0.7767	1.1674	0.6635
σ	2.9724	3.1847	3.2607	3.4435	3.5566	3.6485	7.7757	3.6271
σ_c	3.0751	3.2275	3.3075	3.5173	3.4309	3.65	7.8412	3.6252
Sharpe	0.2664	0.2806	0.2739	0.2537	0.2526	0.2244	0.1893	0.1834
Sharpe_c	0.1358	0.1759	0.2178	0.2176	0.2425	0.2128	0.1489	0.183
FF5								
α	0.0003***	0.0003***	0.0003**	0.0002***	0.0002***	0.0002**	0.0002	-0.0000***
p	0.000	0.000	0.001	0.004	0.005	0.028	0.150	0.012
R^2	0.121	0.197	0.268	0.372	0.471	0.540	0.431	0.983
α_c	0.0002*	0.0002*	0.0002**	0.0002**	0.0002**	0.0001*	0.0001	-0.0000***
p_c	0.078	0.053	0.017	0.023	0.014	0.052	0.582	0.005
R^2_c	0.121	0.197	0.272	0.374	0.474	0.543	0.430	0.983

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5 shows the main regressions results and summary statistics when varying the VIX upper bounds, and the SMA as well as the simple buy- and hold EW portfolio. The Return is the cumulative daily excess return in the period 1991.01.03-2019.12.31. No. of trades is calculated as the summary of changes in weights over the period, where one trade is defined as any change in any asset's weight from one day to the next. μ is the daily mean return in percent during the period. σ is the daily standard deviation in percent of the portfolio. Sharpe is the Sharpe ratio calculated on daily mean and daily volatility. The cost-adjusted statistics are denoted with c; these include commission fees, short-selling fees, and the bid-ask spread. FF5 corresponds to the main regression, where the α is Jensen's alpha from the Fama-French five-factor model. p is the p-value for the regression, derived from Newey-West standard errors to overcome the issue of heteroskedastic and autocorrelated standard errors. R^2 is the r-squared for the model.

In Table 5, the excess returns before costs have risen noticeably, going as high as 5,617% for the SMA strategy and peaking at upper bound 25 for the VIX strategy at 1,858%. Again, similar to the preceding sections, the costs rise as a consequence of increasing the number of transactions. We see a large trade-off between trades and return looking at the cost adjusted returns moving from upper bound 25 to 30. Upper bound 40 still yields the highest cost adjusted excess return, but the SMA dwarfs all the other portfolios. For the VIX strategy, the highest expected excess return, μ_c, and the highest Sharpe_c ratio, are again achieved at the upper bound 40. The volatility in the SMA strategy is higher when using the EW outset portfolio; however, it is offset by a remarkably higher cost adjusted return compared to the MV outset portfolio. Comparing the two outset portfolios suggests that the EW portfolios used by Copeland and Copeland (1999), Faber (2013), and Cloutier et al. (2017) improves the performance of a TAA strategy. However, the other portfolios suggested by DeMiguel et al. (2013) may still improve upon this, but are not explored in this paper.

Looking at the R_c^2, there is a noticeable difference between the two outset portfolios compared to the preceding section 5.1. This may come from that the EW portfolio equally invests in all assets during the sample period. Since there are no variations in weights, this will reflect the market movements to a much higher degree. This is represented by the much higher R_c^2 of the EW portfolio. Further, the alphas are statistically significant to a higher degree than in the MV case.

The DIFF regressions against the SMA yield significant results (see Appendix Table 15), showing that both the EW outset portfolio and the VIX strategy are outperformed by the SMA strategy. This suggests that without the MV estimation errors, the SMA performs better than the VIX strategy. One explanation could be that without estimation errors, the SMA yields higher results in its long strategy during periods where the VIX-level is relatively low enough to the point that it catches up and moves past the VIX strategy.

The statistically proven outperformance of the SMA strategy supports the findings of Faber (2013) to a greater degree. Since even when including costs, their suggested strategy still manages to outperform the others. It can, therefore, be concluded that the SMA strategy dramatically benefits from a stable EW portfolio. Given this result, for the sake of the VIX strategy, looking into the effect of enabling a bullish VIX strategy, exploiting especially calm periods in the VIX-level, is further explored in section 5.4.

5.4 Bull Limit Test

5.4.1 Equal-Weighted Test

Table 6 shows that utilizing low volatility periods by leveraging the VIX-sensitive assets, provides a portfolio with the ability to outperform the market even more than was the case in Table 5. However, there are consequences. If the lower bound is set to 15, the

VIX strategy will reallocate the portfolio too often. This will increase costs substantially while not gaining the bull market upside. Setting the lower bound at 20 captures more of the upside bull market, resulting in a maximum cost adjusted excess return of 2,907% over the sample period, using a |0.5| correlation. Note the difference between the returns before and after the inclusion of transaction costs have risen tremendously compared to Table 5. This is exemplified by reaching a return of more than 200,000%, while the cost-adjusted return is as low as 2,907%. As outlined by Woodside-Oriakhi et al. (2013), the investor is getting penalized by conducting more transactions.

Table 6: Equal Weights Outset Portfolio

Summary Statistics

	Lower bound 15				Lower Bound 20			
Sensitivity Limit	**0.50**	**0.60**	**0.70**	**0.80**	**0.50**	**0.60**	**0.70**	**0.80**
Return	24,673.7029	14,668.3699	8,172.6862	2,018.1729	200,749.363	83,980.2912	28,970.7214	2,746.7274
Return_c	580.3107	661.5144	774.0197	841.7406	2,907.2411	2,250.5391	1,801.0659	1,021.9094
No. of trades	3,709	3,096	2,439	1,048	4,303	3,835	3,077	1,274
Sharpe	0.3733	0.3534	0.3342	0.2632	0.3912	0.3732	0.3582	0.2745
Sharpe_c	0.1336	0.1477	0.17	0.193	0.1924	0.1905	0.2003	0.1983
Correlation Window	**30**	**50**	**70**	**90**	**30**	**50**	**70**	**90**
Return	4,337.1883	3,890.4581	4,879.6593	4,114.7898	14,448.7169	9,869.0587	11,346.6228	10,745.5279
Return_c	523.4772	536.3582	866.8193	820.1746	719.1418	877.5932	1,508.8374	1,564.5919
No. of trades	2,399	2,184	1,878	1,784	3,586	2,874	2,388	2,272
Sharpe	0.3064	0.2887	0.3125	0.2966	0.3392	0.316	0.3362	0.3284
Sharpe_c	0.147	0.1469	0.1866	0.1814	0.1537	0.1684	0.208	0.2108
Bull Trading Limit	**90%**	**60%**	**30%**	**0%**	**90%**	**60%**	**30%**	**0%**
Return	2,001.7067	2,700.81	3,634.8761	4,879.6593	2,184.647	3,816.2654	6,608.9433	11,346.6228
Return_c	1,388.6791	1,190.6328	1,017.4339	866.8193	1,473.8913	1,499.3111	1,510.772	1,508.8374
No. of trades	1,878	1,878	1,878	1,878	2,388	2,388	2,388	2,388
Sharpe	0.2598	0.2798	0.2974	0.3125	0.2646	0.2957	0.3192	0.3362
Sharpe_c	0.2375	0.2213	0.2042	0.1866	0.2402	0.2308	0.2197	0.208

Table 6 shows the summary statistics when varying VIX correlation windows, assets sensitivity limits, and the VIX average lag size. The input variables are the same as mentioned in section 5.1, *i.e.*, in the *Sensitivity Limit* part, the correlation window is 70 and bull trading limit is 0%, and so forth. The Return is the cumulative daily excess return in the period 1991.01.03-2019.12.31. No. of trades is calculated as the summary of changes in weights over the period, where one trade is defined as any change in any asset's weight from one day to the next. Sharpe is the daily Sharpe ratio calculated on daily mean and daily volatility. The cost-adjusted statistics are denoted with c; these include commission fees, short-selling fees, and the bid-ask spread.

Varying the sensitivity limit indicates that the excess returns are upward trending with a lower sensitivity, using a lower bound of 20. This shows the inverse relationship of sensitivity, compared to earlier results in Table 4. An explanation could be that when the VIX-level is low, the correlations during the period are nonsensical in terms of strategy. Since a low VIX-level indicates a bull market where almost all 12 assets yield positive returns on average. It is beneficial for the strategy to trade as many assets as possible. It is not relevant to check for VIX sensitivity but simply better to leverage as many assets as possible, undermining the point of the asset-sensitivity strategy. Therefore, lowering sensitivity means the strategy moves away from its primary purpose of exploiting the asset-sensitivities towards the VIX. This means that the VIX strategy would be an EW portfolio that is more leveraged compared to the EW outset portfolio during especially low volatility market periods.

An upward trend is visible with regards to the correlation window, the longer the window, the better the cost adjusted returns get. Limiting the bull strategy, from a limit of 90% to no limit at all (0%), has small effects on the cost adjusted returns at the 20 bound, whereas limiting the bull strategy using the 15 bound raises returns.

It should be noted that the highest Sharpe ratio is not accompanied by the highest cost adjusted excess return when using the EW outset portfolio, opposite to the case when using the MV outset portfolio. Looking at bound 15 and 20, we achieve the highest Sharpe ratios by limiting the ability to leverage by up to 90%. This means that although the highest cost adjusted excess return is 2907% with a Sharpe ratio of 0.1924, it has a lower Sharpe ratio compared to limiting the bull strategy almost entirely, which produces a Sharpe ratio of 0.2402. Therefore, achieving more substantial returns by leveraging in bull markets yields higher, but much riskier, returns.

Although the strategy somewhat deviates from its original purpose, we note that if we can yield substantial abnormal returns during bull periods in this manner, it falls in line with earlier papers. Both Cloutier et al. (2017), and Copeland and Copeland (1999) exploit bull markets by having a strategy applied during tranquil market periods. However, a conclusion from this is that the importance of asset sensitivity to the VIX diminishes when markets stay in low volatility periods for a longer duration. This essentially boils down to the fact that the best sensitivity strategy in tranquil markets is no sensitivity strategy.

5.4.2 Mean-Variance Test

In Table 7, it should be noted that we yield lower returns when enabling a bull strategy with an MV outset portfolio compared to Table 4. Allowing for the bull strategy, but limiting it at 90% produces similar returns to the ones achieved using only the upper bound strategy. What should be noted, is that for each input variable that decreases trading with the bull strategy, the return increases.

Table 7: Mean-Variance Outset Portfolio

Summary Statistics

	Lower bound 15				Lower Bound 20			
Sensitivity Limit	**0.50**	**0.60**	**0.70**	**0.80**	**0.50**	**0.60**	**0.70**	**0.80**
Return	1,698.3232	1,543.1932	1,003.7403	397.3847	4,101.993	4,157.1125	2,437.7692	491.6111
Return$_c$	64.2779	119.6262	154.4486	185.8912	80.7853	161.0365	240.0489	214.9201
No. of trades	4,090	3,475	2,817	1,424	4,674	4,211	3,455	1,650
Sharpe	0.2673	0.2712	0.2498	0.1759	0.2635	0.2809	0.2744	0.1887
Sharpe$_c$	-0.0215	0.0321	0.0596	0.0864	0.0098	0.0536	0.09	0.0981
Correlation Window	**30**	**50**	**70**	**90**	**30**	**50**	**70**	**90**
Return	665.0567	634.5469	787.1517	715.2718	1,440.027	1,194.5322	1,518.7631	1,379.7479
Return$_c$	122.159	131.3522	192.8215	189.1785	115.5547	168.7657	276.9407	290.8683
No. of trades	2,780	2,562	2,256	2,161	3,975	3,256	2,772	2,643
Sharpe	0.2226	0.2084	0.2344	0.2207	0.2513	0.2335	0.2626	0.2543
Sharpe$_c$	0.0353	0.043	0.0859	0.0834	0.0289	0.0645	0.1134	0.1185
Bull Trading Limit	**90%**	**60%**	**30%**	**0%**	**90%**	**60%**	**30%**	**0%**
Return	442.7838	536.9927	650.5145	787.1517	473.7579	701.993	1,035.0891	1,518.7631
Return$_c$	307.6509	263.9221	225.8794	192.8215	319.6616	306.8632	292.565	276.9407
No. of trades	2,256	2,256	2,256	2256	2,772	2,772	2,772	2,772
Sharpe	0.1836	0.2025	0.2195	0.2344	0.1892	0.2209	0.245	0.2626
Sharpe$_c$	0.1464	0.1266	0.1062	0.0859	0.149	0.1373	0.1253	0.1134

Table 7 shows the summary statistics when varying VIX correlation windows, assets sensitivity limits, and the VIX average lag size. The input variables are the same as mentioned in section 5.1, *i.e.*, in the *Sensitivity Limit* part, the correlation window is 70 and bull trading limit is 0%, and so forth. The Return is the cumulative daily excess return in the period 1991.01.03-2019.12.31. No. of trades is calculated as the summary of changes in weights over the period, where one trade is defined as any change in any asset's weight from one day to the next. Sharpe is the daily Sharpe ratio calculated on daily mean and daily volatility. The cost-adjusted statistics are denoted with c; these include commission fees, short-selling fees, and the bid-ask spread.

E.g., increasing the sensitivity limit from 0.5 to 0.8 lowers the amount of assets that are allowed to trade. This leads to a decrease in the number of trades from 4,674 to 1,650. This increases the return in most cases. However, one exception is the 0.7 sensitivity limit at the lower bound of 20. It yields higher cost adjusted returns compared to a 0.8 limit, indicating there is still an optimal sensitivity limit that we can use to increase the returns. In general, this indicates that the more we deviate from the bull strategy, the more the returns increase. This is the opposite of the case in Table 6, where returns increase when trading increases. Additionally, it is also somewhat contrary to earlier papers by Copeland and Copeland (1999) and Cloutier et al. (2017), where they employ bullish strategies that produce higher Sharpe ratios compared to their buy-and-hold strategies.

One possible reason for the poor performance could be that the estimation errors from the MV outset portfolio are amplified with trading at a lower limit. For example, the MV outset portfolio is shorting an asset which displays positive return during a shorter bullish period—further augmented in the VIX strategy, by leveraging that position in calm periods, yielding significant negative returns. Another possible reason for the decrease in return could be that costs are primarily driven by the total weight allocated to an asset in the portfolio. If there are large allocations given to any assets in the MV outset portfolio, changing that position results in reallocating a large amount of the portfolio and increasing transaction costs. The EW outset portfolio allocates a moderate amount of 7.69%, compared to some of the more extreme allocations in the MV outset portfolio of 23.02% in an asset (see Appendix Table 21). The moderate amount leads to less extreme reallocations in the EW outset portfolio. This reduces the effects of trading more regularly during up and down movements in the VIX-level, explaining why the EW outset portfolio outperforms the MV portfolio given the same VIX strategy.

5.5 Best Outcome

Looking at Figure 4, we can see that the VIX strategy performs better when using an EW outset portfolio, compared to the MV outset portfolio in Figure 2. Further, allowing for a bull strategy to benefit from low volatility periods is beneficial. Especially seen in the bull market from 2010 until 2019, with two more massive setbacks visible. During the setbacks, the VIX was not at a high enough level to trigger the bear strategy. Also, when combining this with the optimal input variables from Table 6:

1. VIX correlation window: 90
2. Sensitivity: 0.5
3. Lag size: 4
4. VIX upper bound: 40
5. VIX lower bound: 20
6. Trading limit bear market: 0%
7. Trading limit bull market: 0%

The VIX strategy yields results that vastly outperform the S&P 500 over the sample period. It is important to note, that although the VIX strategy outperforms, the VIX strategy still cannot be confirmed to yield statistically significant positive alphas (see Appendix Table 23). Before costs are included, the VIX strategy does produce a statistically significant alpha (see Appendix Table 22), but the returns are inflated. Additionally, the best outcome in return may not represent the best outcome from the VIX strategy's perspective in terms of actual strategy. As discussed in section 5.4, decreasing the sensitivity for the assets yields higher returns. Those returns are not directly related to the strategy since it is merely leveraging up all positions when the VIX is below a certain threshold. This means that the strategy is not using the different asset sensitivities to exploit movements in the VIX, and thus, arguably, it is therefore not part of the strategy anymore.

Figure 4: Different VIX Strategies with EW Outset

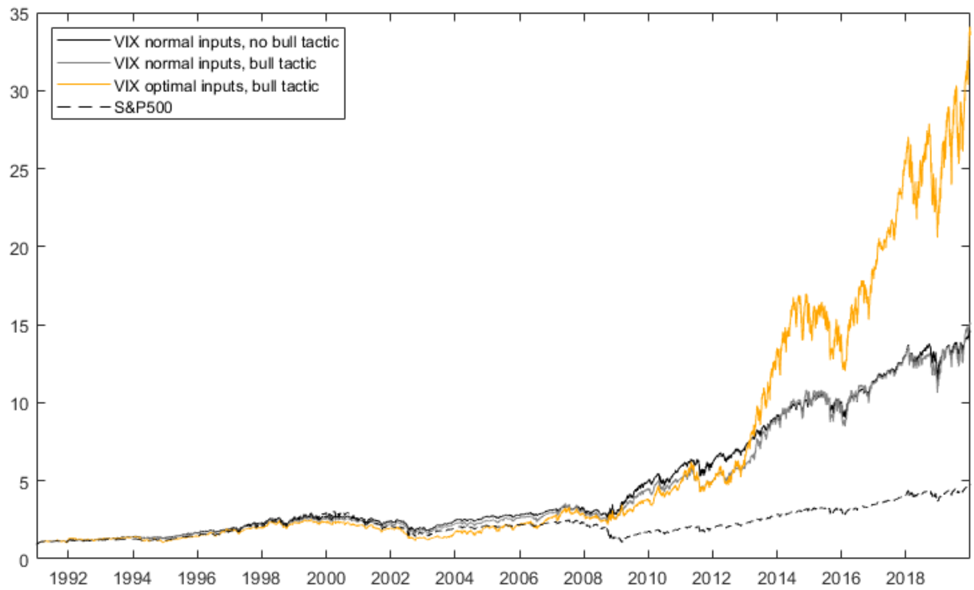

Figure 4 shows the excess cost adjusted return for each portfolio with the excess return of the simple buy-and-hold S&P 500 portfolio. The period depicted is 1991.01.03-2019.12.31. The Y-axis is denoted in hundreds of percent, meaning 1 on the axis corresponds to 100%.

Another variable that may indicate that this is not the optimal solution for the VIX strategy is the Sharpe ratio. Looking at Table 8, we can see that the Sharpe$_c$ ratio has been reduced to 0.1980 from 0.2402, as seen in Table 6, meaning that we have created higher returns with the expense of increased risk substantially. This is visible in Figure 4, which looks at the aforementioned setbacks during the 10-year bull market from 2010 until 2019. The VIX strategy produces the highest μ_c, as well as the highest Sharpe$_c$ ratio. However, as mentioned, the Sharpe$_c$ ratio is only slightly higher than the EW outset portfolio (seen in Appendix Table 15) due to the large increase in volatility. Cloutier et al. (2017) still manage to achieve a Sharpe ratio that is higher than ours, but as noted previously, they do not consider costs.

Using the optimal solution, our strategy applies a similar strategy to Copeland and Copeland (1999). Their strategy is also exploiting calm market periods and utilizing movements in the VIX, using the Fama-French HML and SMB factors. While our optimal VIX strategy leverages up during calm market periods, as opposed to section 5.3.1, where simply a bearish tactic is applied. Additionally, looking at Tables 22 and 13, we can get an idea of how the SMA strategy suggested by Faber (2013) invests compared our VIX strategy, before and after applying the optimal strategy. The SMA strategy, and the VIX strategy, lie closer together in the optimal strategy when looking at factors SMB and HML in Table 22, compared to earlier when there were hardly any similarities at all, as seen in Table 13. Therefore, one can conclude that our optimal solution yields similar exposure to the factors SMB and HML, while yielding a higher Sharpe ratio.

Overall, we can conclude that our VIX strategy performs well compared to the strategies suggested by earlier papers. However, one of the primary goals with this paper is to increase returns, with a lower volatility, using a VIX strategy. It can be argued that the solution with the highest return is indeed the optimal solution. However, given how this increases volatility, it may not be the actual optimal solution. Enabling the bullish strategy induces high volatility, and this is not the point of the VIX strategy. Therefore, it may be the case that the optimal solution to the bullish tactic could benefit from further development, something we do not consider in this paper.

Table 8: Optimal Solution
Summary Statistics

	Return	Return_c	No. of trades	μ	μ_c	σ	σ_c	Sharpe	Sharpe_c
VIX	210,695.3	3,377.378	4,149	2.4054	1.1972	6.1465	6.0463	0.3913	0.198
SMA	5,616.923	1,921.208	942	1.472	1.1674	7.7757	7.8412	0.1893	0.1489
EW	798.8899	793.8085	13	0.6654	0.6635	3.6271	3.6252	0.1834	0.183

Table 8 shows the summary statistics for the best VIX strategy, the SMA strategy, and the EW buy-and-hold portfolio. The Return is the cumulative daily excess return in the period 1991.01.03-2019.12.31. No. of trades is calculated as the summary of changes in weights over the period, where one trade is defined as any change in any asset's weight from one day to the next. Sharpe is the daily Sharpe ratio calculated on daily mean and daily volatility. The cost-adjusted statistics are denoted with c; these include commission fees, short-selling fees, and the bid-ask spread.

5.6 Extended Data Set

In late February 2020, the volatility in the stock markets started to increase because of the evolving Covid-19 pandemic, reflected in the VIX. By mid-March, the VIX closed at a record 82.69, which was even higher than the previous record closing during the last financial crisis. The rapid sell-off after countries started going into lock-down, and quarantines being put into place all over the world, lead to the fastest 30% stock market sell-off ever recorded, according to CNBC[8]. Because of these seldom before seen levels

[8]https://www.cnbc.com/2020/03/23/this-was-the-fastest-30percent-stock-market-decline-ever.html

of the VIX, it is of high interest to see how the VIX strategy performed during the first three months of 2020.

Figure 5: Extended Data Set

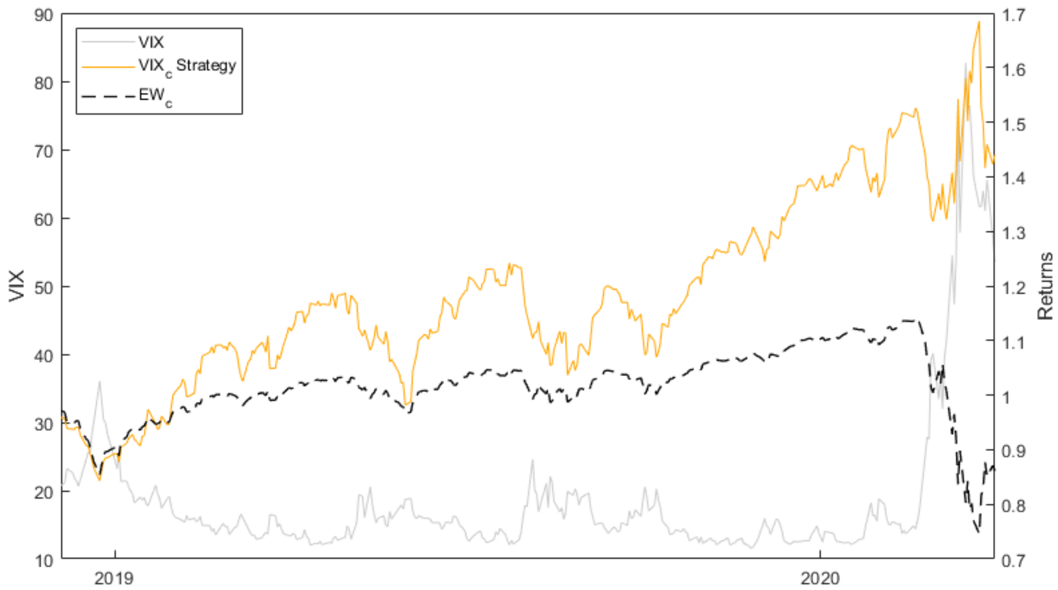

Figure 5 shows the excess return for each portfolio with the excess return of the EW buy-and-hold portfolio. The period depicted is 2018.12.01-2020.03.31. The grey line (left Y-axis) is the VIX-level. The right Y-axis is denoted in hundreds of percent, meaning 1 on the axis corresponds to 100%.

By extending the time-period to also include January through March 2020, up-to-date market data is used. In Figure 5, the VIX, the cost adjusted VIX strategy, and the EW buy-and-hold portfolios are seen. During the lower VIX-levels, the VIX strategy utilizes its bull-strategy, which leads to an overperformance during 2019. Then, going into 2020, where the VIX was below 20 until mid February, the VIX bear-strategy kicks in after the 4-day average is above the upper 40 bound. The strategy did not catch the initial sell-off; however, after the strategy kicks in, it is clear that the strategy works as intended. Looking at the last draw-down, where the market bounces back off of its lows, the VIX strategy is still using its bear-strategy, and thus missing out on the upswing.

As can be seen in Table 24, in the Appendix, the cost adjusted excess return has increased to 3,516% from 3,377% for the optimal VIX strategy. The EW buy-and-hold portfolio has decreased, but the most significant difference can be seen using the SMA strategy, its cost adjusted excessive return has decreased from 1,921% down to 678%, which is close to what an investor would have achieved with the buy-and-hold portfolio. Of high interest is the fact that the volatility (σ_c) using the VIX strategy is almost the same as before, even though the market volatility is spiking. This is not the case for the SMA strategy, where the volatility increases, and the Sharpe$_c$ ratio decreases along with the μ_c. Extending the data with this down-turn sheds light on the performance of our VIX strategy when there is high distress in the market.

After the inclusion of the first quarter of 2020, the VIX strategy achieves statistically significant positive alphas at the 0.05-level, excluding the ΔVIX regressor and at the 0.01-level, including the ΔVIX regressor (Appendix Table 26). The VIX strategy is only slightly worse than it was going into the crisis at the end of February. The draw-down in the EW buy-and-hold portfolio is considerable, as seen in Figure 5.

6 Conclusion

In this paper, we examine the performance of a quantitative tactical asset allocation (TAA) strategy based on the VIX, inspired by Copeland and Copeland (1999) and Cloutier et al. (2017). The strategy is applied to two buy-and-hold strategies, a mean-variance (MV) portfolio, and an equal-weighted (EW) portfolio. We extend the paper by factoring in costs, which are not considered by earlier papers. We also compare our VIX strategy with an SMA strategy, as taken from Faber (2013). The purpose of this paper is to provide a simple quantitative market timing strategy which removes investor behavioral bias, while also increasing the Sharpe ratio and producing a significant alpha. In line with earlier papers, we can conclude that our VIX strategy produces higher returns with lower volatility compared to both buy-and-hold strategies and the SMA strategy. We cannot statistically prove that our VIX strategy generates significant positive alpha, which is contrary to prior studies, that manage to achieve statistically significant alphas. However, when extending the data to March 2020, we can see that we produce a significant positive alpha.

To test our strategy, we construct the buy-and-hold portfolios using both daily and monthly asset data from French's data library from 1983 until 2019. We also collect daily VIX data spanning 1991 to 2019 to use in our VIX strategy. In section 5.6, the data set is extended to include the first quarter of 2020. In addition to the two buy-and-hold outset portfolios, we test for the optimal implementation of the strategy by examining several combinations of input variables. We conclude that the underlying outset portfolio significantly affects the VIX strategy used during the almost 30-year period. This is highlighted by the performance of the bullish VIX strategy during times of low volatility. The MV outset portfolio produces lower returns, while the EW outset portfolio produces higher returns. We can also conclude that the variables that have the most significant effect on the performance of the VIX strategy are the upper and lower bounds set for when the VIX strategy is triggered. This is in line with Copeland and Copeland (1999) who find that triggering their strategy too early or too late significantly impacts the performance of the TAA strategy based on the VIX.

As suggested by previous research, we extend our paper by including rudimentary costs. These transaction costs are derived from the papers by D'Avolio (2002), Do and Faff (2012), Abdi and Ranaldo (2017), and Engelberg et al. (2018). The transaction costs are; short-selling fees, commission fees, and the bid-ask spread. When factoring in costs, we can conclude that the optimal solution for our strategy regarding the input variables changes dramatically. Since the strategy revolves around timing the market with the help of the VIX, including costs shed light on how entering or exiting the market too often can negatively impact the return of a TAA strategy—exemplified by the Sharpe ratio for the optimal solution being reduced from 0.3913 to 0.1980 when factoring in costs. Therefore, contrary to Cloutier et al. (2017), who ignore transaction costs, we can conclude that costs have a substantial effect on the strategy and should always be considered when looking into the performance of a TAA strategy.

First, to test the performance of our VIX strategy compared to the market and other strategies, our primary econometric model is the five-factor model from Fama and French (2015). Using the five-factor model, we can not conclude that our VIX strategy produces significant alpha compared to the market in our normal time-frame. When extending the data, we can conclude that our VIX strategy produces significant positive alpha compared to the market. Second, we use the econometric model suggested by Copeland and Copeland (1999). The model tests for significant differences in the portfolio returns to the variation in the VIX. We can not conclude that our VIX strategy produces positive abnormal returns given the variation in the VIX compared to the buy-and-hold portfolios or the SMA portfolio.

Given our findings on how profoundly affected the strategy is by the input variables and the outset portfolio, we suggest that future research on the area of quantitative TAA should include the following. First, the transaction costs should always be considered, given their effect on the optimal solution. Second, the impact that the neutral buy-and-hold weights have on the performance should always be considered. Third, future research should also focus on shedding light on the effect that input variables have on their TAA strategy. Additionally, a strategy implementing a cost-mitigation tactic could greatly benefit a trading strategy based on the VIX, given our results on the effect of costs.

References

Abdi. Farshid Abdi's database, Retrieved from https://www.farshidabdi.net/data/index.html, March 28, 2020.

Abdi, F. and Ranaldo, A. A simple estimation of bid-ask spreads from daily close, high, and low prices. *The Review of Financial Studies*, 30(12):4437–4480, 2017.

Bloomberg. Retrieved from the Bloomberg Terminal March 17, 2020, and the extended data was retrieved May 1, 2020.

Bollerslev, T. Generalized autoregressive conditional heteroskedasticity. *Journal of econometrics*, 31(3):9307–327, 1986.

Brenner, M. and Galai, D. New Financial Instruments for Hedging Changes in Volatility. *Financial Analysts Journal*, 45(4):61–65, 1989.

CBOE. Chicago Board Options Exchange, VIX white paper, Retrieved from https://www.cboe.com/micro/vix/vixwhite.pdf, March 17, 2020. 2019.

Cloutier, R., Djatej, A., and Kiefer, D. A tactical asset allocation strategy that exploits variations in VIX. *Investment management and financial innovations*, 14(1):27–34, 2017.

CNBC. Consumer News and Business Channel, Retrieved from https://www.cnbc.com/2020/03/23/this-was-the-fastest-30percent-stock-market-decline-ever.html, April 28, 2020.

Copeland, M. M. and Copeland, T. E. Market timing: style and size rotation using the VIX.(Market Volatility Index). *Financial Analysts Journal*, 55(2):73–81, 1999.

CRSP. Center for Research in Security Prices, Wharton Research Data Services, Wharton School of the University of Pennsylvania, Retrieved from https://wrds-web.wharton.upenn.edu/wrds/ds/crsp/index.cfm, April 2, 2020.

Dahlquist, M. and Harvey, C. R. Global tactical asset allocation. *Journal of Global Capital Markets*, 23(1), 2001.

Damodaran, A. Trading Costs and Taxes - NYU Stern. Retrieved from Stern School of Business at New York University: http://people.stern.nyu.edu/adamodar/pdfiles/invphiloh/tradingcosts.pdf. April 1, 2020.

DeMiguel, V., Garlappi, L., and Uppal, R. Optimal versus naive diversification: How inefficient is the 1/N portfolio strategy?. *The review of Financial studies*, 22(5):1915–1953, 2009.

DeMiguel, V., Plyakha, Y., Uppal, R., and Vilkov, G. Improving portfolio selection using option-implied volatility and skewness. *Journal of Financial and Quantitative Analysis*, 48(6):1813–1845, 2013.

Do, B. and Faff, R. Are pairs trading profits robust to trading costs? *Journal of Financial Research*, 35(2):261–287, 2012.

D'Avolio, G. The market for borrowing stock. *Journal of financial economics*, 66(2-3): 271–306, 2002.

Engelberg, J. E., Reed, A. V., and Ringgenberg, M. C. Short-selling risk. *The Journal of Finance*, 73(2):755–786, 2018.

Engle, R. F. Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. *Econometrica: Journal of the Econometric Society*, pages 987–1007, 1982.

Faber, M. T. A quantitative approach to tactical asset allocation. *The Journal of Wealth Management*, 9(4):69–79, 2013.

Fama, E. F. and French, K. R. Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, 33(1):3–56, 1993.

Fama, E. F. and French, K. R. A five-factor asset pricing model. *Journal of Financial Economics*, 116(1):1–22, 2015.

Fleming, J., Ostdiek, B., and Whaley, R. Predicting stock market volatility: A new measure. *Journal of Futures Markets*, 15(3):265–302, 1995.

Fleming, J., Kirby, C., and Ostdiek, B. The Economic Value of Volatility Timing. *Journal of Finance*, 56(1):329–352, 2001.

Fleming, J., Kirby, C., and Ostdiek, B. The economic value of volatility timing using "realized" volatility. *Journal of Financial Economics*, 67(3):473–509, 2003.

Frazzini, A., Israel, R., and Moskowitz, T. J. Trading costs of asset pricing anomalies. *Fama-Miller working paper*, pages 14–05, 2012.

French. Kenneth French data library, Retrieved from https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html, March 17, 2020, and the extended data was retrieved May 1, 2020.

French, K., Schwert, G., and Stambaugh, R. Expected stock returns and volatility. *Journal of Financial Economics*, 19(1):3–29, 1987.

ITG. Investment Technology Group, Retrieved from https://www.virtu.com/uploads/2019/02/ITG-Global-Cost-Review-4Q18.pdf, https://www.virtu.com/uploads/documents/Global-Cost-Review-2019Q4.pdf, March 25, 2020.

Jensen, M. C. The performance of mutual funds in the period 1945–1964. *The Journal of finance*, 23(2):389–416, 1968.

Lee, W. Theory and methodology of tactical asset allocation. *John Wiley Sons*, Vol. 65, 2000.

Markowitz, H. Portfolio Selection. *Journal of Finance*, 7(1):77–91, 1952.

Merton, R. On Estimating the Expected Return on the Market. *Journal of Financial Economics*, 8:323–361, 1980.

Philips, T. K., Rogers, G. T., and Capaldi, R. E. Tactical asset allocation: 1977-1994. *Journal of Portfolio Management*, 23(1)(57), 1996.

Whaley, R. E. Understanding the VIX. *The Journal of Portfolio Management*, 35(3): 98–105, 2009.

Woodside-Oriakhi, M., Lucas, C., and Beasley, J. E. Portfolio rebalancing with an investment horizon and transaction costs. *Omega*, 41(2):406–420, 2013.

Yoshimoto, A. The mean-variance approach to portfolio optimization subject to transaction costs. *Journal of the Operations Research Society of Japan*, 39(1):99–117, 1996.

Zhang, J., Shu, J., and Brenner, M. The new market for volatility trading. *Journal of Futures Markets*, 30(9):809–833, 2010.

Appendix

Table 9: Asset Descriptions

Asset	Asset Description	Industries
NoDur	Consumer Nondurables	Food, Tobacco, Textiles, Apparel, Leather, Toys
Durbl	Consumer Durables	Cars, TVs, Furniture, Household Appliances
Manuf	Manufacturing	Machinery, Trucks, Planes, Off Furn, Paper, Com Printing
Enrgy	Energy	Oil, Gas, and Coal Extraction and Products
Chems	Chemicals	Chemicals and Allied Products
BusEq	Business Equipment	Computers, Software, and Electronic Equipment
Telcm	Telecommunication	Telephone and Television Transmission
Utils	Utilities	Utilities
Shops	Shops	Wholesale, Retail, and Some Services (Laundries, Repair Shops)
Hlth	Health	Healthcare, Medical Equipment, and Drugs
Money	Finance	Finance
Other	Other	Mines, Constr, BldMt, Trans, Hotels, Bus Serv, Entertainment

Table 10: Asset's Corresponding SIC-codes

NoDur	**Durbl**
0100-0999, 2000-2399, 2700-2749, 2770-2799, 3100-3199, 3940-3989	2500-2519, 2590-2599, 3630-3659, 3710-3711, 3714-3714, 3716-3716, 3750-3751, 3792-3792, 3900-3939, 3990-3999
Manuf	**Enrgy**
2520-2589, 2600-2699, 2750-2769, 3000-3099, 3200-3569, 3580-3629, 3700-3709, 3712-3713, 3715-3715, 3717-3749, 3752-3791, 3793-3799, 3830-3839, 3860-3899	1200-1399, 2900-2999
Chems	**BusEq**
2800-2829, 2840-2899	3570-3579, 3660-3692, 3694-3699, 3810-3829, 7370-7379
Telcm	**Utils**
4800-4899	4900-4949
Shops	**Hlth**
5000-5999, 7200-7299, 7600-7699	2830-2839, 3693-3693, 3840-3859, 8000-8099
Money	**Other**
6000-6999	The Rest

Markowitz' Mean-Variance

$$\max_{w} w'\mu$$

Subject to.

$$w'\Sigma w = \bar{\sigma}_p^2$$

$$w'\iota = 1$$

Therefore stated as a the following Lagrangian:

$$w'\mu - \lambda_1(w'\Sigma w - \bar{\sigma}_p^2) - \lambda_2(w'\iota - 1)$$

Where w' is a vector of the asset weights, μ is a matrix of expected returns, ι is a vector of ones, Σ is a variance covariance matrix, and $\bar{\sigma}_p^2$ is a volatility scalar. By taking the first order condition of the Lagrangian one can solve for the portfolio variance:

$$\bar{\sigma}_p^2 = \frac{1}{\iota'\Sigma^{-1}\iota}\left(1 + \frac{(\iota'\Sigma^{-1}\iota\,\bar{\mu}_p - \mu_p'\Sigma^{-1}\iota)^2}{\mu'\Sigma^{-1}\mu\,\iota'\Sigma^{-1}\iota - \mu'\Sigma^{-1}\iota}\right) \tag{13}$$

Further, one can solve for the portfolio return as:

$$\bar{\mu}_p = \frac{\mu'\Sigma^{-1}\iota}{\iota'\Sigma^{-1}\iota} + \frac{1}{\iota'\Sigma^{-1}\iota}\sqrt{(\iota'\Sigma^{-1}\iota\,\bar{\sigma}_p^2 - 1)(\mu'\Sigma^{-1}\mu\,\iota'\Sigma^{-1}\iota - (\mu'\Sigma^{-1}\iota)^2)} \tag{14}$$

Table 11: Bid-Ask Spread Cost per Asset Class

NoDur	**Durbl**	**Manuf**	**Enrgy**	**Chems**	**BusEq**	**Telcm**	**Utils**	**Shops**	**Hlth**	**Money**	**Other**
0.0107	0.0102	0.0111	0.0125	0.0109	0.0145	0.0134	0.0066	0.0121	0.0164	0.0116	0.0147

Table 11 shows the corresponding bid-ask spread cost for each of the 12 assets.

Table 12: Varying Upper Bound MV Setting

Summary Statistics and Regressions Results

STATS	**20**	**25**	**30**	**35**	**40**	**45**	**SMA**	**MV**
Return	440.2212	465.3267	449.5513	388.8763	415.1045	311.7862	392.3947	219.5394
Return_c	134.5022	172.5663	251.2019	259.2105	323.5275	262.0611	146.2378	202.7941
No. of trades	1,936	1,597	1,038	788	611	526	1,226	390
μ	0.4521	0.4716	0.461	0.4204	0.4405	0.3579	0.5326	0.2569
μ_c	0.1135	0.1868	0.2945	0.3048	0.3667	0.3079	0.2522	0.2341
σ	2.2548	2.3991	2.3709	2.4141	2.4909	2.4876	5.2342	2.4724
σ_c	2.3735	2.4353	2.4184	2.4572	2.4014	2.486	5.2979	2.4722
Sharpe	0.2005	0.1966	0.1944	0.1741	0.1768	0.1439	0.1017	0.1039
Sharpe_c	0.0478	0.0767	0.1218	0.1241	0.1527	0.1238	0.0476	0.0947
MAIN REGRESSION								
FF5								
α	0.0002***	0.0001**	0.0001*	0.0001	0.0001	0.0000	0.0000	-0.0001**
p	0.006	0.025	0.060	0.235	0.276	0.826	0.785	0.001
R^2	0.022	0.072	0.125	0.228	0.315	0.385	0.241	0.765
α_c	0.0000	0.0000	0.0000	0.0000	0.0000	-0.0000	-0.0002	-0.0001***
p_c	0.866	0.876	0.526	0.759	0.600	0.834	0.187	0.000
R_c^2	0.023	0.072	0.129	0.228	0.318	0.388	0.238	0.765
FF5+ΔVIX								
α	0.0003***	0.0003***	0.0003***	0.0002***	0.0002***	0.0001*	0.0003**	-0.0001**
p	0.000	0.000	0.000	0.002	0.004	0.065	0.012	0.014
R^2	0.090	0.140	0.192	0.288	0.365	0.423	0.342	0.768
α_c	0.0001**	0.0001**	0.0002***	0.0001**	0.0001**	0.0001	0.0002	-0.0001***
p_c	0.036	0.034	0.008	0.023	0.023	0.147	0.162	0.006
R_c^2	0.091	0.140	0.198	0.289	0.368	0.425	0.340	0.768
DIFF REGRESSION								
MV								
α_c	-0.0001*	-0.0001	-0.0000	0.0000	0.0000	0.0000	0.0001	-
p_c	0.068	0.225	0.753	0.993	0.447	0.725	0.343	-
R_c^2	0.118	0.081	0.058	0.034	0.020	0.016	0.074	-
SMA								
α_c	-0.0002*	-0.0002	-0.0001	-0.0001	-0.0001	-0.0001	-	-0.0001
p_c	0.019	0.055	0.194	0.264	0.505	0.370	-	0.343
R_c^2	0.247	0.223	0.205	0.181	0.158	0.140	-	0.074

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 12 shows the main regression results and summary statistics when varying the VIX upper bounds, and the SMA as well as the mean-variance strategy. The Return is the cumulative excess return in the period 1991.01.03-2019.12.31. No. of trades is calculated as the summary of changes in weights over the period, where one trade is defined as any change in any asset's weight from one day to the next. μ is the daily mean return in percent during the period. σ is the daily standard deviation in percent of the portfolio. Sharpe is the Sharpe ratio calculated on daily mean and daily volatility. The cost-adjusted statistics are denoted with c; these include commission fees, short-selling fees, and the bid-ask spread.

FF5 corresponds to the main regression, where the α is Jensen's alpha from the Fama-French five-factor model. p is the p-value for the regression, derived from Newey-West standard errors to overcome the issue of heteroskedastic and autocorrelated standard errors. R^2 is the r-squared for the model. FF5+ΔVIX, is the Fama-French five-factor model extended by adding the variable ΔVIX. The DIFF-title corresponds to the difference regression derived from Copeland and Copeland (1999), where the α is the constant obtained from regressing the differences in returns against the ΔVIX. The MV-title, under the DIFF-title, corresponds to the VIX strategy minus mean-variance returns, and SMA corresponds to the difference in return between the VIX strategy and the SMA strategy.

Table 13: Main Regressions Results

	VIX	SMA	MV	VIX	SMA	MV
Mktrf	0.3213***	0.5659***	0.5135***	0.1879***	0.1716**	0.4802***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.015)	(0.000)
SMB	0.1081***	0.3992***	0.1506***	0.0949***	0.3601***	0.1472***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
HML	0.0500	0.1056	0.2292***	0.0637	0.1462**	0.2326***
	(0.260)	(0.172)	(0.000)	(0.125)	(0.031)	(0.000)
RMW	0.0028	0.1477**	0.1054***	-0.0226	0.0726	0.0990***
	(0.922)	(0.017)	(0.000)	(0.436)	(0.188)	(0.000)
CMA	0.2475***	0.4718***	0.1690***	0.2184***	0.3859***	0.1617***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Δ VIX	-	-	-	-0.0287***	-0.0849***	-0.0072***
				(0.000)	(0.000)	(0.000)
Constant	0.0001	-0.0000	-0.0001***	0.0002***	0.0003**	-0.0001**
	(0.276)	(0.785)	(0.001)	(0.004)	(0.012)	(0.014)
R-squared	0.315	0.241	0.765	0.365	0.342	0.768

p-values in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 13 shows the results from running the regression $\mu_p = \alpha_i + \beta_1(R_{M,t} - R_{f,t}) + \beta_2(SMB_t) + \beta_3(HML_t) + \beta_4(RMW_t) + \beta_5(CMA_t) + \epsilon_{i,t}$ for the mean-variance outset portfolio, SMA strategy and VIX strategy. The regression is run on daily excess returns in the period 1991.01.03-2019.12.31. Mktrf is the Fama-French excess market return, SMB is the small minus big factor, HML is the high minus low factor, RMW is the robust minus weak factor, CMA is the conservative minus aggressive factor. ΔVIX is the monthly percentage change of the VIX in the same period. Alpha is Jensen's Alpha. P-values are derived from Newey-West standards errors to overcome the issue of heteroskedastic and autocorrelated standard errors.

Table 14: Main Regressions Results Cost Adjusted

	VIX_c	SMA_c	MV_c	VIX_c	SMA_c	MV_c
Mktrf	0.3208***	0.5646***	0.5137***	0.1871***	0.1700**	0.4804***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.015)	(0.000)
SMB	0.1136***	0.3953***	0.1511***	0.1003***	0.3561***	0.1478***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
HML	0.0508	0.1034	0.2283***	0.0646	0.1441**	0.2317***
	(0.252)	(0.178)	(0.000)	(0.120)	(0.032)	(0.000)
RMW	0.0054	0.1473**	0.1062***	-0.0201	0.0721	0.0999***
	(0.854)	(0.017)	(0.000)	(0.485)	(0.192)	(0.000)
CMA	0.2465***	0.4673***	0.1696***	0.2173***	0.3813***	0.1623***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Δ VIX	-	-	-	-0.0288***	-0.0850***	-0.0072***
				(0.000)	(0.000)	(0.000)
Constant	0.0000	-0.0002	-0.0001***	0.0001**	0.0002	-0.0001***
	(0.600)	(0.187)	(0.000)	(0.019)	(0.162)	(0.006)
R-squared	0.318	0.238	0.765	0.368	0.340	0.768

p-values in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 14 shows the results from running the regression $\mu_p = \alpha_i + \beta_1(R_{M,\,t} - R_{f,\,t}) + \beta_2(SMB_t) + \beta_3(HML_t) + \beta_4(RMW_t) + \beta_5(CMA_t) + \epsilon_{i,\,t}$ for cost adjusted returns of the mean-variance outset portfolio, SMA strategy and VIX strategy. The regression is run on daily excess returns, adjusted for commissions fees, short-selling fees and bid-ask-spread, in the period 1991.01.03-2019.12.31. Mktrf is the Fama-French excess market return, SMB is the small minus big factor, HML is the high minus low factor, RMW is the robust minus weak factor, CMA is the conservative minus aggressive factor. ΔVIX is the monthly percentage change of the VIX in the same period. Alpha is Jensen's Alpha. P-values are derived from Newey-West standards errors to overcome the issue of heteroskedastic and autocorrelated standard errors.

Table 15: Varying Upper Bound EW Setting

Summary Statistics and Regressions Results

STATS	**20**	**25**	**30**	**35**	**40**	**45**	**SMA**	**EW**
Return	1,337.1576	1,857.7141	1,837.5725	1,678.9793	1,810.4707	1,362.4181	5,616.9229	798.8899
Return_c	362.0435	598.5943	1,005.8976	1,140.529	1,458.9412	1,176.6485	1,921.2081	793.8085
No. of trades	1,559	1,232	661	411	234	149	942	13
μ	0.7919	0.8937	0.893	0.8738	0.8983	0.8189	1.472	0.6654
μ_c	0.4177	0.5677	0.7204	0.7654	0.8319	0.7767	1.1674	0.6635
σ	2.9724	3.1847	3.2607	3.4435	3.5566	3.6485	7.7757	3.6271
σ_c	3.0751	3.2275	3.3075	3.5173	3.4309	3.65	7.8412	3.6252
Sharpe	0.2664	0.2806	0.2739	0.2537	0.2526	0.2244	0.1893	0.1834
Sharpe_c	0.1358	0.1759	0.2178	0.2176	0.2425	0.2128	0.1489	0.183
MAIN REGRESSON								
FF5								
α	0.0003***	0.0003***	0.0003**	0.0002***	0.0002***	0.0002**	0.0002	-0.0000***
p	0.000	0.000	0.001	0.004	0.005	0.028	0.150	0.012
R^2	0.121	0.197	0.268	0.372	0.471	0.540	0.431	0.983
α_c	0.0002*	0.0002*	0.0002**	0.0002**	0.0002**	0.0001*	0.0001	-0.0000***
p_c	0.078	0.053	0.017	0.023	0.014	0.052	0.582	0.005
R^2_c	0.121	0.197	0.272	0.374	0.474	0.543	0.430	0.983
FF5+ΔVIX								
α	0.0005***	0.0005***	0.0004**	0.0004***	0.0004***	0.0003***	0.0007***	-0.0000**
p	0.000	0.000	0.000	0.000	0.000	0.001	0.000	0.012
R^2	0.168	0.245	0.316	0.414	0.503	0.561	0.500	0.983
α_c	0.0003***	0.0003***	0.0004***	0.0003***	0.0003***	0.0003***	0.0005***	-0.0000**
p_c	0.001	0.000	0.000	0.000	0.000	0.003	0.002	0.010
R^2_c	0.168	0.245	0.321	0.416	0.507	0.564	0.499	0.983
DIFF REGRESSION								
EW								
α_c	-0.0002**	-0.0001	-0.0000	-0.0000	0.0000	0.0000	0.0004***	-
p_c	0.022	0.153	0.611	0.943	0.560	0.721	0.004	-
R^2_c	0.139	0.094	0.063	0.037	0.022	0.017	0.144	-
SMA								
α_c	-0.0007***	-0.0006***	-0.0005***	-0.0004***	-0.0004***	-0.0004***	-	-0.0004***
p_c	0.000	0.000	0.000	0.001	0.003	0.002	-	0.004
R^2_c	0.368	0.343	0.323	0.296	0.272	0.245	-	0.144

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 15 shows the main regressions results and summary statistics when varying the VIX upper bounds, and the SMA as well as the simple buy- and hold equal weighted portfolio. The Return is the cumulative daily excess return in the period 1991.01.03-2019.12.31. No. of trades is calculated as the summary of changes in weights over the period, where one trade is defined as any change in any asset's weight from one day to the next. μ is the daily mean return in percent during the period. σ is the daily standard deviation in percent of the portfolio. Sharpe is the Sharpe ratio calculated on daily mean and daily volatility. The cost-adjusted statistics are denoted with c; these include commission fees, short-selling fees, and the bid-ask spread. FF5 corresponds to the main regression, where the α is Jensen's alpha from the Fama-French five-factor model. p is the p-value for the regression, derived from Newey-West standard errors to overcome the issue of heteroskedastic and autocorrelated standard errors. R^2 is the r-squared for the model. FF5+ΔVIX, is the Fama-French five-factor model extended by adding the variable ΔVIX. The DIFF-title corresponds to the difference regression derived from Copeland and Copeland (1999), where the α is the constant obtained from regressing the differences in returns against the ΔVIX. The EW-title, under *DIFF REGRESSION*, corresponds to the VIX strategy minus EW returns, and SMA corresponds to the difference in return between the VIX strategy and the SMA strategy.

Table 16: Mean-Variance Outset Portfolio

Summary Statistics

	Lower bound 15				Lower Bound 20			
Sensitivity Limit	**0.50**	**0.60**	**0.70**	**0.80**	**0.50**	**0.60**	**0.70**	**0.80**
Return	1,698.3232	1,543.1932	1,003.7403	397.3847	4,101.993	4,157.1125	2,437.7692	491.6111
Return$_c$	64.2779	119.6262	154.4486	185.8912	80.7853	161.0365	240.0489	214.9201
No. of trades	4,090	3,475	2,817	1,424	4,674	4,211	3,455	1,650
μ	0.8691	0.8361	0.7039	0.4266	1.168	1.1594	0.9842	0.4923
μ_c	-0.0716	0.0981	0.1615	0.207	0.0453	0.2257	0.3113	0.2533
σ	3.2517	3.0836	2.8182	2.4251	4.4329	4.1275	3.5873	2.609
σ_c	3.3265	3.0555	2.7087	2.3974	4.6225	4.2106	3.4587	2.582
Sharpe	0.2673	0.2712	0.2498	0.1759	0.2635	0.2809	0.2744	0.1887
Sharpe$_c$	-0.0215	0.0321	0.0596	0.0864	0.0098	0.0536	0.09	0.0981
Correlation Window	**30**	**50**	**70**	**90**	**30**	**50**	**70**	**90**
Return	665.0567	634.5469	787.1517	715.2718	1,440.027	1,194.5322	1,518.7631	1,379.7479
Return$_c$	122.159	131.3522	192.8215	189.1785	115.5547	168.7657	276.9407	290.8683
No. of trades	2,780	2,562	2,256	2,161	3,975	3,256	2,772	2,643
μ	0.5795	0.5692	0.6303	0.6038	0.8216	0.7679	0.8339	0.8061
μ_c	0.0902	0.1127	0.2221	0.217	0.0905	0.1968	0.337	0.3508
σ	2.6028	2.7317	2.6883	2.7353	3.2693	3.2892	3.1753	3.1695
σ_c	2.5567	2.6197	2.5839	2.6023	3.1284	3.0509	2.9728	2.9591
Sharpe	0.2226	0.2084	0.2344	0.2207	0.2513	0.2335	0.2626	0.2543
Sharpe$_c$	0.0353	0.043	0.0859	0.0834	0.0289	0.0645	0.1134	0.1185
Bull Trading Limit	**90%**	**60%**	**30%**	**0%**	**90%**	**60%**	**30%**	**0%**
Return	442.7838	536.9927	650.5145	787.1517	473.7579	701.993	1,035.0891	1,518.7631
Return$_c$	307.6509	263.9221	225.8794	192.8215	319.6616	306.8632	292.565	276.9407
No. of trades	2,256	2,256	2,256	2,256	2,772	2,772	2,772	2,772
μ	0.4594	0.5163	0.5732	0.6303	0.4797	0.5976	0.7157	0.8339
μ_c	0.3523	0.3089	0.2655	0.2221	0.3642	0.3562	0.3471	0.337
σ	2.5026	2.5488	2.611	2.6883	2.5355	2.705	2.9211	3.1753
σ_c	2.4062	2.4391	2.4991	2.5839	2.444	2.5935	2.7714	2.9728
Sharpe	0.1836	0.2025	0.2195	0.2344	0.1892	0.2209	0.245	0.2626
Sharpe$_c$	0.1464	0.1266	0.1062	0.0859	0.149	0.1373	0.1253	0.1134

Table 16 shows the summary statistics when varying VIX correlation windows, assets sensitivity limits, and the VIX average lag size. The input variables are the same as mentioned in section 5.1, i.e., in the *Sensitivity Limit* part, the correlation window is 70, and the bull trading limit is 0%, and so forth. The Return is the cumulative daily excess return in the period 1991.01.03-2019.12.31. No. of trades is calculated as the summary of changes in weights over the period, where one trade is defined as any change in any asset's weight from one day to the next. μ is the daily mean return in percent during the period. σ is the daily standard deviation in percent of the portfolio. Sharpe is the daily Sharpe ratio calculated on daily mean and daily volatility. The cost-adjusted statistics are denoted with c; these include commission fees, short-selling fees, and the bid-ask spread.

Table 17: Equal Weights Outset Portfolio

Summary Statistics

	Lower bound 15				Lower Bound 20			
Sensitivity Limit	**0.50**	**0.60**	**0.70**	**0.80**	**0.50**	**0.60**	**0.70**	**0.80**
Return	24,673.7029	14,668.3699	8,172.6862	2,018.1729	200,749.363	83,980.2912	28,970.7214	2,746.7274
Return$_c$	580.3107	661.5144	774.0197	841.7406	2,907.2411	2,250.5391	1,801.0659	1,021.9094
No. of trades	3,709	3,096	2,439	1,048	4,303	3,835	3,077	1,274
μ	1.6968	1.5364	1.3539	0.9294	2.3891	2.1076	1.7592	1.026
μ_c	0.6114	0.6374	0.6663	0.6753	1.1495	1.0487	0.9442	0.7396
σ	4.545	4.3473	4.051	3.5311	6.1066	5.6476	4.9119	3.7376
σ_c	4.5777	4.3163	3.9195	3.4996	5.9745	5.5043	4.7137	3.7296
Sharpe	0.3733	0.3534	0.3342	0.2632	0.3912	0.3732	0.3582	0.2745
Sharpe$_c$	0.1336	0.1477	0.17	0.193	0.1924	0.1905	0.2003	0.1983
Correlation Window	**30**	**50**	**70**	**90**	**30**	**50**	**70**	**90**
Return	4,337.1883	3,890.4581	4,879.6593	4,114.7898	14,448.7169	9,869.0587	11,346.6228	10,745.5279
Return$_c$	523.4772	536.3582	866.8193	820.1746	719.1418	877.5932	1,508.8374	1,564.5919
No. of trades	2,399	2,184	1,878	1,784	3,586	2,874	2,388	2,272
μ	1.1601	1.1335	1.1957	1.1477	1.5394	1.4277	1.4614	1.4481
μ_c	0.5457	0.5553	0.6909	0.6756	0.6598	0.7159	0.8699	0.8801
σ	3.7868	3.9256	3.8265	3.8695	4.5379	4.5185	4.3471	4.4101
σ_c	3.7134	3.78	3.7027	3.7235	4.2917	4.2521	4.1824	4.175
Sharpe	0.3064	0.2887	0.3125	0.2966	0.3392	0.316	0.3362	0.3284
Sharpe$_c$	0.147	0.1469	0.1866	0.1814	0.1537	0.1684	0.208	0.2108
Bull Trading Limit	**90%**	**60%**	**30%**	**0%**	**90%**	**60%**	**30%**	**0%**
Return	2,001.7067	2,700.81	3,634.8761	4,879.6593	2,184.647	3,816.2654	6,608.9433	11,346.6228
Return$_c$	1,388.6791	1,190.6328	1,017.4339	866.8193	1,473.8913	1,499.3111	1,510.772	1,508.8374
No. of trades	1,878	1,878	1,878	1,878	2,388	2,388	2,388	2,388
μ	0.928	1.017	1.1063	1.1957	0.9545	1.1233	1.2922	1.4614
μ_c	0.8181	0.7756	0.7332	0.6909	0.8367	0.8485	0.8595	0.8699
σ	3.5722	3.6347	3.7198	3.8265	3.6067	3.7993	4.0488	4.3471
σ_c	3.4446	3.5044	3.5911	3.7027	3.4841	3.6761	3.9112	4.1824
Sharpe	0.2598	0.2798	0.2974	0.3125	0.2646	0.2957	0.3192	0.3362
Sharpe$_c$	0.2375	0.2213	0.2042	0.1866	0.2402	0.2308	0.2197	0.208

Table 17 shows the summary statistics when varying VIX correlation windows, assets sensitivity limits, and the VIX average lag size. The input variables are the same as mentioned in section 5.1, i.e., in the *Sensitivity Limit* part, the correlation window is 70, and the bull trading limit is 0%, and so forth. The Return is the cumulative daily excess return in the period 1991.01.03-2019.12.31. No. of trades is calculated as the summary of changes in weights over the period, where one trade is defined as any change in any asset's weight from one day to the next. μ is the daily mean return in percent during the period. σ is the daily standard deviation in percent of the portfolio. Sharpe is the daily Sharpe ratio calculated on daily mean and daily volatility. The cost-adjusted statistics are denoted with c; these include commission fees, short-selling fees, and the bid-ask spread.

Table 18: Varying Correlation Window

Summary Statistics and Regressions Results

STATS	30	40	50	60	70	80	90	100
Return	1,437.6528	1,369.6047	1,446.526	1,617.1649	1,810.4707	1,667.032	1,571.4024	1,587.2845
Return$_c$	1,101.4071	1,063.8733	1,109.1855	1,261.5054	1,458.9412	1,345.9143	1,266.2938	1,299.5827
No. of trades	290	270	282	268	234	233	230	208
μ	0.8295	0.8161	0.8364	0.8649	0.8983	0.8771	0.8601	0.8635
μ_c	0.7497	0.7401	0.7555	0.7889	0.8319	0.8114	0.7936	0.8014
σ	3.4915	3.5071	3.6488	3.5417	3.5566	3.6403	3.6411	3.6564
σ_c	3.4048	3.4107	3.5147	3.4056	3.4309	3.5172	3.5093	3.5196
Sharpe	0.2376	0.2327	0.2292	0.2442	0.2526	0.2409	0.2362	0.2362
Sharpe$_c$	0.2202	0.217	0.215	0.2317	0.2425	0.2307	0.2261	0.2277

Table 18 shows the summary statistics when varying VIX correlation windows. The Return is the cumulative daily excess return in the period 1991.01.03-2019.12.31. No. of trades is calculated as the summary of changes in weights over the period, where one trade is defined as any change in any asset's weight from one day to the next. μ is the daily mean return in percent during the period. σ is the daily standard deviation in percent of the portfolio. Sharpe is the daily Sharpe ratio for each iteration of the correlation window size. The cost-adjusted statistics are denoted with c; these include commission fees, short-selling fees, and the bid-ask spread.

Table 19: Varying Asset Sensitivity

Summary Statistics and Regressions Results

STATS	0.50	0.55	0.60	0.65	0.70	0.75	0.80	0.85
Return	1,709.7506	1,708.2578	1,706.9825	1,654.6092	1,672.1994	1,810.4707	1,308.2988	867.2961
Return$_c$	1,268.7098	1,280.1989	1,287.5162	1,259.5108	1,298.5666	1,458.9412	1,118.7141	813.4053
No. of trades	286	275	270	265	251	234	189	88
μ	0.8852	0.8848	0.8846	0.8751	0.8761	0.8983	0.7998	0.6865
μ_c	0.7948	0.7973	0.7988	0.7919	0.7988	0.8319	0.7541	0.6682
σ	3.6654	3.6602	3.6594	3.6443	3.5876	3.5566	3.4128	3.5624
σ_c	3.5312	3.5272	3.5223	3.5066	3.4516	3.4309	3.3963	3.565
Sharpe	0.2415	0.2417	0.2417	0.2401	0.2442	0.2526	0.2344	0.1927
Sharpe$_c$	0.2251	0.226	0.2268	0.2258	0.2314	0.2425	0.222	0.1874

Table 19 shows the summary statistics when varying VIX asset sensitivity. The Return is the cumulative daily excess return in the period 1991.01.03-2019.12.31. No. of trades is calculated as the summary of changes in weights over the period, where one trade is defined as any change in any asset's weight from one day to the next. μ is the daily mean return in percent during the period. σ is the daily standard deviation in percent of the portfolio. Sharpe is the daily Sharpe ratio for each iteration of sensitivity limit. The cost-adjusted statistics are denoted with c; these include commission fees, short-selling fees, and the bid-ask spread.

Table 20: Varying Lag Size

Summary Statistics and Regressions Results

STATS	3	4	5	6	7	8	9	10
Return	2,118.8755	1,810.4707	1,802.3244	1,577.5171	1,576.5322	1,463.4226	1,441.1042	1,360.2527
Return$_c$	1,546.2132	1,458.9412	1,423.5006	1,316.9899	1,316.25	1,233.7732	1,215.0023	1,145.9798
No. of trades	330	234	251	197	197	187	187	187
μ	0.9439	0.8983	0.8986	0.8585	0.8583	0.8375	0.8329	0.8149
μ_c	0.8496	0.8319	0.826	0.8025	0.8023	0.7841	0.7795	0.7618
σ	3.5601	3.5566	3.6009	3.5548	3.5545	3.5758	3.5697	3.5312
σ_c	3.4546	3.4309	3.4634	3.4341	3.4339	3.4458	3.4417	3.4175
Sharpe	0.2651	0.2526	0.2496	0.2415	0.2415	0.2342	0.2333	0.2308
Sharpe$_c$	0.2459	0.2425	0.2385	0.2337	0.2337	0.2275	0.2265	0.2229

Table 20 shows the summary statistics when varying VIX lag size level. The Return is the cumulative daily excess return in the period 1991.01.03-2019.12.31. No. of trades is calculated as the summary of changes in weights over the period, where one trade is defined as any change in any asset's weight from one day to the next. μ is the daily mean return in percent during the period. σ is the daily standard deviation in percent of the portfolio. Sharpe is the daily Sharpe ratio for each iteration of lag size. The cost-adjusted statistics are denoted with c; these include commission fees, short-selling fees, and the bid-ask spread.

Table 21: Max and Min Weights Allocated for each Outset Portfolio

Summary Statistics

MV Outset Portfolio Max Weights

NoDur	Durbl	Manuf	Enrgy	Chems	BusEq	Telcm	Utils	Shops	Hlth	Money	Other	Rf
0.2038	0.1761	0.1927	0.1532	0.1357	0.1748	0.0896	0.0807	0.1834	0.2172	0.1550	0.2302	0.7964

MV Outset Portfolio Min Weights

NoDur	Durbl	Manuf	Enrgy	Chems	BusEq	Telcm	Utils	Shops	Hlth	Money	Other	Rf
-0.1042	-0.0075	-0.0884	0.0235	-0.0070	-0.0629	0.0588	0.0743	-0.0751	-0.1233	-0.0345	-0.0304	-0.4271

EW Outset Portfolio Max Weights

NoDur	Durbl	Manuf	Enrgy	Chems	BusEq	Telcm	Utils	Shops	Hlth	Money	Other	Rf
0.0769	0.0769	0.0769	0.0769	0.0769	0.0769	0.0769	0.0769	0.0769	0.0769	0.0769	0.0769	0.0769

Table 22: Main Regressions Results Best Outcome

	VIX	SMA	EW	VIX	SMA	EW
Mktrf	0.9094***	1.2211***	0.9062***	0.5367***	0.7274***	0.9022***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
SMB	0.1935***	0.1972***	0.0212***	0.1565***	0.1482**	0.0208***
	(0.000)	(0.003)	(0.000)	(0.001)	(0.013)	(0.000)
HML	-0.3435***	-0.4101***	0.0616***	-0.3051***	-0.3592***	0.0620***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)
RMW	0.1603*	0.3507***	0.1750***	0.0892	0.2566***	0.1742***
	(0.051)	(0.000)	(0.000)	(0.261)	(0.007)	(0.000)
CMA	0.5288***	0.4628***	0.1905***	0.4476***	0.3552***	0.1896***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.004)	(0.000)
ΔVIX	-	-	-	-0.0802***	-0.1063***	-0.0009**
				(0.000)	(0.000)	(0.040)
Constant	0.0008***	0.0002	-0.0000***	0.0011***	0.0007***	-0.0000**
	(0.000)	(0.150)	(0.006)	(0.000)	(0.000)	(0.012)
R-squared	0.403	0.431	0.983	0.469	0.500	0.983

p-values in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 22 shows the results from running the regression $\mu_p = \alpha_i + \beta_1(R_{M,\,t} - R_{f,\,t}) + \beta_2(SMB_t) + \beta_3(HML_t) + \beta_4(RMW_t) + \beta_5(CMA_t) + \epsilon_{i,\,t}$ for the equal-weighted outset portfolio, SMA strategy and VIX strategy. The regression is run on daily excess returns in the period 1991.01.03-2019.12.31. Mktrf is the Fama-French excess market return, SMB is the small minus big factor, HML is the high minus low factor, RMW is the robust minus weak factor, CMA is the conservative minus aggressive factor. ΔVIX is the monthly percent change in VIX in the same period. Alpha is Jensen's Alpha. P-values are derived from Newey-West standards errors to overcome the issue of heteroskedastic and autocorrelated standard errors.

Table 23: Main Regressions Results Best Outcome Cost Adjusted

	VIX_c	SMA_c	EW_c	VIX_c	SMA_c	EW_c
Mktrf	0.9199***	1.2189***	0.9063***	0.5289***	0.7247***	0.9022***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
SMB	0.2084***	0.1909***	0.0211***	0.1696***	0.1418**	0.0207***
	(0.000)	(0.003)	(0.000)	(0.000)	(0.016)	(0.000)
HML	-0.3460***	-0.4134***	0.0614***	-0.3057***	-0.3625***	0.0618***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
RMW	0.1722**	0.3486***	0.1753***	0.0977	0.2544***	0.1745***
	(0.037)	(0.001)	(0.000)	(0.217)	(0.007)	(0.000)
CMA	0.5237***	0.4586***	0.1907***	0.4385***	0.3509***	0.1898***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.004)	(0.000)
ΔVIX	-	-	-	-0.0842***	-0.1064***	-0.0009**
				(0.000)	(0.000)	(0.037)
Constant	0.0002	0.0001	-0.0000***	0.0005***	0.0005***	-0.0000**
	(0.116)	(0.582)	(0.005)	(0.000)	(0.002)	(0.010)
R-squared	0.407	0.430	0.983	0.479	0.499	0.983

p-values in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 23 shows the results from running the regression $\mu_p = \alpha_i + \beta_1(R_{M,t} - R_{f,t}) + \beta_2(SMB_t) + \beta_3(HML_t) + \beta_4(RMW_t) + \beta_5(CMA_t) + \epsilon_{i,t}$ for cost adjusted returns of the equal-weighted outset portfolio, SMA strategy and VIX strategy. The regression is run on daily excess returns, adjusted for commissions fees, short-selling fees, and bid-ask-spread in 1991.01.03-2019.12.31. Mktrf is the Fama-French excess market return, SMB is the small minus big factor, HML is the high minus low factor, RMW is the robust minus weak factor, CMA is the conservative minus aggressive factor. ΔVIX is the monthly percent change in VIX in the same period. Alpha is Jensen's Alpha. P-values are are derived from Newey-West standards errors to overcome the issue of heteroskedastic and autocorrelated standard errors.

Table 24: Optimal Solution Extended

Summary Statistics

	Return	$Return_c$	No. of trades	μ	μ_c	σ	σ_c	Sharpe	$Sharpe_c$
VIX	226,818.1927	3,516.3014	4,188	2.4075	1.1998	6.1433	6.0424	0.3919	0.1986
SMA	2,042.0191	678.0401	955	1.2447	0.9387	8.3684	8.4452	0.1487	0.1112
EW	624.5229	620.5505	13	0.5937	0.5918	3.7282	3.7264	0.1593	0.1588

Table 24 shows the summary statistics for the best VIX strategy, the SMA strategy, and the EW buy-and-hold portfolio. The Return is the excess cumulative return in the period 1991.01.03-2020.03.31. No. of trades is calculated as the summary of changes in weights over the period, where one trade is defined as any change in any asset's weight from one day to the next. μ is the daily mean return in percent during the period. σ is the daily standard deviation in percent of the portfolio. Sharpe is the daily Sharpe ratio for each iteration of the correlation window size. The cost-adjusted statistics are denoted with c; these include commission fees, short-selling fees, and the bid-ask spread.

Table 25: Main Regressions Results Extended

	VIX	SMA	EW	VIX	SMA	EW
Mktrf	0.7664***	1.3339***	0.9050***	0.3553***	0.9064***	0.9025***
	(0.000)	(0.000)	(0.000)	(0.007)	(0.000)	(0.000)
SMB	0.1475***	0.2396***	0.0251***	0.1090**	0.1995***	0.0248***
	(0.008)	(0.001)	(0.000)	(0.034)	(0.004)	(0.000)
HML	-0.4299***	-0.3276***	0.0662***	-0.3731***	-0.2686**	0.0665***
	(0.000)	(0.008)	(0.000)	(0.000)	(0.022)	(0.000)
RMW	0.0219	0.4687***	0.1725***	-0.0479	0.3961***	0.1721***
	(0.832)	(0.000)	(0.000)	(0.624)	(0.001)	(0.000)
CMA	0.5018***	0.4781***	0.1842***	0.4131***	0.3859***	0.1836***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.003)	(0.000)
ΔVIX	-	-	-	-0.0914***	-0.0951***	-0.0006
				(0.000)	(0.000)	(0.229)
Constant	0.0009***	0.0001	-0.0000***	0.0013***	0.0005***	-0.0000**
	(0.000)	(0.593)	(0.008)	(0.000)	(0.009)	(0.012)
R-squared	0.315	0.466	0.983	0.401	0.515	0.983

p-values in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 25 shows the results from running the regression $\mu_p = \alpha_i + \beta_1(R_{M,t} - R_{f,t}) + \beta_2(SMB_t) + \beta_3(HML_t) + \beta_4(RMW_t) + \beta_5(CMA_t) + \epsilon_{i,t}$ for the equal-weighted outset portfolio, SMA strategy and VIX strategy. The regression is run on daily excess returns in the period 1991.01.03-2020.03.31. Mktrf is the Fama-French excess market return, SMB is the small minus big factor, HML is the high minus low factor, RMW is the robust minus weak factor, CMA is the conservative minus aggressive factor. ΔVIX is the monthly percent change in VIX in the same period. Alpha is Jensen's Alpha. P-values are derived from Newey-West standards errors to overcome the issue of heteroskedastic and autocorrelated standard errors.

Table 26: Main Regressions Results Extended Cost Adjusted

	VIX_c	SMA_c	EW_c	VIX_c	SMA_c	EW_c
Mktrf	0.7771***	1.3318***	0.9051***	0.3484***	0.9034***	0.9025***
	(0.000)	(0.000)	(0.000)	(0.008)	(0.000)	(0.000)
SMB	0.1621***	0.2338***	0.0250***	0.1219**	0.1936***	0.0248***
	(0.004)	(0.001)	(0.000)	(0.017)	(0.005)	(0.000)
HML	-0.4307***	-0.3330***	0.0659***	-0.3714***	-0.2738**	0.0663***
	(0.000)	(0.007)	(0.000)	(0.000)	(0.018)	(0.000)
RMW	0.0340	0.4669***	0.1728***	-0.0388	0.3942***	0.1724***
	(0.742)	(0.000)	(0.000)	(0.690)	(0.001)	(0.000)
CMA	0.4951***	0.4751***	0.1844***	0.4026***	0.3827***	0.1838***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.003)	(0.000)
ΔVIX	-	-	-	-0.0954***	-0.0953***	-0.0006
				(0.000)	(0.000)	(0.219)
Constant	0.0003**	-0.0001	-0.0000***	0.0007***	0.0003*	-0.0000**
	(0.035)	(0.748)	(0.007)	(0.000)	(0.074)	(0.010)
R-squared	0.320	0.465	0.983	0.412	0.514	0.983

p-values in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 26 shows the results from running the regression $\mu_p = \alpha_i + \beta_1(R_{M,t} - R_{f,t}) + \beta_2(SMB_t) + \beta_3(HML_t) + \beta_4(RMW_t) + \beta_5(CMA_t) + \epsilon_{i,t}$ for cost adjusted returns of the equal-weighted outset portfolio, SMA strategy and VIX strategy. The regression is run on monthly excess returns, adjusted for commissions fees, short-selling fees and bid-ask-spread, in the period 1991.01.03-2020.03.31. Mktrf is the Fama-French excess market return, SMB is the small minus big factor, HML is the high minus low factor, RMW is the robust minus weak factor, CMA is the conservative minus aggressive factor. ΔVIX is the monthly percent change in VIX in the same period. Alpha is Jensen's Alpha. P-values are derived from Newey-West standards errors to overcome the issue of heteroskedastic and autocorrelated standard errors.