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Profiting from Fear

A study of the variance risk premium in the Trump Era

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”We simply attempt to be fearful when others are greedy and to be greedy only when others are fearful”

Warren Buffett

Abstract

The Variance Risk Premium ("VRP"), constituting the spread between option-implied and actual realized variance, has historically proven a stable and dominant predictor of future stock returns, especially at the quarterly horizon. Motivated by the extraordinarily low market volatility along with increased political uncertainty evident in recent years, we not only confirm the VRP's ability to predict a nontrivial fraction of stock returns on the S&P 500 index, but we find a strengthened effect after the financial crisis, albeit at a slightly longer horizon. Viewing the VRP as an indicator of investor fear, we thus demonstrate that it is possible to 'profit from fear' across the sample period. However, in a post-US election setting, we find that the VRP has lost its dominant predictive ability. By using President Trump's Twitter Feed as a proxy for political events, we discover that Trump does not act as a catalyst for market volatility, but rather acts as a risk reliever contrary to common conviction. Hence, our findings indicate that a change in current investor sentiment has occurred: a disconnect between actual volatility and investor fear could potentially be driving the change in predictability, with investors strongly overestimating actual crash risk given the current level of volatility, while Trump seems to be alleviating some of this fear.

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Executive Summary

The equity premium puzzle has entertained many agents within various fields for decades, stretching from theoretical researchers to investment professionals. In recent years, focus has shifted towards examining how investor fear potentially offers predictability through a model-free options-pricing approach, which provides a metric that effectively isolates the Variance Risk Premium ("VRP") of stock returns in the form of the spread between the implied and realized volatility. In light of the recent financial crisis, the market recovery and the current uncertain political environment, it seems more appropriate than ever to investigate the link between volatility, investor sentiment and stock returns. The thesis sets out to investigate how the predictability of the VRP has evolved in recent years, and how the incumbent American president, Donald J. Trump, may affect investor sentiment and the volatility of stock returns.

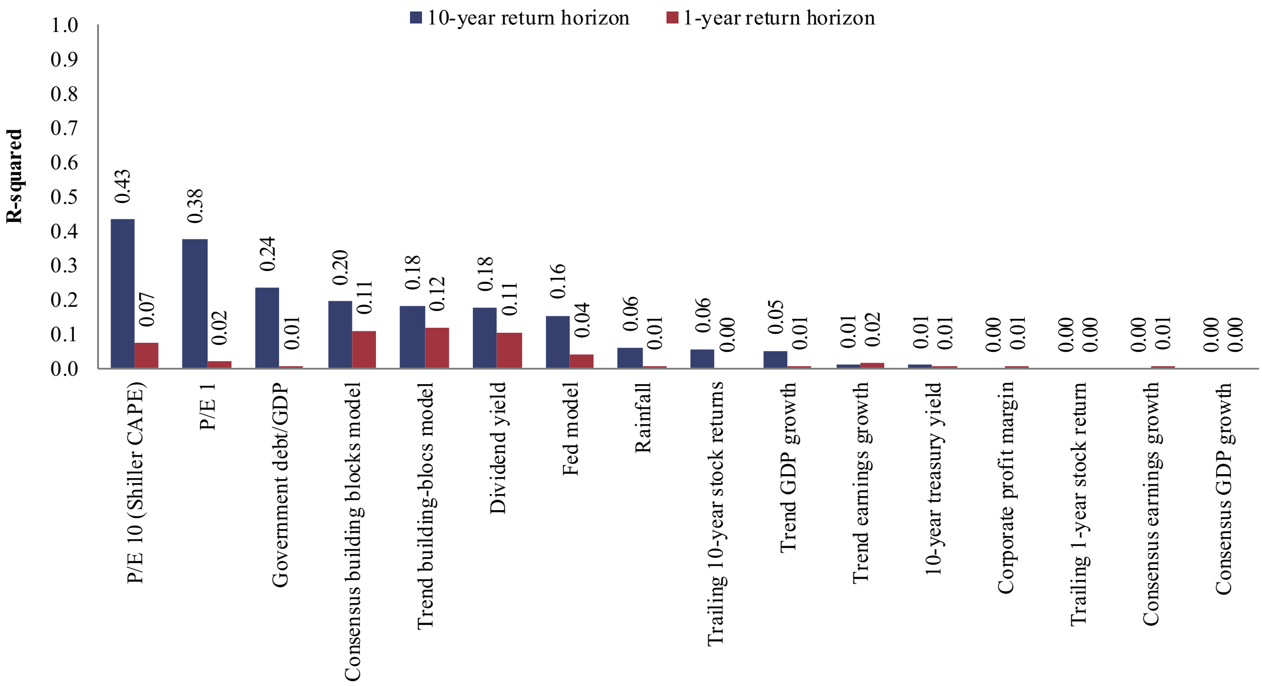
Based on an extension of the methodology proposed by Bollerslev, et al. (2009) and a temporal case study of political events, proxied by President Trump's Tweets, the thesis investigated the VRP's predictability on the S&P 500 index in the timeframe from 2002-2018. The thesis contributes to earlier literature on several accounts, firstly by confirming that the VRP continues to be a significant and dominant predictor relative to traditional predictor variables on the short return horizon of 3.5-months. Furthermore, the empirical findings reveal an outwards shift in predictability to the 4-month return horizon after the crisis, seemingly driven by an increase in the persistence of the volatility-of-volatility of stock returns or the intertemporal elasticity of substitution ("IES"). IES can be interpreted as investor sensitivity to uncertainty regarding potential tail risk, which seems to have increased. The importance of these findings is substantiated by presenting a trading strategy on the VRP, which allows market agents to 'profit from fear'.

The thesis furthermore provides findings that bridge two separate fields in academia, namely studies of the VRP and political impact on stock returns. The VRP loses accuracy in predicting returns in the Trump era, and a disconnect seems to transpire as investor fear increase disproportionally with actual crash risk. However, a case study of political events surprisingly indicate that the President relieves investor fear in the market. The thesis thus points to a shift in investor sentiment in the Trump Era: market participants seem to needlessly overestimate tail risk relatively to earlier years, which inflates the VRP metric, all the while Trump's effect on volatility proves to be negative, contrary to common belief.

1 Introduction

From Keynes to Warren Buffett, the driving forces of investment decisions have confounded academics and market agents alike for decades. In his attempt to decode the enigma of investment yields, Keynes found no rationality to the way in which stocks move – rather, investors seem driven by "animal spirits", composed of irrational fears and wishes. Under such a claim, stocks behave like dust in water and no investor can claim to possess a superior ability to predict the path of tomorrow. Naturally, many will scoff at the idea; how can some investors or hedge funds consistently outperform the market, if there is no pattern to the movement of stock returns? Are they simply a representation of the lucky few? In terms of prediction, stock returns seem essentially unpredictable at short time-horizons; as seen in figure 1.A below, estimated historical R^2 are close to zero for most traditional predictors. However, the result is hardly surprising, given the poor track record of market-timing and various asset allocation strategies.

Figure 1.A: Proportion of variance explained by various metrics, 1926 - 2012



Adapted from Davis, et al. (2012). An overview of R2 from two regression models, 10 years ahead and 1 year ahead, respectively. Real, annualized stock returns on each variable is fitted over a sample stretching from January 1926 to June 2012 (except for corporate profits, which are fitted from 1929 and beyond due to data limitations). P/E ratios are from Robert Shiller's website; P/E 1 denotes the nominal price over the prior 12 months, while P/E 10 (Shiller CAPE) denotes the nominal price over the prior 120 months. Building blocks models consist of a combination of dividend and earnings growth models. Returns are constructed from a bundle of US stock indices, please refer to Davis, et al. (2012) for a complete overview.

On the back of such findings, multiple researchers have concurred with Keynes' interpretation of stock returns and claim that investor psyche is a significant driver of the lack of predictability especially on the short horizons. As argued by both Adam Smith (1776 / 1997) and Menger (1871 / 2007), market agents are inherently ambiguity or uncertainty averse. As a natural instinct, dislike for uncertainty permeates every aspect of human life; from the hunter's fear of missing game, to the British population pondering the uncertain consequence of Brexit. When it comes to investor fear, the talk often turns to the VIX index, also coined the "Fear Index". Constructed from the implied volatility of out-of-the-money options, the VIX depicts the market's expectation of volatility over the next 30 days on the S&P 500 index. Over the past years, the VIX index has been shown to have a significant negative contemporaneous correlation with stock returns – an empirical phenomenon often associated with the leverage effect[1].

In reality, the VIX is a combination of two volatility components: the physical or realized variance, and a premium consisting of investor fear, added on top of the physical variance. Termed the *Variance Risk Premium* (the "VRP"), this premium can be viewed as a "true" fear index, comprising only investor expectation. Historically, the VRP has been found to be a highly significant and robust predictor of future stock returns, especially at the 3-6-month horizons, with coefficients of determination in the ranges 5-10% (Bollerslev, et al., 2009). Relative to the classical predictor variables described above, such R^2 are impressive overall and especially considering the relatively short return horizon. Based on this, the truth of the drivers of return most likely lies somewhere in-between with investor psyche dominating the realm of short-term predictability while the longer-term is driven by more fundamental factors, such as earnings ratios, growth in earnings and the economy and the level and change in interest rates.

However, after the financial crisis, the pricing behavior of stocks has changed dramatically; with the introduction of quantitative easing programs, bond prices soared as their yields plunged towards zero. This pushed portfolios into massive equity purchases in search for yield, causing the leading indices

1 The leverage effect was first described in Black (1976). The effect describes that over a short period of time, while a company's debt is relatively fixed, the market value of equity is fluid. A crash in the market can thus lead to an inflation in the debt-to-equity ratio, ceteris paribus making the firm more leveraged and thus riskier (Coval & Shumway, 2001)

to rise to not just pre-crisis levels, but historical highs (Balatti, et al., 2018). Meanwhile, the VIX index dipped to its lowest historical levels in 2017, with investors heralding a new era of financial tranquility (Bullock, et al., 2018). Simultaneously, political instability seemed to be smoldering under the peaceful surface: With inequality levels on the rise, populist movements started to take root across the Western World (O'Connor, 2017). These populist movements were increasingly inward-looking, seeking to reinforce national sovereignty, constituting a direct clash with years of increasing globalization and international integration (Fukuyama, 2018). This culminated in 2016 with the British vote to leave the European Union and the election of President Donald J. Trump ("Trump") as the 45th President of the United States. Today, the political reality seems uncharacteristically unstable with real tangible economic repercussions in its wake; examples include the US-government shutdown in January 2018, the potential introduction of wide-scale trade tariffs on key production inputs and the UK attempting to guide their way through an upcoming Brexit. In this brave new world, does the VRP continue to be a significant and dominant predictor of stock returns? And how is the VRP and its components affected by political events imposed by Trump?

1.1 Research Question

Following these two perspectives, the specific research question for this thesis is:

> ***How has the VRP and its ability to predict stock returns on the US stock market been affected in recent years by the economic and financial development and the increased political uncertainty apparent in the Trump Era?***

To further focus the contribution of this paper to the existent body of literature, we have chosen to structure the analysis around the four following guiding questions:

(i) What is the VRP and what evidence exists for its ability to predict stock returns?

(ii) How has the VRP developed in the years following the global financial crisis and does it maintain its predictive prowess?

(iii) How has recent years' political instability in the Trump era affected the VRP and its components?

(iv) What does the evolvement of the VRP and its potential exposure to political uncertainty imply about current investor sentiment?

1.2 Motivation

The answers to this research agenda carry relevance across several arenas, which, in one way or another, are interlinked with the VRP. In terms of academic research, the contribution of this paper relates to three principal areas: 1) Few papers considering the VRP have dealt with the time period following the Global Financial Crisis ("GFC") and, to our knowledge, no such studies have dealt with the recent period of unprecedented low volatility in particular. 2) Furthermore, this paper uniquely bridges the chasm between two previously separated bodies of research: the study of the VRP and the effect of politics on the financial markets. 3) Lastly, the construction of the VRP causes it to convey highly relevant information on investor sentiment, especially regarding fear of extreme tail risk. Hence, these contributions are tied together to further describe investor sentiment in both a new period and in regard to political events.

In addition to the relevance of this thesis to researchers within the field of finance, the findings may also of interest to practitioners; especially since the VRP has historically been a very strong predictor of stock returns on the 3-6-month horizon. Hence, including this as a factor in trading considerations may allow the informed trader to obtain abnormal returns on their portfolio. To crystallize such a possibility, we include a trading strategy that may serve as testament to the predictive power of the VRP. Furthermore, the study of how the VRP reacts to political events may also allow the trader to gain a deeper understanding of how these might alter the volatility in the market and to gain abnormal returns on such changes. The additional investor sentiment implications of the study may further be of interest to the market agent exposed to the current sentiment, for an example in terms of timing an initial public offering or other sentiment-critical events.

1.3 Scope and Delimitations

Based on the theories underlying derivative pricing, the VRP is nested in a relatively large field of financial-economic theory. Hence, keeping in mind the scope of this paper, it is assumed that the reader has a fundamental understanding of the two following areas of research: 1) Asset pricing models, especially the CAPM and the Black-Scholes model for option pricing and 2) the fundamentals of statistics and econometrics. While the conclusions of this paper can be understood and utilized by readers without such prior knowledge, the underlying methodology may be too specifically bound to its theoretical roots. For the reader with a special interest in the underlying theory, we will point to further readings under way, which we find to be of particularly good quality.

The VRP has been the focal point of several studies since the introduction of Long-Run Risks model (Bansal & Yaron, 2004) and formal testing in Bollerslev, et al. (2009) (also referred to as the "BTZ paper"). In general, the results from Bollerslev, et al. (2009) have been found to hold for the square root process as well; that is, return predictability from the *volatility* risk premium is relatively similar to that of the variance risk premium. For this reason, we use the terms volatility and variance interchangeably, unless otherwise clearly stated. However, for formula purposes, we denote the VRP in capital letters ("*VRP*"), with the volatility risk premium in small letters ("*vrp*"). Likewise, as we generate the implied variance measure from the square of the VIX index, we use the terms "the squared VIX" and "the implied variance" interchangeably. Instances in which we use the term "the VIX" or "VIX" denotes the value of index itself – for an example in the use for formulating a trading strategy. For a complete overview of utilized abbreviations, please refer to Appendix A.

In recent studies, the VRP has been found to not only show significant return predictability in US data, but also across other geographies. However, in order to center this study on the research question set out above, we do not consider it prudent to extend this analysis across multiple markets. This is due to several considerations: firstly, a key contribution of this paper is to study the VRP in a more recent time sample. To ease the comparability of this contribution to previous studies it is found to be of higher relevance to study US data, which more papers have delved into. Secondly, the access to market data in the US is less cumbersome relative to other markets. Especially as this paper is looking at intraday data, this is of key concern. Lastly, as we wish to study the impact of political events, it seems sensible to focus on one single market as to not confound the analysis by the imposition of potentially false assumptions of similarity across different political systems.

In similar form, this study focuses on the VRP derived for the S&P 500 index, as this has a readily-made index for model-free implied volatility through the VIX. Meanwhile, there is no hindrance in constructing the VRP for different indices or even other asset classes. This may be an interesting topic for further research, as different asset classes, for an example currencies and commodities, do not show the same volatility smirk as equities, but rather tend to show a pronounced smile (Hull, 2012). Hence, the resulting VRP, may take a shape entirely different from the one evident in equities, and potentially yield different results. However, for the scope of this paper, such possibilities are not entertained, as it would remove the focus from the key research contribution. In terms of time horizon, we are limited by data availability: While the VIX index has existed since 1990, we are not able to obtain data on the intraday frequency further back than 1996. Hence, we are unable to study the effects of the VRP over the long return horizons spanning multiple years in line with the study of other predictors included in figure 1.A.

In terms of theoretical backbone, this paper follows the economic model described in Bansal & Yaron (2004) and further elaborated upon in Bollerslev, et al. (2009). This is done in order to ease comparability and to maintain a clear line of argument. However, several extensions are possible, such as the inclusion of jump risk, a decomposition of the VRP and the implied volatility-of-volatility (as generated from the VVIX) to more directly study the downside risk. However, we maintain these ideas as opportunities for further research. On a more technical note, this paper makes several choices in terms of the empirical methodology. While we will address most of these as we cross the bridges, key choices include i) our choice of standard errors and ii) our choice of non-parametric estimation and a multiplicative component GARCH to model expected realized variance. Naturally, we address some alternatives to these choices, but as the focal point of this paper is not an econometric study of the most "correct" realized volatility modelling, we keep such considerations at a minimum.

1.4 Overview and Structure of the Paper

With a point of departure in the research question set out above, this paper follows a 6-section structure which covers a broad outline of the existent literature, the specific analytical approach of this paper, the results of this analysis, as well as interpretation and conclusions of these results. The specific contents of each segments are as follows:

Section 1: The aim of this section is to set the scene of the paper, providing both an introduction to the overall subject, as well as a brief overview of the motivation for the research question, including the relevance to both academics and practitioners. Furthermore, as there are multiple ways of answering our research question, we wish to provide an overview of the delimitations of this paper.

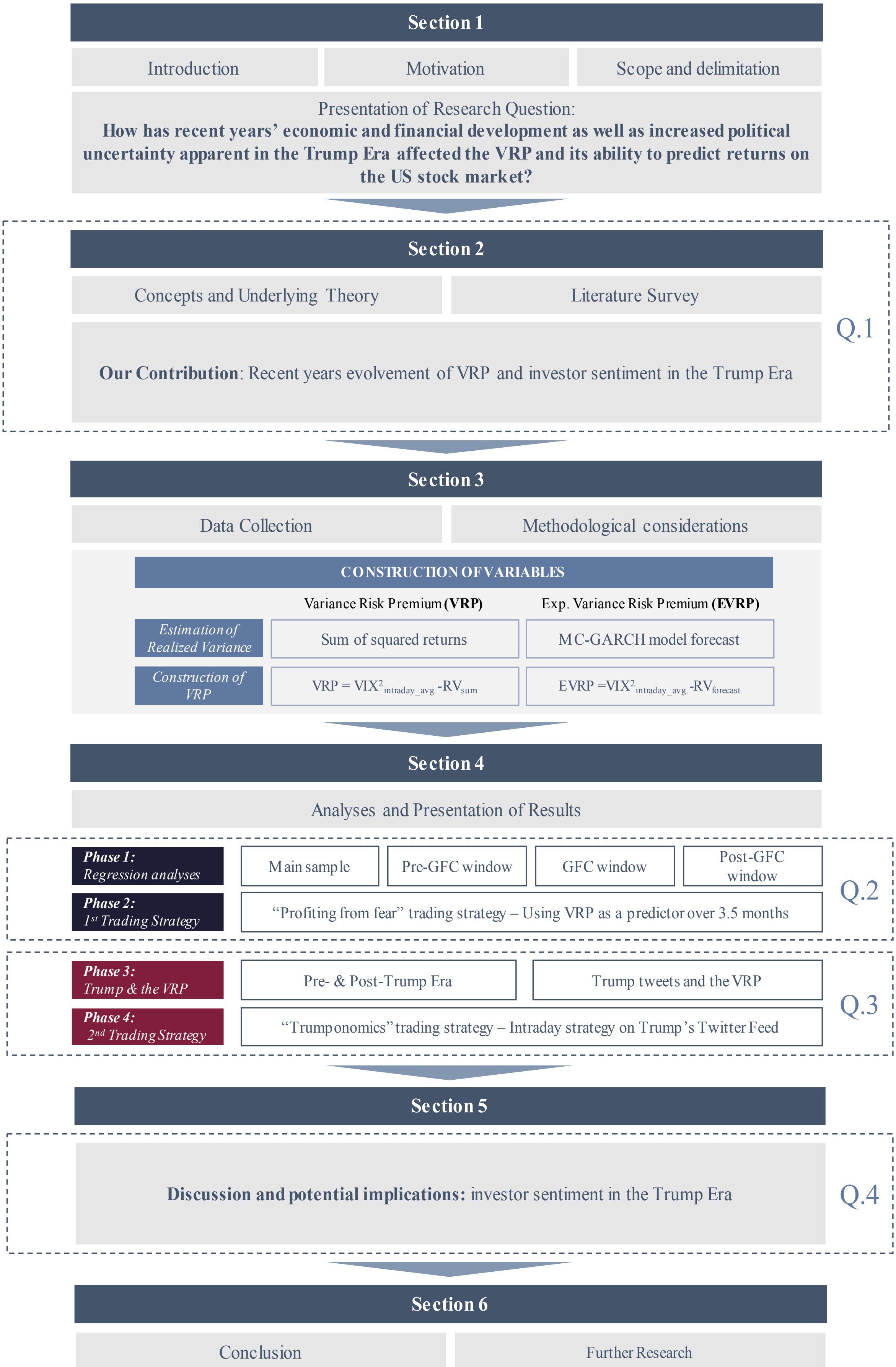
Section 2: In the second section of this study, we aspire to answer our first guiding research question by providing the reader with an understanding of the academic foundation in which this paper is nested. We seek to offer an understanding of how the VRP is derived from the concepts and underlying theory with a focus on the derivation of implied variances. With this as a starting point, we provide an overview of the interlink between the VRP and stock returns, including an introduction to the underlying economic model and empirical results from precedent studies creating the foundation for our second guiding research question. Further, to create a footing for the remaining guiding research questions, we outline the previous research in the intersection of finance and politics. From these building blocks, we finally place *our* specific contribution in the network of previous research.

Section 3: In continuation of section 2, we guide the reader through the analytical methods underlying our paper: We introduce the econometric method, including the construction of key variables and the regressions run, as well as the data utilized, such as the type of variables and time period studied. Furthermore, we outline strengths and weaknesses associated with the choice of data and methods.

Section 4: Based on this method and data overview, we present the results from our analysis. As illustrated in figure 1.B on the following page, our analysis is split into four phases: the first two phases directly relate to our second guiding research question regarding the VRP as a stock return predictor, while the following two seek to examine our third question regarding the effects of politics on the VRP. In order to solidify the results from our regression analyses, Phases 2 and 4 seek to establish profitable trading strategies, which may help the reader clearly see the implications of the results in a different setting.

Section 5: The fifth section seeks to answer the fourth guiding research question, by discussing and interpreting the two analyses, and further aims to outline the implications of the presented findings in terms of current investor sentiment in the Trump era.

Section 6: Finally, we will tie the sections together to provide the reader with a conclusion to our initial research question. Furthermore, with respect to the scope of this paper, we have excluded several interesting topics from the analysis. Conclusively, we thus explore topics, which we consider particularly interesting for future studies.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2 The Variance Risk Premium as a Predictor of Stock Returns

As an adherent to the tenets of stoicism, Marcus Aurelius famously said: "*If you are distressed by anything external, the pain is not due to the thing itself, but your estimate of it; and this you have the power to revoke at any moment*". Whether one subscribes to a stoic worldview or not, it is clear that the distinction between physical and perceived uncertainty has been a feature of philosophical thought for millennia. It is vital that one understands the role played by both types of uncertainty in the economy and how they affect financial markets and decision sciences. Within the sphere of derivative pricing, this is of particular importance as uncertainty in the form of volatility directly influence option prices (Black & Scholes, 1973). Furthermore, not only does the perception of economic uncertainty impact derivatives, asset prices are also affected by cash flow risk which feeds back into derivate prices as well (Drechsler & Yaron, 2009). Hence, in order to answer our first guiding research question, the following segment focuses on describing the driving forces behind the VRP; how it captures investors attitude towards uncertainty and its superior predictive powers in terms of asset returns; key concepts within financial option theory; and especially the role of volatility.

2.1 Concepts and Underlying Theory

While option-like contracts have at least existed since the time Aristotle wrote his, by now, legendary work *Politics*, options trading remained a relatively esoteric activity, confined to a relatively small group of specialized market agents prior to the mid-19th century (Poitras, 2008). The modern options contracts we know today, are generally considered to have been born with the establishment of the Chicago Board of Exchange ("CBOE") in 1973. Despite such a short contemporary history, options pricing theory has come far; from the still dominant Black-Scholes model, to the modern model-free pricing methodologies. From this body of knowledge, interesting conclusions arise, in particular in terms of fear: Fear as measured through expectations of volatility, seems to be a mean-reverting process, which carries significant predictive power for stock returns.

2.1.1 Option pricing according to the Black-Scholes Model

One of the most famous and pivotal option pricing models was introduced in 1973, known as the Black-Scholes (-Merton) model (Black & Scholes, 1973; Merton, 1973). The model has since then had a large influence on how traders trade and hedge options. Not surprisingly, the cornerstone-model received its well-deserved acknowledgment in 1995, when Scholes and Merton were awarded the Nobel prize for economics (Hull, 2017)[2].

As mentioned in the scope and delimitation of this paper, the general introduction and dynamics of the calculus behind this well-known model will not be described in great depth, as it is not within the scope of this paper[3]. However, it is nevertheless important to highlight the key assumptions of this model and their shortcomings – which leave room for possible improvements within the space of option pricing, such as the model-free formulation, deployed in the construction of the VRP. There are seven overarching assumptions underlying the Black-Scholes ("BS") model (Hull, 2017; Munk, 2017; Hull, 2012):

1. *Stock price behavior corresponds to the lognormal model, which is characterized by having a constant mean μ and volatility σ*
2. There are no transaction costs or taxes
3. The underlying pays no dividends during the life of the option
4. There are no riskless arbitrage opportunities
5. Securities trading is continuous
6. Investors can borrow or lend at the same risk-free rate of interest
7. The short-term risk-free rate of interest is constant and the same for all maturities

While each of these assumptions are violated easily in real asset market data, what is of particular interest (and concern) when considering the aim of this paper, is the first assumption. Asset prices are assumed to have a constant expected rate of return, a constant relative volatility and can be described to a Geometric Brownian Motion ("GBM") similar to a Generalized Wiener Process (Munk, 2005; Björk, 2009; Hull, 2012). That is, asset prices follow a stochastic development around an expected drift (Björk, 2009), causing their returns to be independent and unpredictable. It is important to note, in a risk-neutral world, the expected return equals the risk-free rate (Hull, 2012).

Additionally, the Generalized Wiener Process of an asset is a particular type of a stochastic Markov process. The Markov property states that future movements in a variable (i.e. asset prices) is indepen-

2 Fisher Black died in 1995.
3 For the interested reader, the authors recommend J. Hull, "*Fundamentals of futures and options markets*", 8 (2017): 315-338.

dent and only rely on current information and not the history of variable movements. The Markov process of asset prices is thus consistent with a weak-form of market efficiency, as it is impossible for investors to gain superior returns based on interpretations of historical stock prices. This provides support for the BS model assumption of no riskless arbitrage opportunities, as any deviation from the Markov (and GBM) process would be quickly exploited by potential arbitrage investors, eliminating such deviations (Hull, 2012)

Given that assets follow a stochastic path over time, we need additional tools to model their movement. In particular, the use of stochastic calculus is necessary: Itô's Lemma employs a Taylor approximation creating a differentiable stochastic process. This reflects how Geometric Brownian Motions can have rough paths over small intervals, and further has non-zero quadratic variation. In such an Itô process, the drift rate and the variance are functions of time and the underlying variable (Hull, 2012). Furthermore, the Wiener process of the asset price and the function of its stochastic process becomes subject to the same underlying source of uncertainty. Itô's Lemma further helps describe how the stock prices are log-normally distributed in the BS model over longer periods of time, and hence how the continuously compounded stock return is approximately normally distributed (ibid). Contrarily to the normal distribution, the log-normally distributed variable is restricted, as it can only take positive values, and the distribution is skewed with a different mean, median and mode compared to the symmetrical normal distribution (Hull, 2017). Based on this, the underlying assumption of asset prices following a GBM over time, causes the continuously compounded return to be normally distributed, independent and constant, furthermore with a constant volatility (Hull, 2012; Björk, 2009; Hull, 2017)[4]. It is important to note that this assumption is a regular feature in many financial models and is as such not just a shortcoming of the BS model.

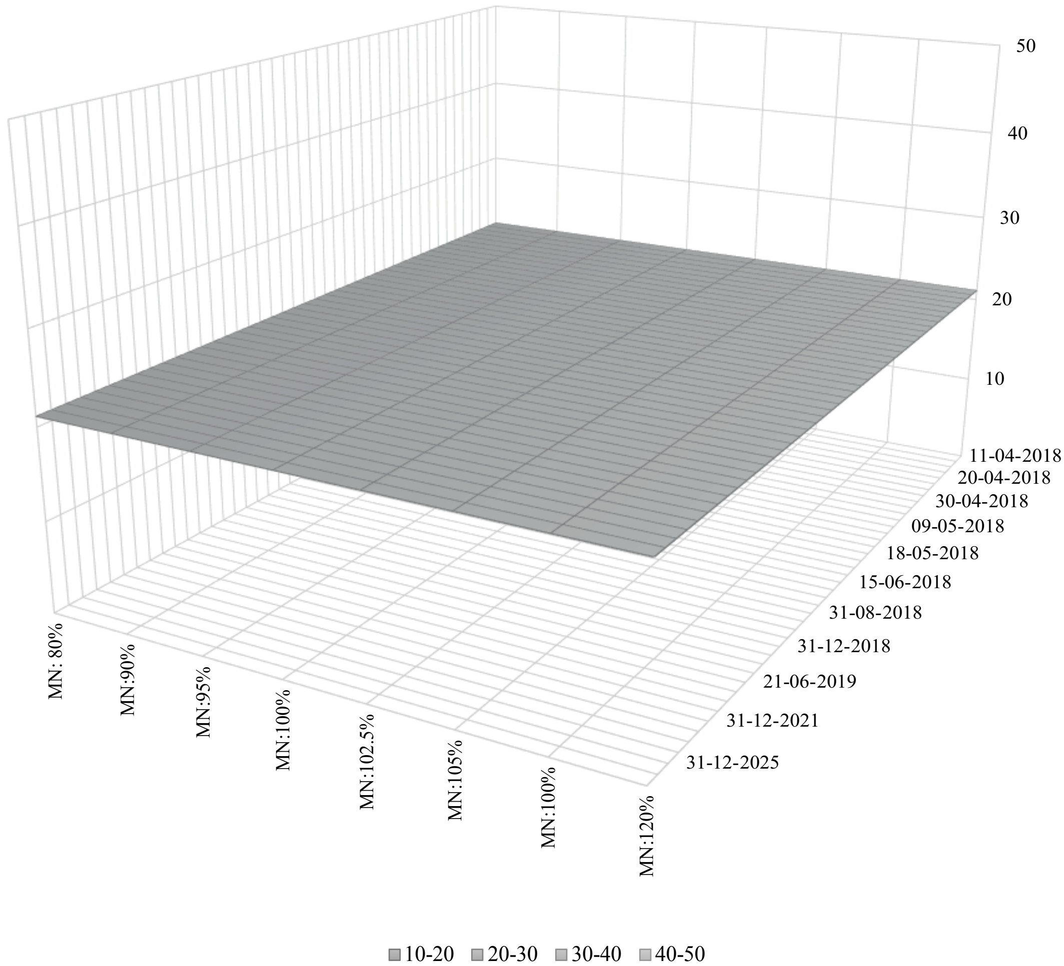
2.1.2 The volatility surface and returns outside the sphere of Black-Scholes

When volatility is assumed to be constant, the time value of money and the expected risk premium of stock returns can be easily hedged. Directional risk (i.e. market risk) is hedged via delta hedging, and thus earn the risk-free rate of return (Hull, 2017; Hull, 2012). However, this is only true in a world based on BS assumptions. When considering real market data, returns are more negatively skewed than in a normal distribution, and extreme events are more likely, resulting in fatter tails (ibid). Hence, over short time horizons asset returns actually have finite variances and semi-heavy tails.

4 If more detail is needed on stochastic processes, the authors kindly refer to J. Hull, "*Options, futures, and other derivatives*", 8 (2012), chapter 13.

More importantly, options are not only subject to directional risk, but also volatility risk, which is stochastic. Hence, a critical flaw is the assumption of constant volatility. According to the BS model, holding all else constant, a one-to-one relationship exists between the call (and put) option price and volatility, and volatility is the same for all maturities (Hull, 2012). This is due to the fact that the asset prices are assumed to follow a GBM, hence asset prices do not jump, and asset returns are normally distributed. Considering the volatility surface within the domain of BS, a plot of option implied volatility by strike price (moneyness and delta) and time to maturity, is thus flat along both dimensions.

Figure 2.A: The volatility surface in the Black-Scholes world



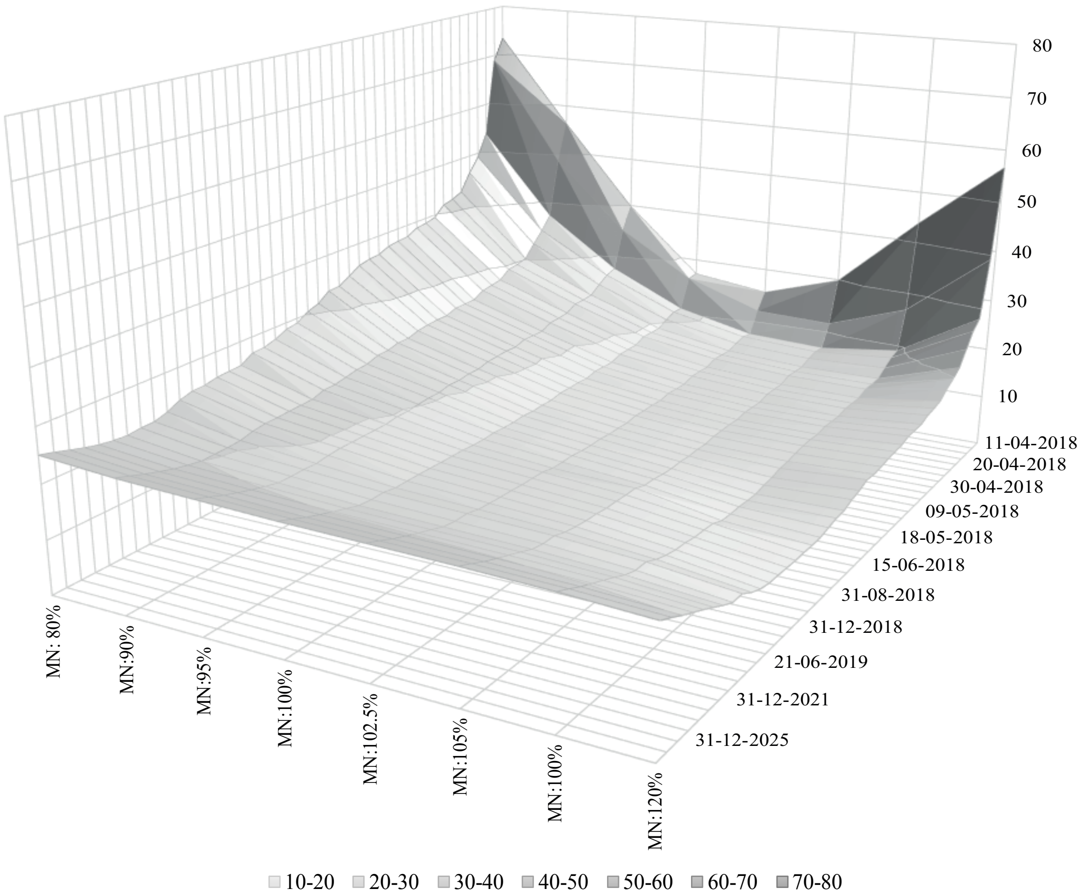
Graph of the volatility surface of S&P 500 options on April 10th, 2018 in a Black Scholes world. MN indicates the moneyness while the dates indicate the expiry date. The value axis indicates the implied volatility; we have set the implied volatility to the average of actual, implied volatilities on that date. Data source: Bloomberg (2018)

However, when considering real market data, we see a different picture: market prices jump, and volatility becomes skewed and non-constant. Volatility is the one term in BS that cannot be directly observed – hence traders work with a term known as ‘implied volatility’, i.e. the volatilities implied by option prices observed in the market. In essence, investors pay in volatilities, as higher volatilities yield higher options prices. This implied volatility thus gives a picture of the market’s opinion of the volatility of a stock going forward (whereas realized or historical volatilities are backward looking) (Hull, 2017). The implied volatility surface for Black-Scholes priced options is pictured in figure 2.A below.

According to BS, OTM put options are priced with the same volatility as at-the-money (“ATM”) put options. However, in reality OTM put options tend to be more expensive than otherwise predicted by BS. This is due to the existence of a volatility skew, or often termed a smirk, which can be illustrated by plotting implied volatility against the moneyness of the option (Breeden and Litzenberger, 1978). The volatility skew implies a different return distribution than the otherwise assumed log-normal distribution dictated by the GBM: the implied return distribution is actually more negatively skewed with fatter tails. (Hull, 2012). Given that deep-out-of-the-money (“DOTM”) put options only yield a pay-off in times of economic distress, that is, times of high marginal utility, they have an insurance-like pay-off structure. As this protects against extreme downside risk, investors tend to be willing to pay a premium for such insurance. The prices of DOTM puts thus become inflated, which results in a higher implied volatility as well.

In addition to the volatility skew, options also tend to show a non-flat term structure of volatility. The volatility exhibits a stationary mean-reverting behavior: If volatility today is higher than average, one would expect volatility to fall in the future and should thus price long-maturity options with lower volatilities. If volatility is above the long-run average, the term structure will thus be downward sloping. This causes the term structure of volatility to look different in real world data relative to the BS world, as the shape depends on the current relative level of volatility (Hull, 2012). Tabulating implied volatility by strike price and maturity, the volatility surface in real world data becomes:

Figure 2.B: The volatility surface of S&P 500 options on April 10th, 2018



Graph of the actual implied volatility surface of S&P 500 options on April 10th, 2018. MN indicates the moneyness, while the dates indicate the expiry date. The value axis indicates implied volatility. Data from Bloomberg (2018)

In line with the argument above, we see a tendency for a downward sloping term structure of volatility, suggesting that the implied volatility levels were above average on April 10th, 2018. Furthermore, we see a pronounced skew in terms of moneyness with both tails being bid up, but the out-of-the-money puts having notably higher volatilities.

2.1.3 Evidence from option returns

Several suggested explanations of the existence of the volatility skew have been proposed, of which the two most dominant are the "leverage effect"[5] and the "fear of crashes"[6]. As higher implied volati-

5 Leverage effect describes how over a short period of time, a company's debt is relatively fixed, however, as the market value of equity is fluid, a crash in the market will lead to an inflation in the debt-to-equity ratio, ceteris paribus making the firm more leveraged and thus more risky (Coval & Shumway, 2001).

6 Fear of crashes refers to the 1987 stock market crash (Coval & Shumway, 2001)). Prior to this crash, there was no pronounced skew in option markets. However, following the crash the demand for market puts grew substantially, causing a skew in the implied volatility

lity permeates through to option returns: when assets follow a Geometric Brownian Motion, options become redundant securities and with a few additional assumptions, both the Black-Scholes option pricing model and the CAPM will hold contemporaneously, as suggested by Coval and Shumway (2001). Hence, call options must have positive betas, while put options must have negative betas. However, in the study from 2001, Coval & Shumway find that average option returns significantly underperform their CAPM predicted returns.

Furthermore, studies of index option returns seem to suggest that investors are willing to pay a substantial premium to hedge not just downside risk, but volatility itself: As noted above, options are not simply exposed to directional risk, but also to volatility risk as the term structure of volatility is not flat. Hence, as option prices increase in value with volatility, a long-option position creates a hedge against increases in volatility. Thus, if investors dislike states of high volatility, as implied by the leverage effect, investors should conceivably be willing to pay a considerable premium to hedge against such states of the economy. Hence, the returns on an options portfolio that carries no directional risk, but still contains a positive volatility exposure, should command a negative premium. This has been confirmed for a wide array of studies regarding zero-beta straddles (Coval & Shumway, 2001), delta-hedged option returns (Bakshi & Kapadia (2003), and even for volatility-of-volatility measures such as the VVIX (Huang et al., 2018). Thus, it seems that both volatility and the volatility-of-volatility have negative market prices.

While premiums in options prices is consistent in the data, it can also be modelled directly in an economic setting: In their paper from 2014, Chen et al. seek to establish an economic model, in which the economy's crash risk is exogenously determined. The model contains two types of agents, investors and broker-dealers, of which investors are net-demanders of crash insurance, while broker-dealers are net-providers. Through their model, they find that the equilibrium pricing of DOTM puts imply a higher crash risk in the economy that the actual, exogenously determined crash risk. This tendency for net-demanders of crash insurance to over-pay for DOTM puts causes the volatility skew to become more pronounced, indicative of the "Fear of Crashes" as a viable explanation of the data-observed volatility skew. The study further finds that extraordinary supply shocks to the economic system can cause the price of DOTM puts to rise dramatically, for an example when broker-dealers go from being net suppliers of options liquidity to becoming net demanders. This tendency is further confirmed empirically through a study of the public net open to buy orders of index options (ibid).

2.1.4 A popular measure of implied volatility: the VIX index

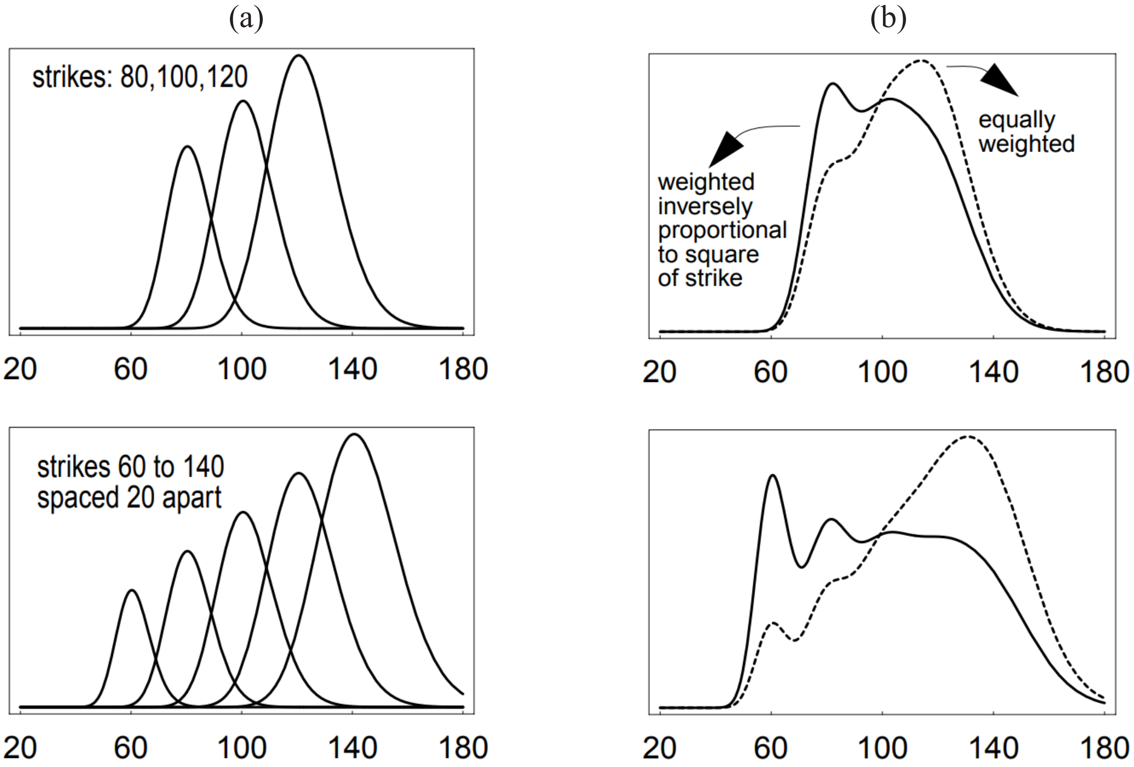
It seems as if the volatility skew is not simply a curiosity in the data, but rather a consistent feature of options prices and further seems indicative of a more fundamental part of investor psyche, in particular regarding investor fear. Building upon this understanding, as well as how implied volatility reflects investor expectations, it is of the utmost importance for the purpose of this study that the reader is introduced to the VIX index and the "Variance Risk Premium". The CBOE publishes implied volatility indices, where the most popular is the SPX VIX index (Hull, 2012). Viewed as the premier benchmark for US stock market volatility (CBOE, 2014), the VIX has become the industry standard for measuring investor expectation of future volatility. The SPX VIX measures the market's risk-neutral expectation of the volatility on the S&P 500 index 30 days ahead by averaging the weighted prices of puts and calls on the S&P 500 over a wide array of strikes. An index value of 18 implies that the implied volatility on a portfolio with an average maturity of 30 days on the S&P 500 index is approximately 18% (ibid). Throughout our sample, we find an average value of the VIX of 21, while the long run average since 1990 is around 19 (CBOE, 2015).

The calculation of the VIX index is an estimate of the model-free implied volatility measure originally proposed by Breeden and Litzenberger (1989, in Johnson, 2017). It is based on a model-free formulation, founded on the pricing mechanism of a variance swap[7] (Hull, 2012). As options are exposed to directional and volatility risk, one way to hedge volatility risk could be via variance swaps. A variance swap rate can be replicated using a portfolio of put and call options, just like the VIX is based on a portfolio of options. Like a variance swap, the VIX portfolio consists of OTM stock options with non-zero strikes[8], weighted inversely proportional to the square of their respective strikes. This offers a constant exposure to variance regardless of stock prices, which generates a theoretically correct variance swap price (Demeterfi, Derman, Kamal and Zou, 1999) – contrarily to an equally-weighted portfolio of options. This is due to the fact that a portfolio's exposure to variance changes as the stock price changes (an exposure known as vega), which is further illustrated in 2.C, figures (a) below. It is evident from the solid line in figures (b) that the inversely weighted portfolio flattens out the vega of the portfolio, yielding a constant exposure regardless of the current stock price relative to the equally-weighted portfolio (represented by the dashed lines).

7 A variance swap is an agreement to exchange the realized variance rate $\bar{V}$ between time *0* and *T* for a pre-specified variance rate, which is computed as the square of the volatility. (Hull, 2012)

8 OTM options are used for their greater liquidity

Figure 2.C: Option portfolio vega with different weights



From Goldman Sachs (1999). Figures (a) shows the vega of options with different strikes. Figure (b) shows the vega of the portfolio of options from figure (a) with different weights; the dashed line represents an equally weighted portfolio, while the solid line represents a portfolio inversely weighted by the strikes of the options

Building this on model-free assumptions of general stock price processes, the fair price of a variance swap based on S&P500 options yields the VIX index. Hence, based on the fair pricing equation for a variance swap[9], the VIX index yields the implied variance for the S&P500 options on a model-free basis and can be calculated as:

$$VIX^2 = \frac{2}{T}\sum_i \frac{\Delta K_i}{K_i^2} e^{r_f T} Q(K_i) - \frac{1}{T}\left[\frac{F}{K_0}-1\right]^2 \quad (2.1)$$

By many financial journals and other media outlets, the VIX is often referred to as the "fear index", as its inverted strike-weight causes it to spike, when market fear rises and investors demand more of the insurance-like DOTM puts. Hence, when investors regard the future development of financial market as more uncertain, they bid up the VIX index, even if the actual realized volatility does not imply

9 $K = \frac{2}{\tau}\left[r_f\tau - \left(\frac{S_t e^{r_f\tau}}{S^*}-1\right) - \log\frac{S^*}{S_t} + e^{r_f\tau}\int_0^{S^*}\frac{1}{K^2}P(K)dK + e^{r_f\tau}\int_{S^*}^{\infty}\frac{1}{K^2}C(K)dK\right]$ (2.2)

the same level of turmoil in the market. Thus, volatility hedging behavior creates a gap between the higher implied volatility and the realized volatility (Hull, 2012). This spread between implied and realized variance has been defined as the “Variance Risk Premium” and is calculated as:

$$VRP \equiv VIX_t^2 - RV_t \quad (2.3)$$

The ex-post realized variance, RV_t, is unobservable, but can be estimated in several ways, however, studies have found that one of the most precise estimation methods is the non-parametric summing of high-frequency intraday data on the squared returns on the focal index (Andersen, et al., 2001; Barndorff-Nielsen & Shephard, 2002; Meddahi, 2002; Schwert, 1990; Hsieh, 1991). Furthermore, the most accurate estimate of the ex-ante implied volatility remains the squared VIX index, especially compared to model-dependent methods such as the Black-Scholes pricing formula (Britten-Jones & Neuberger, 2000; Jiang & Tian, 2007).

This generated spread can be viewed as a *true* fear index, as it removes the actual realized volatility and shows only the level of investor fear. Across multiple precedent studies (including Bollerslev, et al. (2009), Huang & Shaliastovich (2018) and Kilic & Shaliastovic (2017) among others), this spread is found to be positive on average. This lends support to the findings in Chen et al. (2014), that is, investor perceived crash risk is higher than the actual crash risk in the market. However, the level is not constant: As the magnitude of volatility risk increases, investors pay an increasing premium for put options, potentially causing the implied and realized variances to diverge, resulting in a larger VRP. As markets calm again, the heightened fear evaporates and the VRP reverts towards its mean. Hence, it seems that investor fear, as established through the VRP, is a mean reverting process. Given the influence of investor psyche on stock returns and the role of the VRP as a barometer for the perceived risk in financial markets, it seems a natural step to consider the interlink to stock returns. Thus, over the past years, several studies have delved into this area, uncovering a strong predictive power between the VRP and stock index returns, especially over the short to medium term (3-5 months horizon returns). These findings hold both in the US and across other geographies.

3 Literature Survey

Within financial research, few factors have shown the same predictive prowess as the VRP on the short to medium time horizon. Hence, in the following segment, this paper will outline both the economic and empirical background of the VRP, including two manners in which it may maintain predictive power over equity prices: through volatility risk and its indication of changing perceptions of extreme tail risks. Furthermore, this segment will also consider how political events may influence stock markets and how previous studies have attempted to uncover the workings of this relation. Altogether, this leads us to how this thesis makes its contribution to this network of former research, in particular by establishing a node of research between the VRP and political economics – a nexus that, to our knowledge, does not currently exist.

3.1 Stock Return Predictability

The fundamental question and conundrum that has challenged many researchers and investors throughout the past decades, is whether stock market returns can be predicted (Ang & Liu, 2007; Kreps & Porteus, 1978; Weil, 1989; Epstein & Zin, 1991; Drechsler & Yaron, 2009; Drechsler, 2013; Han & Zhou, 2011; Bollerslev, et al., 2009; Bollerslev, et al., 2010; Bansal & Yaron, 2004). Overall, any predictor has two channels of influence on stock returns: either through cash flows or through the discount rate. Of these two, the cash flow channel tends to be evasive with very few predictors robustly maintaining any predictive power and commonly only showing both statistical and economic significance on longer time horizons. On the other hand, the discount rate effect has been proven across a much greater spectrum, especially governed by the well-known intertemporal CAPM model proposed by Merton in 1973, focusing on the understanding of risk-return tradeoffs in assets relative to aggregate market returns (Bollerslev, et al., 2009).

By assuming returns to be a mean-reverting process driven by arbitrage processes, predictability occurs through current mispricing of assets with respect to its specific risk characteristics relative to the market portfolio. While the empirical search for estimating the focal equity premium in the CAPM in order to robustly predict expected market return has been extensive, the findings have remained mostly inconclusive (ibid). This can partly be explained by the flaws of the model's basic assumptions, as these are easily violated by existing macroeconomic and microstructural dynamics and frictions. Furthermore, it has proven difficult to reproduce reasonable CAMP-predicted values in evident asset market data. Thus, several extensions were later made to the CAPM, for example by including more risk factors[10], as well as the relation to other predictive factors, such as dividend ratios and price-earnings ratio. However, finding successful predictors of returns on shorter horizons has, prior to the introduction of the VRP, been considered unrealistic, inconclusive or insignificant. Overall, the VRP affects equity prices through the discount factor channel and, in particular, through transient risk in financial markets. In the following paragraphs we seek to outline the empirical background of the VRP and explain the source of its predictive powers.

3.1.1 The beginnings of the Variance Risk Premium: The Long-Run Risks Model

In their paper from 2004, Bansal & Yaron proposed a discrete-time model named the Long-Run Risks Model in attempt to solve certain asset pricing puzzles (Bansal & Yaron, 2004). The primary concern was how (and if) macroeconomic risk drive the equity risk premia in asset markets, based on the fundamentals from Merton's CAPM (1973). The paper proposed a model that could justify the equity premium, a low risk-free rate, and the volatility of the market return, which had otherwise been challenging in earlier years (Mehra & Prescott, 1985; Weil, 1989; Hansen & Jagannathan, 1991; Shiller, 1981; LeRoy and Porter, 1981). With the inclusion of two basic components, the LRR model has the opportunity to explain the otherwise unproven features in asset market data mentioned above: (1) the use of Epstein-Zin (1989) and (Weil, 1989) recursive preferences, and (2) modeling consumption and dividend growth in a novel manner.

1) Epstein-Zin (1989) and Weil (1989) recursive preferences are based on the dynamic choice theory and utility functions presented by Kreps & Porteus in 1978. Intertemporal preferences are represented by utility functions that generalize a conventional, time-additive, expected utility. Applied to consumption or portfolio choice problems of an infinitely-lived representative agent, the utility functions with recursive preferences gives testable restrictions on observable behavior which better separates risk aversion and intertemporal elasticity of substitution (IES) of the agent[11].

10 See for example the Fama-French three factor model (Fama & French, 1993), later extended with the fourth factor "momentum" (Carhart, 1997).

11 When the IES is larger than 1, the LRR model shows that the agents demand a higher equity risk premium since they fear a reduction in annual growth rates or an increase in economic uncertainty, both lowering asset prices.

2) In Bansal and Yaron (2004), consumption and dividend growth rates are modelled containing *persistence in expected growth rate components* and *fluctuating volatility* to capture time-varying economic uncertainty. With such a specification for consumption and dividends, the LRR model yields results consistent with the asset market data, relative to earlier research. The inclusion of persistence in growth rates has been proven to be important, as volatility can be detected within these processes when considering price-dividend ratios (Bansal & Lundblad, 2002; Barsky & DeLong, 1993). In the LRR model, fluctuations in the persistence in the expected growth rates affects the price-dividend ratio's volatility when the model is in equilibrium, which in turn affects the risk premium of the asset (Bansal & Yaron, 2004). Furthermore, by allowing for fluctuations in the volatility itself, that is, time-varying risk premia, the LRR model incorporates conditional volatility of future growth rates and how it changes. Given the underlying recursive preferences, agents have a preference for early resolution of uncertainty and hence dislike increasing economic uncertainty. Under such preferences, economic uncertainty becomes a priced source of risk, leading to time-varying risk premia (volatility feedback effect)[12].

Summing up, approximately 50% of the volatility in price-dividend ratios in the LRR model stems from fluctuations in the persistence of expected growth rates, and approximately 50% stems from variation in economic uncertainty. This directly affects the equity premia and asset volatility. Thus, the LRR model's empirical results show how risk is related to varying growth prospects in the economy, and how fluctuating consumption volatility affects time-varying economic uncertainty. The LLR model thus makes it possible to predict the price-dividend ratio based on consumption volatility, and help justify the observed equity premia, risk free rate and volatility in observed market returns. A non-trivial relationship exists between news about consumptions and its impact on long-term expected growth rates and hence economic uncertainty, in which asset prices are sensitive to these news – thus helping to explain some of the asset market puzzles (Bansal & Yaron, 2004; Bansal & Lundblad, 2002).

While the LRR model presented by Bansal & Yaron (2004) helped predict asset market returns over a multi-year horizon using consumption innovations and persistence in growth rates, Bollerslev, et al.

12 The volatility feedback effect stems from the consumption volatility channel, where return news and news about return volatility are negatively correlated (Bansal & Yaron, 2004).

(2009) extended the LRR model with superior findings (the BTZ paper): via the innovative construction of the VRP variable, the study yielded evidence of extraordinary predictive powers of the VRP in terms of expected market returns over a quarterly horizon. As the economic model in the BTZ paper forms the foundation for the empirical findings of this study, the following segment will elaborate on the details of the model. This includes the constructed VRP variable and their convincing empirical results, which explain a non-trivial fraction of the variation in the aggregate stock market return post-1990 (ibid).

3.1.2 The Variance Risk Premium from the LRR model

While the Bansal & Yaron (2004) grounded their work in the long-run risk derived from consumption growth, Bollerslev et al. (2009) instead focuses on the realized volatility dynamics to explain the equity premium and volatility in returns. The proposed economic model includes a two-factor structure that endogenously yields the equity risk premium directly linked to underlying factors in consumption growth. With the VRP derived as the spread between risk-neutral implied and realized return variance, a factor associated with consumption growth volatility is effectively isolated. Hence, building upon Bansal & Yaron's (2004) findings, Bollerslev et al. (2009) find that the VRP serves as a dominant predictor for returns over a quarterly horizon, where these risk factors are of greater importance relative to other predictors.

As mentioned, the basic model presented by Bollerslev et al. (2009) builds upon the framework of the discrete-time LRR model. In particular, the VRP model includes stochastically time-varying volatility-of-volatility ("VOV"), a stance supported by extensive empirical evidence on volatility dynamics stemming from time-varying consumption growth volatility (Bekaert & Liu, 2004; Bansal, et al., 2003; Bekaert, et al., 2009; Lettau, et al., 2008). Simplifying their model, the study excludes the long-run risk factor in consumption growth in the LRR model (Bansal & Yaron, 2004), and focuses instead on the role on time-varying volatility.

3.1.3 Proposed economic model

The model proposed by Bollerslev, et al. (2009) comprises a self-contained general equilibrium model. It has a two-factor structure for an endogenously determined equity risk premium based on the assumption of a geometric growth rate of consumption in the economy. That is, the consumption growth over time is unpredictable, but conditional on a constant mean growth, a conditional variance and a normally distributed innovation process. This compares to the dividend growth in a Lucas-tree type economy (Bollerslev, et al., 2009) and can be formulated as:

$$g_{t+1} = \mu_g + \sigma_{g,t} z_{g,t+1} \quad (3.1)$$

In which $g_{t+1} = \log\left(\frac{c_{t+1}}{c_t}\right)$ is unpredictable, μ_g represents the constant mean growth rate, $\sigma_{g,t}$ is the conditional variance of the growth rate and $\{z_{g,t+1}\}$ is an i.i.d. N(0,1) innovation process. The volatility dynamics in this model are assumed to be governed by two discrete-time versions of continuous-time square root-type processes. The first of these processes represents the time-varying economic uncertainty regarding consumption growth with an additional source of temporal variation derived from the second process which is a volatility-of-volatility process. As described above, the economic model has agents with Epstein-Zin-Weil recursive preferences (Epstein & Zin, 1991; Weil, 1989), yielding an agent preference for early resolution of uncertainty. Hence, the inclusion of the additional volatility-of-volatility process will carry a positive risk premium, as agents prefer not to be exposed to time-varying variance. This further induces asset prices to fall with volatility shocks, which is consistent with the leverage effect, now endogenously found within the model (Bollerslev, et al., 2009).

With assets assumed to yield a consumption endowment infinitely, through the Campbell & Shiller (1988) approximation, Bollerslev, et al. (2009) solve returns as a function of the two volatility processes above, that is, the endowment volatility and the volatility of volatility. In particular, they find that returns are increasing in both parameters which reflects a risk compensation in similar form to the CAPM; the higher the volatility, the higher the return (Merton, 1973). However, *innovations* in the future volatility will tend to affect returns negatively in line with the leverage effect and the agency dislike of uncertain volatility.

The model's implied equity premium is composed of two separate, but additive, parts: The first part comprises a classic CAPM-type risk-return tradeoff relationship, which, as described above, continues to be elusive in empirical research. This relation does not contain information regarding a true volatility risk premium, it rather forms part of the model's equity premium as it induces shifts in the price of consumption risk. The second part of the equity premium however comprises a pure premium for holding volatility risk, as the premium is reactive to both shocks to volatility and the volatility-of-volatility. This second part of the equity risk premium, which contains a priced factor for being exposed to time-varying volatility, is an entirely different source of risk, which has not been studied in previous research on the traditional risk premium of consumption. This additional term is further absent in Bansal and Yaron's (2004) LRR model.

3.1.4 Volatility risk and return predictability

To further understand the differential effect of the endowment volatility and the volatility-of-volatility, along with their relationship to the expected excess returns, as defined in the two-term equity premium above, a more formal result must be defined. What is of particular interest is the ability of the VRP to effectively isolate the volatility-of-volatility risk (Bollerslev, et al., 2009). To formally establish this result, it can be found that the conditional variance at the time interval *t* to *t+1* is directly influenced by the two stochastic processes from above, the underlying economic volatility and the volatility of this volatility. While this conditional variance is known at time *t*, the one-period ahead conditional variance (for time *t+1*) remains unknown. The difference between the objective and risk-neutral expectation of the conditional variation (that is, the VRP) will then depend on how the volatility risk is priced.

While the objective expectation can be readily computed, the implied risk-neutral conditional expectation cannot be computed in a log-linear approximation. From this, Bollerslev, et al. (2009) compare the two different expectations of the same future variance: They find that volatility-of-volatility interestingly drives changes in the risk premium alone. Furthermore, given the specific values of chosen input parameters, the derived VRP is guaranteed to be positive. Comparing this finding to the two-term equity risk premium above, it seems that, in this economic model, the VRP should be a useful predictor of actual, realized future returns, in which the volatility-of-volatility is the predominant source of variance. This is further in line with previous studies, such as (Ang & Liu, 2007), in which models with first-order risk aversion (parameterized by Epstein-Zin-Weil recursive preferences) can exhibit *positive* volatility risk-return linkages.

3.1.5 Return regressions

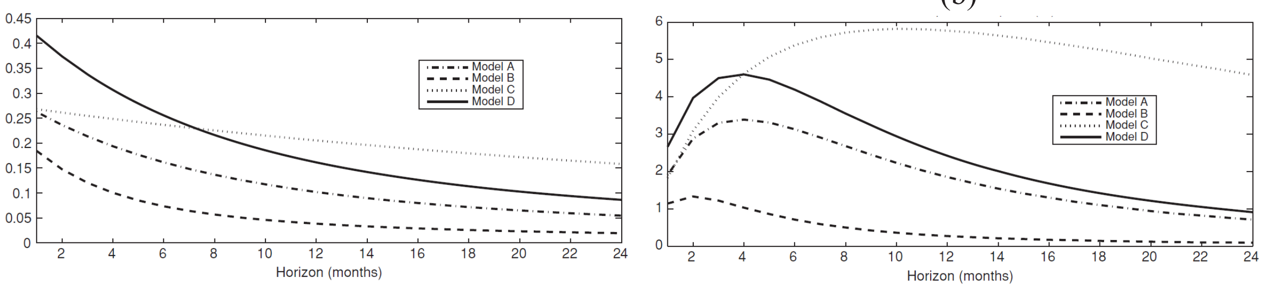
In order to test the positive relationship between the VRP and return volatility, it is further necessary to determine under which time frame the VRP should have the greatest predictive power. To do this, (Bollerslev, et al., 2009) determine the following multi-period return regression for the equilibrium model, with the relation tested across different return horizons (h);

$$\frac{1}{h}\sum_{j=1}^{h} r_{t+j} = b_0(h) + b_1(h)\left(E_t^Q\left(\sigma_{r,t+1}^2\right) - \sigma_{r,t-1}^2\right) + u_{t+h,t} \quad (3.2)$$

In which the summed return of an asset r_{t+j} is regressed against the VRP, as denoted by the term $\left(E_t^Q\left(\sigma_{r,t+1}^2\right) - \sigma_{r,t-1}^2\right)$. This regression shows how the volatility-of-volatility ("VOV") process and its persistence and magnitude compare to other risk factors in terms of β-coefficient and coefficient of determination, as it has been found to be directly (and positively) linked to the variance difference[13]. Depending on the specific values determined in the stylized model setup for the variables of (i) the growth rate of consumption, (ii) the time-varying volatility process in consumption growth, (iii) the VOV process, (iv) the intertemporal marginal rate of substitution ("IES") and (v) the price-dividend ratio, the model-implied slope and explanatory power can be affected. From the equation above, it is further evident that the variance premium may depend nontrivially on the return horizon h. By calibrating this model, Bollerslev et al. (2009) succeeds in discovering how the predictability varies with the model parameters and h, and thus derives the slopes and explanatory powers plotted in figure 3.A below.

Figure 3.A: Model-implied slopes and R^2s

(a) (b)



From Bollerslev, et al. (2009). (a) shows the model-implied slope coefficients, while (b) shows the R2. Four different configurations are utilized with return horizons stretching up to 24 months.

Model A is based on the same values as applied in the LRR model (Bansal & Yaron, 2004), whereas model B has a decreased persistence in the volatility-of-volatility. Model C comprises an increase in the persistence in volatility-of-volatility and model D has a higher intertemporal elasticity of substitution. It is clear that compared to the baseline model, decreasing the persistence in volatility-

13 Furthermore, the VOV driven risk premium also depends on the recursive utility (IES), as it follows that , $\left(E_t^Q\left(\sigma_{r,t+1}^2\right) - \sigma_{r,t-1}^2\right) = (\theta - 1)k_1 A_\sigma q$ where θ is the subjective discount factor involving IES and a risk aversion expression, and q is VOV.

of-volatility results in systematically lower slopes (and vice versa). Increasing the IES (as in model D) increases the relation between returns and the VRP, which in turn results in a systematically higher slope parameter across all horizons. Intuitively, the IES enhances the effects of volatility-of-volatility: If investors become more sensitive in their intertemporal consumption allocation, under Epstein-Zin-Weil preferences, greater volatility-of-volatility will be amplified by a higher IES, as investors will prefer to resolve uncertainty earlier. Looking at the model-implied explanatory power (R^2) for the baseline model, the degree of predictability is at its maximum around the quarterly horizon. Lowering the degree of persistence within the volatility-of-volatility process results in a maximum around two months instead, while increasing the persistence results in an increase of predictability for a longer period. Finally, for model D with a higher IES, the time-varying volatility-of-volatility process is stronger, which also increases the overall predictability of the model. It thus seems that the predictive ability of the VRP is affected by both sources, in which the volatility-of-volatility indicates the uncertainty faced by market agents, while the IES parameterizes the sensitivity of market agents to this uncertainty.

Summing up, it is clear that the simple stylized general equilibrium model yields significant regression coefficients and return predictability over shorter time horizons, with the exact timing of peak predictability affected by the intertemporal elasticity of substitution and the persistence in the volatility-of-volatility. From this, the VRP on the RHS of the regression can be seen as a 'pure volatility bet' where everything else is risk-neutralized away. As derived above, due to the Epstein-Zin-Weil preference structure, the VRP is driven solely by the volatility-of-volatility, and thus the price of this risk changes if the variance of the priced factors changes. Hence, the VRP effectively isolates the systematic risk associated with the volatility-of-volatility process and becomes a useful predictor of future returns (Bollerslev, et al., 2009)

3.1.6 Model-free formulation of realized and implied variances

In the theoretical model above, the difference between risk-neutral expectation of future return variance and current return variance seems to be a useful predictor for future stock returns. In order to study this in depth, Bollerslev, et al. (2009) further run the return regressions in an empirical setting, looking at the predictive power of a US-based VRP on the returns on the S&P 500 index over the period 1990 to December 2007. In order to generate the VRP, the study utilizes model-free return parameters for both constituent parts of the spread. Inspired by several former papers (Carr & Madan, 1998; Demeterfi, et al., 1999; Britten-Jonas & Neuberger, 2000), Bollerslev, et al (2009) use the squared model-free VIX index, based on the pricing of variance swaps. This model-free measurement is a natural empirical version of the $E_t^Q\left(\sigma_{r,t+1}^2\right)$ term from the discrete-time model defined in equation 3.2 above. As mentioned, the model-free formulation represents a far stronger approximation than one based on the inversion of the typical BS formula with close-to-ATM options (Jiang & Tian, 2005; Bollerslev, et al., 2011).

In line with the definition from our Concepts and Underlying Theory, Bollerslev, et al. (2009) utilize the sum of squared logarithmic returns to generate an estimate of the realized variance (Andersen, et al., 2001; Barndorff-Nielsen & Shephard, 2002; Meddahi, 2002):

$$RV_t \equiv \sum_{j=1}^{n}\left[p_{t-1+\frac{j}{n}} - p_{t-1+\frac{j-1}{n}(\Delta)}\right]^2 \rightarrow \text{Return variation}(t-1,t) \quad (3.3)$$

To ensure accuracy, the Bollerslev et al. (2009) study utilizes intraday data to achieve more accurate ex post observations as close to the true return variation as possible. Finally, their model predictor and key empirical finding is the difference between the two terms; i.e. the VRP for the time interval of *[t;t+1]-[t-1;t]* becomes $VRP_t \equiv IV_t - RV_t$, in which the implied volatility runs forward 30 days, while the realized variance runs backward 30 days. An advantage of this formulation is that the VRP is directly observable at time *t*, which is key when attempting to forecast stock market returns.

3.1.7 Main Empirical Findings

Following the line of thought in the calibrated return regressions section, the BTZ study starts out by looking at the return horizon predictability. For the estimated slope coefficient associated with the VRP, the study finds statistical significance at the 5%-level. Furthermore, they find that the VRP has the strongest predictive power at the quarterly horizon, where R^2 maximizes at 6.32%. For comparison, the R^2 is 1% at the one-month horizon, and from the quarterly horizon up until six months, the slope coefficient remains significant, albeit with a decreasing significance and explanatory power (Bollerslev, et al., 2009). Thus, the study supports the notion of a predictive relationship between the VRP and expected returns, in line with the economic model set out above. Comparing the empirical estimates for all monthly horizons until 24 months, the shapes seen in the regression outputs fit the regressions reasonably well. Hence, it seems that the VRP does indeed succeed in separating the systematic risk factor associated with time-varying volatility of consumption growth volatility in real market data as argued in the economic model (ibid).

The study progresses by comparing the predictor variable VRP with more traditional variables from the existent literature, such as the price-earnings ("P/E") ratio and the consumption-wealth ("CAY") ratio (Lettau & Ludvigson, 2001), as well as the term spread and relative risk-free rate. None of these classic predictors dominate the VRP's degree of predictability on a quarterly (or monthly) horizon. Furthermore, the term spread and risk-free rate actually reduce the adj. R^2. Combining the P/E ratio with the VRP results in an R^2 of 3.7% in excess of the sum of the two R^2's from the individual regressions, and they both remain significant. However, none of the *t*-statistics for any other predictor variable comes close to the VRP's *t*-statistic of 2.86, and all maintain lower adj. R^2's. This is thus testament to the dominance of the VRP in terms of predictability. However, it is important to note that in multiple regression outputs they find that combining predictor variables such as the VRP and the P/E ratio jointly capture short- and long-term risks in market returns, yielding even stronger *t*-statistics[14].

The highest *t*-statistic found in the multiple regression is when the VRP, P/E, term-spread and risk-free rate is included. No matter which variables are included in the regression, the estimated VRP coefficients remain stable and significant at the 1%-level. Hence, the BTZ study provide impressive empirical evidence that the stock market return can be predicted by a model-free formulation of the VRP, based on robust results across many different specifications and regressions, as found for the simple regressions. The degree of predictability is at its maximum at the quarterly horizon, but the VRP remains a stable predictor at other horizons between 3-6 months in particular. These findings can alternatively be seen as a proxy for the total degree of risk aversion in the market, as time-varying volatility risk and risk aversion both play an important role when seeking to explain the temporal variation in expected returns (ibid).

3.1.8 The variance risk premium in other geographies

While the BTZ study was restricted to studying the VRP in the period 1990 to 2007, the results from

14 However, combining CAY and the P/E ratio yields insignificant t-statistics for both variables.

the study have been confirmed for the US stock market in later time periods, including the financial crisis (see for example Huang, et al. (2018), Drechsler & Yaron (2009) and (Kelly & Jiang, 2014). Furthermore, a spatial dependence for the phenomenon of a consistently priced factor of aggregate risk aversion and economic uncertainty, seems too bold a statement. In their study from 2014, Bollerslev, et al. thus attempt to corroborate their results by utilizing the same methodology from their 2009 study on a wider selection of countries.

Due to data availability issues, they restrict their study to the main stock indeces in France, Germany, Switzerland, the Netherlands, Japan, Belgium, the United Kingdom and the United States. Across all countries, the predictability pattern found on the US market holds, and all show similar hump-shaped regression coefficients and adjusted R^2s. However, many of the geographies show the strongest predictability at slightly longer horizons (4 to 5 months, relative to 3 months on the US market) and with somewhat attenuated coefficients relative to the US market. Based on the economic model in Bollerslev, et al. (2009) this may indicate a slightly higher persistence in the volatility-of-volatility, as well as a slightly lower intertemporal elasticity of substitution. Based on the apparent commonality in predictability patterns, they further define a "global" VRP based on the main indeces from the above mentioned geographies. Utilizing this global VRP as a predictor for stock returns on the country-specific indeces, Bollerslev, et al. (2014) find even stronger commonalities and pattern uniformity across countries. For all individual countries, the global VRP serves as a highly significant predictor especially at the 4- and 5-month horizons. They further find that results are consistent when running regressions with an forward-looking VRP, constructed from a heterogeneous autoregressive model of realized volatility.

While the results from the 2014 study are striking, it is notable that the study only considers well-developed economies. In order to study the VRP outside these relatively well-researched geographies, Chen, et al. (2017) attempt to study the phenomenon on the Chinese stock market. Noting that no previous studies exist on the Chinese market due to a lack of an options market, Chen et al. (2017) estimate a time-varying VRP based on a general equilibrium asset pricing model. In line with previous studies, they find the strongest predictive power at the 4-5 months horizons. Interestingly, in contrast to the studies of other geographies, the Chen, et al. (2017) study finds coefficients that exceed the empirical results for the US market; the estimated beta for the VRP against Chinese stock market returns is 1.43 for the 3-month horizon, while the same beta estimate for the US market is 0.47 (Bollerslev, et al., 2009). Thus, it seems that the Chinese market may be characterised by a more persistent volatility-of-volatility, as well as a higher intertemporal elasticity of substitution. Further, in the multiple regressions including other economic variables, the VRP causes a significant increase in the coefficient of determination. This implies that for the Chinese market, as for the markets studied in previous research, the VRP comprises additional forecasting information regarding stock market returns in excess of that embedded in classical economic variables.

3.2 Extensions: Further Exploration of the Driving Forces of the VRP

In addition to the studies of the return predictability of the VRP, several extensions to the formulation and drivers of the VRP have been suggested. These include further study into the volatility-of-volatility as a risk factor; applying jump-diffusion modeling to the intersection of the VRP and equity pricing; considering asymmetric volatility preferences; and the VRP as an indicator for investor demand for tail risk hedging. These expansions stem from both an economically motivated standpoint, model-independent big-data analysis, as well as from a more behavioral finance perspective.

3.2.1 Diffusive jump-shocks as the driver of the predictive power in the VRP

Several papers (e.g. (Pan, 2002), (Eraker, 2004), (Broadie, et al., 2007)) have suggested that in order to study option-pricing with both physical and risk-neutral data, the inclusion of jump risk is necessary. In particular, it has been found the combination of recursive preferences and large, rare shocks to a persistent component in cash-flow growth is capable of generating the prominent option implied volatility skew or smirk (Benzoni, et al., 2005). Hence, extensions to both the LRR model by Bansal & Yaron (2004) and the VRP studies have taken their point of departure in jumps in both volatility and cash flows. Building on Eraker's (2008) general equilibrium model including non-Gaussian shocks and endogenously occurring market crashes, Drechsler and Yaron (2009) extends the LRR model to the link between the VRP and jump risk. In particular, the 2009 extension focuses on the stochastic volatility process governing the level of uncertainty about shocks and long-run components of cash-flows. Under the assumption of Epstein-Zin-Weil preferences, it is found that the inclusion of jump shocks helps create a model capable of generating a positive, time-varying VRP, capable of predicting future stock returns.

In his study regarding time-varying fear and the effect to asset prices, Drechsler (2013) argues that the asset pricing process includes both risk and uncertainty, drawing on the concept of Knightian uncertainty, capturing the ambiguity in the data-generating process itself. That is, there is a distinction between *risk* and *uncertainty*, where risk captures situations in which we do no not know the outcome, but where we can measure the odds. Uncertainty, on the other hand, applies to situations where we do not have enough information to set accurate odds. The paper confirms the role of jump-shocks as the primary driver of the predictive power of the VRP, but further finds that this power arises from a combination of jump risk in the reference model and uncertainty regarding the underlying model, in which model uncertainty amplifies concerns regarding jump shocks. Higher levels of model uncertainty thus entail that smaller jumps can generate a significant VRP. This is in line with the findings in Chen, et al. (2014) who found that market participants tend to overestimate an exogenously determined crash risk.

3.2.2 Positive and negative volatility: Asymmetric volatility preferences

It seems that the inclusion of jump shocks is capable of capturing, to a large extend, the size and predictive power of the VRP, as this reveals variation and uncertainty regarding the intensity of shocks to the economy. However, Kilic & Shaliastovich (2017) suggest that the inability to differentiate between negative and positive volatility conflates potential opposite effects of good and bad jumps. Building on the intuition that investors like good uncertainty, as this increases the potential for gains, and dislike bad uncertainty, with an increase to the probability of substantial losses, Kilic & Shaliastovich (2017) suggest a model with a decomposition of the pricing of good and bad asset-price jumps. Building on the econometric approach from Segal, et al. (2015), Kilic & Shaliastovich (2017) find that "good" and "bad" variance have opposing effects on the level and variation in the risk-return relationship on the market: They find that a good VRP predicts future returns with positive signage, while a bad VRP predicts with a negative signage.

This adds to previous studies that consider the intersection of the VRP and tail risk. In their study from 2015, Bollerslev, et al. statistically disentangle the diffusive jump components of the VRP and show that this decomposition leads to stronger return predictability. It is particularly driven by variation to left tail jumps, consistent with the notion that most of the predictability is driven by investor fear. This supports the finding by Gou, et al. (2014) who find that short-term excess stock returns and economic fundamentals are well predicted by realized positive and negative jump volatilities and that total jump variation has little predictive power. In further extension, Feunou, et al. (2015) found that the VRP is primarily driven by downside risk through their study of the empirical implications of a decomposition of the VIX into downside and upside components.

3.2.3 The informational content of the VRP: Liquidity provision and tail risk hedging

As suggested by Bollerslev, et al. (2015), it seems that most of the predictive ability of the VRP stems from asymmetric volatility and in particular jumps in the far-left tail of the return distribution. In their paper from 2016, Fan, et al. argues that one should be able to infer information regarding investor demand for hedging downside tail-risk from option market data, and the intermediary willingness to meet this demand. This builds on the finding that the volatility risk premium represents option market makers' willingness for inventory absorption and liquidity provision (as found in Gârleanu, et al. (2009) and Nagel (2012)), along with the tendency for buy-side investors to be net buyers of index options (Gârleanu, et al., 2009). From this, the VRP may be understood as the compensation that market makers require for intermediation and liquidity supply to meet investors' hedging demand, in line with the argument made by Chen, et al. (2014).

The study finds that when the demand for hedging increases, the deviation between implied and realized variance deepens, as market makers require an increasing premium for taking the short position. As noted by Fan, et al. (2016), a positive volatility risk premium[15] is justified theoretically and, for the most parts, supported by the data. However, the large negative spikes during the financial crisis, seems paradoxical. Drawing on the findings in Bakshi & Kapadia (2003), the study finds that the periods with a negative VRP are consistent with positive returns on delta-hedged put positions. To the extent that this coincides with severe shocks in the supply of puts, it is possible that a negative VRP is representative of the restricted supply of liquidity in the market for hedging tail risk.

3.2.4 Behavioral finance: Loss aversion and distorted probability assessment

While the VRP can be modelled under classical agent preferences, it may also carry a large informational content about investor behavior and sentiment if modelled considering an asymmetric

15 Note here this is positive under the specification of this study, (Fan, et al., 2016) uses the opposite specification

preference structure with a specific weight on rare events. However, this requires a different view of agent preferences: Known as prospect theory, the model developed by Kahneman & Tversky (1979) (extended in Tversky & Kahneman (1992)), represents an alternative model for decision making under risk. In particular, the model is capable of capturing the demand for insurance (taking small, frequent losses in order to cap large downsides) and distorted probability views in which the probability of extreme tail events is overweighed. Given that options tend to significantly underperform their CAPM-predicted returns (Coval & Shumway, 2001; Driessen & Maenhout, 2007), these two factors may help in describing the investor psyche underlying the strong demand for hedging volatility risk, in particular downside risk. Indeed, as found in Driessen & Maenhout (2007), any investor, even with loss-aversion preferences, should prefer to hold *short* positions in DOTM puts, and should only prefer to hold long positions with highly distorted probability assessments, as modelled under prospect theory.

If investors are viewed through this lens of prospect theory, it seems that the VRP, as constructed via the model-free formulation, is suggestive of changes in investor perception of extreme tail events. Indeed, Driessen, et al. (2014) find that the variance risk premium seems primarily driven by distorted probability perceptions, which would imply that when the probability of extreme events changes, the effect is compounded by investors. Hence, while the physical probability of an event is very low, as long as it is non-zero and has a large potential effect, its impact on the volatility surface, and hence the VRP, may be large. Thus, it seems that the variation in the VRP is suggestive of tail risk fear – and hedging – under both economically-motivated arguments (for example (Kilic & Shaliastovich, 2017) and (Bollerslev, et al., 2015)), under model-independent analysis (Fan, et al., 2016) and under the lens of prospect theory (Driessen, et al., 2014).

3.2.5 Investor sentiment and stock returns

Several previous studies have been engaged in investigating the existence of a link between different economic trends, stock returns and volatility. An interesting angle within this field is examining how economic trends affect investor sentiment and how this in turn affects stock returns. Hence, while the VRP seems affected by investor psyche, the market in a broader sense may also be affected. Lee, et al. (2002) study exactly this relationship, testing the "Investors' intelligence sentiment index" in connection with conditional volatility, founded on earlier determined noise trader models[16] in finance. The study finds that investor sentiment is a systematically priced risk, in which shifting sentiment is positively correlated with excess returns. The study shows how bearish (bullish) changes in sentiment leads to an upward (downward) revision in volatility, followed by lower (higher) future excess returns. This can be described as the "hold more" effect – noise traders increase (decrease) their holdings of risky assets when their sentiment becomes more bullish (bearish), which raises market risk and return.

On the other hand, contrarily to many other studies, Chung, et al., (2012) actually find an asymmetry in the predictive power of investor sentiment across expansion and recession states of the economy. They find that only during an economic expansion does investor sentiment have a robust predictive power of stock returns, while during a recession the results are found to be insignificant. Nevertheless, many studies have considered numerous angles when trying to solve the equity premium puzzle, and how it might be related to investor sentiment. This spectrum spans much wider than to states of the economy: some have chosen to focus on the predictive power of general macroeconomic trends; some on the more extreme cases of tail risk events often referred to as market crashes; some on political elections and crises (Almeida & Ferreira, 2002; Niederhoffer, 1971) and some even on natural catastrophes (Brounen & Derwall, 2010; Shelor, et al., 1990).

3.2.6 The effects of world events on the stock market

While we often consider tail risk to be driven by the risk of financial crashes, other factors or events may also cause investor perception of extreme risk to change. In his study from 1971, Niederhoffer examines several different "world events" on the stock market. Based on data from the S&P 500 index, he investigates the relationship with world events taken from headlines in the New York Times. He finds evidence that these different kinds of world events affect fluctuations in the S&P 500, and that these events further induce abnormality in stock returns. In the years following the financial crisis of 2007-2009, many researchers have focused on the case of extreme tail risk events and investor sentiment. One paper constructs a new measure for a "tail-risk index" in order to investigate the risk premium and future market returns (Almeida, et al., 2017). They find that investors' marginal utility

16 The Noise Trader Model was proposed by De Long, Shleifer, Summers and Waldmann in 1990. They modeled influence of noise trading on equilibrium prices. Noise trading is acting on non-fundamental signals. They found that it introduces systematic risk, as the deviation in price created by changes in investor sentiment become unpredictable (Lee et. Al, 2001).

is increasing in tail risk and measure the magnitude of a "tail risk premium". The study further finds that the tail risk measure can anticipate and capture stock market movements in terms of financial, economic and political events such as the Korean War, Pearl Harbor, Eisenhower's heart attack or the Kennedy Slide of 1962. Furthermore, they argue that contrarily to option pricing and VaR measure (which focus on individual systemic risk) tail risk is more broadly applicable as it considers a wider spectrum of risk provoked by catastrophic events and disasters, which affect all firms in the market (ibid). Hence, they criticize the model-free options-derived methodology from Bollerslev, et al. (2009)'s, but also find a correlation between their measure and the VIX of 0.56. Such correlation yields support for both methodologies, showing that risk-neutralization measures capture investors' crash fears and risk attitudes, across both the financial and political spectrum.

Another approach in the literature has been to focus the impact of politics and political uncertainty on investor sentiment, risk attitudes and volatility in the market. While several studies have considered the connection between stock returns and political events, fewer have focused on volatility. For instance, Herron, et al. (1992) identified 15 economic sectors where stock prices react differently to changes in expectations of the results of the presidential election in the US in 1992. In 2000, Herron estimated that the stock market would have dropped 5% with a simultaneous increase in volatility, had the Labor party won the election in the UK. Furthermore, the study shows that the probability of Al Gore winning the presidential election in 2000 has been found to lead to lower levels of volatility in the US stock market. Jensen & Schmith (2005) investigate the political setting in Brazil and its impact on the Brazilian stock market. Contrarily to others, they suggest that greater certainty in elections was associated with *higher* levels of volatility. However, they put forward the hypothesis of 'Candidate Uncertainty', in which some presidential candidates might drive more stock market volatility than others. For instance, as the popularity of the Brazilian presidential candidate Lula rose, they find that "*the uncertainty in the financial markets was not because of an uncertain election; rather, it was because of uncertainty about Lula's policies*." (ibid). Hence, some candidates can have negative impact on the stock market while others can drive positive returns, and this can in turn spike more volatility if an unfavorable candidate is expected to win.

Combined with such considerations of the different effects on volatility given the presidential candidacy, studies have also considered more general effects of political risk and instability.

Bittlingmayer (1998) finds evidence for a causal relationship between political instability and stock prices in Germany. The study shows that political instability has negatively affected industrial production in Germany, as well as increased stock market volatility. He further finds evidence that revolution, crumbling governments and wars also resulted in higher volatility in stock returns. Nazir, et al. (2014) investigate the impact of political risk in Pakistan on the country's equity market returns and confirm that political risk increases the equity risk premium by 7.5-12%. In terms of signage, a Canadian study (Beaulieu, et al., 2005) finds that the impact of political risk on the volatility of stock returns is asymmetric – namely that the response to unfavorable political news results in larger volatility spikes than positive news, yielding a stronger potential for tail risk events. Finally, a recent Malaysian study investigates the relationship of political instability to stock prices (Irshad, 2017). Their results confirm the negative relationship between stock prices and political instability, as well as suggesting that an unstable political system ultimately leads to lower stock prices.

When considering the recent US election, Trump does not come across as the most stable and predictable political actor. According to previous studies, this unpredictable behavior should have spiked more volatility in the stock market returns, and maybe even lower stock market returns. Nevertheless, the fear index – the VIX - has since the election been characterized as lying far below the historical average of 19 (with one exception in February 2018) going against all intuition on the subject: with growing geopolitical tensions due to Trump's increasingly protectionist policies, investors may be expected to seek to insure themselves against extreme tail events via DOTM puts, propping up the VIX. Many articles have been written on the topic, and following many of Trump's policies, experts are expecting stock prices to fall (Redder, 2018). However, the stock market in the era of "Trumponomics" has repeatedly reached all-time highs over the past year, which presents a conundrum given the previous findings of the effects of political instability on the stock market. It is thus of the utmost importance to study whether Trump is in fact driving stock market performance, and whether his seemingly unpredictable character generates a more volatile stock market setting after all.

4 Contribution: Volatility in the Era of Trump

Given its superior predictive ability, it seems only natural that the VRP has been the subject of many recent studies within economic finance. Since the pivotal paper by Bollerslev, et al. (2009), extension studies have primarily focused on model improvements; either focusing on the inclusion of jump-diffusion modeling, decomposition of upside and downside variance terms, and indication of tail risk hedging demand. Common for all these studies is the result that the VRP seems strongly driven by the left tail of the return distribution and particularly investors' fear of extreme tail events. While the VRP is a young field of research, few of these papers have dealt with the post-GFC recovery market, and with the recent period of extraordinarily low volatility.

Extreme tail events are often considered to take the form of a sudden market crash, for an example the GFC or the Black Monday crash of 1987 (Hull, 2012). However, tail risk may also be politically driven: several previous studies have examined the link between politics and stock returns, including the effects of presidential elections, war, terror and more general political events. While this intersection of finance and politics is well-researched, few of these former papers deal with what must be assumed to be the root of this interaction: investor fear – and none of them consider the VRP. Thus, this paper seeks to examine more directly how investor sentiment is affected by political events by utilizing the VRP as a pure form of investor fear. In particular, we focus on how the VRP may help explain investor response to a highly tumultuous political climate, such as the one observed since the recent US presidential election. Hence, as described in our introduction, this paper seeks to answer the following research question and guiding sub-questions:

> ***How has the VRP and its ability to predict stock returns on the US stock market been affected in recent years by the economic and financial development and the increased political uncertainty apparent in the Trump Era?***

(i) What is the VRP and what evidence exists for its ability to predict stock returns?

(ii) How has the VRP developed in the years following the global financial crisis and does it maintain its predictive prowess?

(iii) How has recent years' political instability in the Trump era affected the VRP and its components?

(iv) What does the evolvement of the VRP and its potential exposure to political uncertainty imply about current investor sentiment?

5 Methodology and Analytical Approach

As outlined above, our contribution covers three areas: The research of the VRP in a new temporal setting, the interconnection of the VRP and political-financial research and the implications of these considerations on investor sentiment. In terms of research designs, several avenues exist for answering the guiding questions. Hence, in the following segment, we seek to outline the methodological approach of this paper; the data utilized; the treatment of this data and the methods applied.

5.1 Research Methodology

Taking a point of departure in the overall problem statement, our thesis is nested in a body of existent theory and precedent empirical findings. Notably, neither of our guiding questions take the form of falsifiable statements or hypotheses, but rather are open-ended guided by the previous literature within the field. Based on this, we find it most appropriate to take a deductive approach in terms of research design, as it allows the paper to utilize the precedent findings in discussions of the results (Chalmers, 2013). The first phase of the analysis of this thesis seeks to examine the relation between the VRP and stock return predictability, in essence testing the results from the BTZ paper, in a new temporal setting. In the second phase of the analysis, we focus on the predictive ability under the current scene of political uncertainty and remarkably low VIX-values evident throughout 2017. Furthermore, with the theoretical evaluation and application of traditional and reformed options pricing theory in mind, this paper further attempts to uncover what may be discovered regarding investor sentiment for the focal period in the fourth guiding research question. We apply this deductive methodology to secondary data to test the predictive power of the VRP through a set of regressions with a basis in the data as well as key predictors from the existent literature.

In terms of our third guiding research question, we choose a narrow approach to examining the implications of politics on the VRP and its components. In particular, we choose a case study-type research design in which we consider the time period in and of itself, without comparing to previous periods in time. An alternative measure may have been to choose a methodology, which allows for direct comparability across different time periods, however, given the potential for the focus of this paper to drift, we find it to be of utmost importance to utilize a parsimonious methodology. Thus, by applying a case-like approach, it allows us to focus the discussion directly on the time period of interest and answer the question set out above most directly (Rugg & Petre, 2007).

5.2 Utilized Data

It requires the use of several types of data to answer the research questions set out above; from broad index data; to macroeconomic indicators and political proxies. Hence, to acquire such data, we have had to turn to several different sources. As the study has an American perspective and wishes to maintain comparability with the bulk of previous research, the utilized index, and the basis of the established VRP, is the aggregate S&P 500 composite index. Meanwhile, we base the implied variance on the squared VIX index (in line with Bollerslev, et al. (2009) and (2014) and Huang, et al. (2018) among others). The construction of the VRP requires an estimate of both the implied and realized variance to be as accurate as possible. Thus, following the previous literature, we rely on high-frequency intraday data for the S&P 500 index and the VIX, as obtained via the Thomson Reuters DataScope Select database (2018). Note, that this paper samples the VIX on an intraday frequency as well, while previous studies have sampled the VIX on a daily frequency. This is done to allow the study of the intraday relation between the VRP and returns on the S&P 500.

It is recognized by the authors of this paper that historical intraday prices may be recorded with error. However, for our sample, which only covers trading hours, we noted no clear outliers in the data that may have been caused by recording error for the S&P 500 index. However, for the intraday VIX sample, we noted a total of 18 outliers that seemed to be caused by error in the price records. These instances were checked against secondary sources (primarily Yahoo Finance), in which we compare the high and low price of the day to make sure that these "outliers" were in fact falsely recorded. These were then removed by taking the last sensible price. The errors were contained to the sample prior to the global financial crisis and concentrated around market opening.

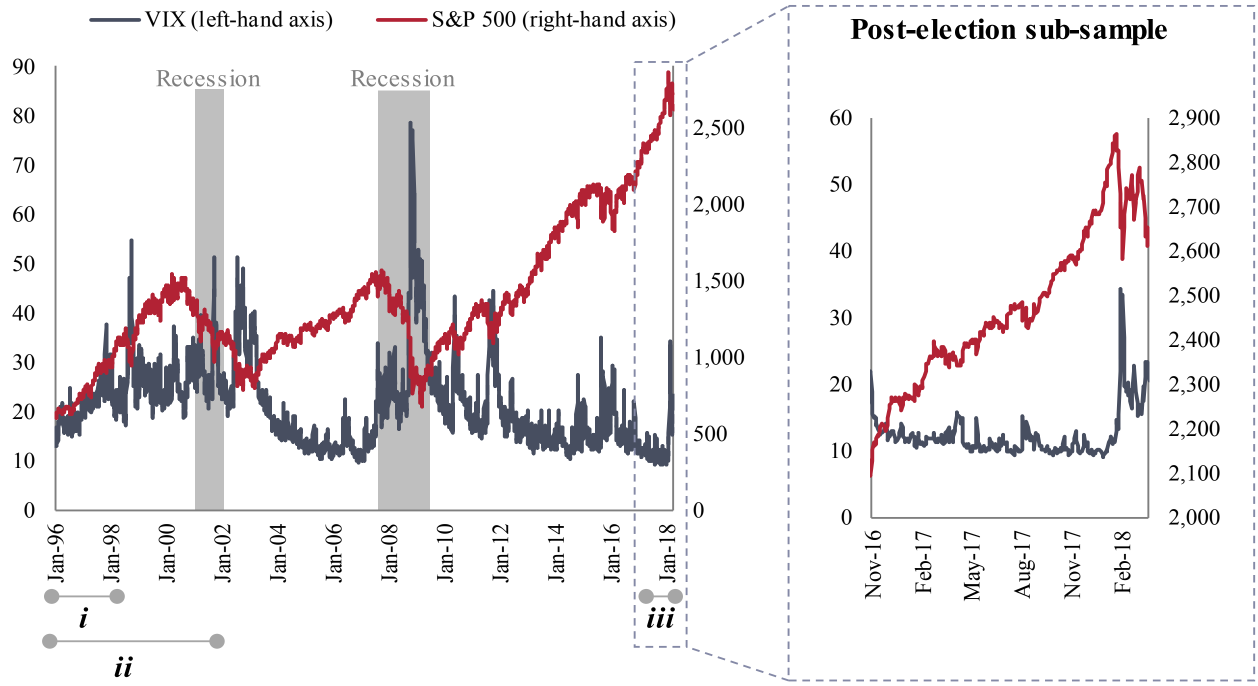
5.2.1 Sample size

The initial sample period stretches from January 1996 to March 2018. This is due to several considerations: (i) Firstly, we wish to generate a sample with sufficient overlap to previous studies to ease comparability. (ii) Secondly, we wish to generate a model that covers several economic states including periods of economic prosperity (2002 to 2007) and recession (2007 to 2009) . (iii) In this connection, it is necessary to have a significant amount of data prior to and after the financial crisis in order to test whether relations have changed during the course of the crisis. (iv) Additionally, to test the effects of the election of President Trump, we naturally require a time sample during which he has been elected. (v) Lastly, as will be elaborated upon in further detail, we need a significant timespan to generate returns and train various models, such as the MC-GARCH model for modelling realized variance. Altogether, this leaves us with a *raw* testing sample spanning from February 24th 1999 to February 27th 2018, for a sample of 4,648 days, or 362,544 intraday observations.

We further decrease the sample size due to two considerations: Firstly, in order to conduct sensible controls for regressions, we include the price-earnings and price-dividend ratios on the S&P 500 index, in line with Bollerslev et. al (2009). However, as this information is only available from January 1st, 2000 and onwards, and we further need to generate lags up to 2 years on the variables, our *final* testing sample stretches from January 10th 2002 onwards. Additionally, the latest measurement of the Consumption-Wealth Ratio from Lettau and Ludvigson (2001) is dated to September 2017. Hence, the final testing sample ends on September 27th 2017. Thus, our final testing sample comprises 3,850 days, constructed from 300,300 intraday observations. While this does comprise a considerable sample size, we include the final part of the sample from September 2017 to March 2018 in the sample covering the elective period of Trump and chose not to control for the CAY ratio. Thus, the post-election sample comprises 318 days of data or 24,804 intraday observations. For an overview of the sample, please refer to figure 5.A below.

17 With recessions defined in accordance with National Bureau of Economic Research (NBER, 2018)

Figure 5.A: Overview of sample utilized and sample cuts



Sample cuts

i) Training of models, ***ii)*** Generation of lags and returns, ***iii)*** Lack of data points on the CAY ratio

Data sample studied including the development in the VIX index and the S&P 500 index. Recessions defined as per the National Bureau of Economics (2018). Price data from Thomson Reuters (2018)

5.2.2 The relevance of intraday data

For the purposes of this study, intraday data is highly relevant, as it yields more precise volatility estimates (Taylor, 2007): The many additional daily observations enable the authors to analyze how prices react to information on a much finer scale and hence heightens the estimation accuracy. According to Bollerslev, et. al (2009) and Hansen & Lunde (2006) realized variance calculated as the sum of squared intraday returns, should in theory be a consistent (and perfect) estimator of volatility, as the sampling frequency *n* goes to infinity. Furthermore, with more frequent portfolio rebalancing and an increasing availability of intraday data, volatility modelling and forecasting of high frequency data have become much more relevant and important to address within the literature of today. Intraday data contains more information of volatility dynamics and can vary greatly within a few days (thus the high frequency allows for more accurate forecasting models). For instance, during the financial crisis of 2007-2009, volatility spiked not only on a daily but on an intradaily basis.

Later, on the 6th of May, 2010 the US market experienced the 2010 Flash Crash, which lasted a mere 36 minutes in which the broad market indices crashed and rebounded at an astounding velocity (Kirilenko, et al., 2017). While the crash was short, it constituted a significant drop: "*[B]etween 2:40 p.m. and 3:00 p.m., over 20,000 trades (many based on retail-customer orders) across more than 300 separate securities, including many ETFs, were executed at prices 60% of more away from their 2:40 p.m. prices […] By 3:08 p.m. […] the E-mini prices [were] back to nearly their pre-drop level […]*" (Kirilenko, et al., 2017). Although the magnitude of the intraday price drop was extraordinary, the rapid rebound meant that the drop was only mildly reflected at close, with the S&P 500 down 3.2% on the day and 6.6% by the end of May. Clearly this does not nearly reflect the potential 60% price plunge experienced by some investors. Hence, as this paper seeks to generate the most efficient model for financial volatility, intraday data is key, and the findings of this study can furthermore help provide better protection against drastic price fluctuations and major losses in the future (Narsoo, 2016).

Despite these advantages, intraday returns are affected by a bias problem that grows in magnitude when the frequency increases below a few minutes; the observations become contaminated by noise arising from market microstructure. These microstructure effects, also known as minute operational details, occur due to price discreteness, rounding, interpolation, bid-ask bounce and data recording mistakes - as well as the fact that the mere size of the dataset, even for just a few years, may entail significant computational effort in estimation (Goodhart & O'Hara, 1997; Taylor, 2007). Furthermore, the market microstructure noise induces autocorrelation in the intraday returns, enhancing any autoregressive conditional heteroscedastic ("ARCH") tendencies already existent in the data and causing estimated realized variances to become inconsistent. The trade-off between bias and accuracy in the variance estimation thus affect the choice of sampling frequency, and a moderate sampling frequency such as five minutes has been found to be the most consistent and is the most widely used (Hansen & Lunde, 2006).

5.2.3 Sampling frequency and return measurement

The balance between high sampling frequency to ensure estimation precision and the increasing impact of microstructure noise, is thus a fine line. Based on this and following previous studies (such as Bollerslev et. al (2009) Huang et al. (2018) and Kilic & Shaliastovich (2017) among others), we use a sampling frequency of 5 minutes. The data is sampled for the five trading days per week in which we disregard any prices falling outside the normal trading window of 9:30 a.m. to 4:00 p.m., notably, we thus disregard the last 15 minutes of trading on the CBOE in order to ensure that the VIX and S&P 500 indices line up. With a normal trading window, this gives 78 daily observations, for a month comprising 1,716 “five-minute” returns, assuming a typical trading month of 22 days. We calculate the continuously compounded return as follows:

$$r_{SPX,t} = \ln\left(\frac{P_{SPX,t}}{P_{SPX,t-1}}\right) \quad (5.1)$$

In which $P_{SPX,t}$ represents the price on the S&P 500 index at time *t*. This study utilizes logarithmic returns for two primary reasons: Firstly, with relatively small returns (such as those observed on the 5-minute horizon) logarithmic returns and simple returns converge. Secondly, logarithmic returns exhibit time-additivity, hence, to generate returns over a longer time horizon it is sufficient to sum the intermediary returns.

5.3 Estimation and Construction of Variables

Based on the measured returns, we estimate the lower part of the VRP spread; the realized variance, while we estimate the implied variance from the VIX index. We further create a proxy for political events through Trump’s Twitter feed and include several variables from the previous literature. In the following segment, we seek to outline the estimation, construction and sourcing of these variables.

5.3.1 Estimation of realized variance

As suggested by Andersen, et al. (2009), realized variance created from finely-sampled squared returns comprises a good, non-parametric estimate which is well-accepted in the literature (e.g. Barndorff-Nielsen & Shephard (2004), Bollerslev et al. (2009) and Huang et al. (2018)). However, like returns at coarser frequencies, intraday returns tend to show significant volatility clustering or ARCH effects. Hence, it also seems appropriate to model volatility with frameworks capable of handling this behavior in order to support the non-parametric approach.

5.3.2 Model-free variation measure

From the returns described above, it is relatively straightforward to measure the model-free return variation. In the following equation, p_t denotes the logarithmic price of the S&P 500 index, from which the realized variance over the period can be measured as:

$$RV_t \equiv \sum_{j=1}^{n}\left[p_{t-1+\frac{j}{n}} - p_{t-1+\frac{j-1}{n}(\Delta)}\right]^2 \rightarrow \text{Return variation}(t-1,t) \quad (5.2)$$

In which convergence is based on $n \rightarrow \infty$, that is, an ever-increasing number of in-sample squared returns. However, as described above, a 5-minute return horizon seems to offer the strongest balance between estimation accuracy and microstructure noise. While this model-free measure has obvious strength in its simplicity and stability, it further poses a range of issues: (i) Firstly, as described above, it does not directly handle ARCH effects in the returns. (ii) Secondly, from a forecasting perspective, it does not allow the realized and implied variances to line up in terms of time subscript. Naturally, this does not matter if realized variance is assumed to be a martingale difference sequence, that is its expectation with respect to the past is zero and hence contains no autocorrelation. This would, of course, imply that no ARCH-effects are present in the returns, which is rarely the case for financial time series. Hence, it seems appropriate to model the time series with autocorrelation in the volatility.

5.3.3 GARCH-modelling of intraday volatility

In high frequency studies, as in studies with lower frequencies, GARCH models reign supreme in modelling autocorrelation in volatility. Furthermore, several extensions have been made to allow the GARCH models to capture observed market tendencies, in particular asymmetric effects of large shocks and price declines, adding to its dominance in volatility forecasting (Goodhart & O'Hara, 1997). Few other approaches have emerged, of which the most prevalent method includes utilizing option implied volatility as a predictor of realized volatility, which has historically compared well with GARCH models. However, the use of option implied volatility to predict intraday realized volatility has remained cautious, mainly due to concerns as to whether option markets are sufficiently developed to allow for meaningful intraday volatility estimates (ibid). Furthermore, utilizing the option-implied volatility to model the realized variance for the purpose of estimating the VRP, which is the spread between these two volatilities, would introduce dependence, which may confound the analysis. Another methodology suggested by Bollerslev, et al. (2014) is the use of a heterogeneous autoregressive model for modelling realized variance (HAR-RV). In this methodology, realized variance is regressed against its lagged values across different horizons, thus taking into account the autoregressive tendencies in the realized variance. However, considering the general dominance of GARCH-models in the field, GARCH-modelling is considered the most robust modelling methodology for the purposes of this study. Furthermore, including HAR-RV modelling in addition to GARCH-modelling, runs the risk of clotting the analysis with an overabundance of statistical considerations.

Despite its dominance within the field, GARCH modelling also suffers from issues when modelling intraday data, primarily related to (i) shock decay, and (ii) distributional issues. Firstly, the frequency of the data causes the coefficients of the GARCH models to sum to approximately one. This common feature causes volatility to become a random walk, potentially drifting out towards zero or infinity, and not necessarily follow a mean-reverting process. However, assuming the coefficients to sum to less than unity requires shocks to volatility to decline exponentially, yielding excessively fast decay rates (Goodhart & O'Hara, 1997). In terms of more stylized facts, intraday returns tend to diverge from lower-frequencies in terms of both the fourth and second moments: Intraday returns tend to be highly fat-tailed and hence distinctly unstable. Furthermore, intraday returns are inclined to exhibit seasonal heteroscedasticity in the form of daily and weekly volatility clustering, which may also be a driver of the high level of fat tails (Gençay, et al., 2001). This volatility pattern typically arises from market events, e.g. market opening and closing and lunch hours. Such phenomena are similar to lower-frequency seasonality and pose similar issues for GARCH modelling (Goodhart & O'Hara, 1997).

These distributional factors cause conventional GARCH models to be unsatisfactory in modelling intraday returns. In particular, as found in (Bollerslev & Andersen, 1997) estimation of MA(1,1)-GARCH(1,1) models at intraday frequencies yields parameters that are inconsistent with parameters at other frequencies and further do not comply with the theoretical results of Drost & Nijman (1993) on the time aggregation of GARCH processes. The driving factor behind these inconsistencies seem to be a pronounced diurnal volatility pattern and trading activity (Engle & Sokalska, 2012), which cannot be handled by traditional GARCH/ARMA models, which are geared towards exponential decay patterns. Hence, in order to handle such patterns Engle & Sokalska (2012) introduced the Multiplicative Component GARCH (MC-GARCH), which decomposes the volatility into multiplicative components that are relatively easy to estimate and interpret separately (Narsoo, 2016).

5.3.4 Multiplicative Component GARCH

The MC-GARCH assumes that the conditional variance of the high-frequency time series is the product of three components: (i) the daily volatility, (ii) the diurnal volatility and (iii) stochastic intraday volatility. We let $R_{t,i}$ be the logarithmic returns on the S&P 500 index, in which t represents a particular day and i the regularly spaced intraday time period, for our purposes 5 minutes. In the MC-GARCH, the intraday return process is thus modelled as:

$$R_{t,i} = \sqrt{h_t s_i q_{t,i}}\varepsilon_{t,i} \quad (5.3)$$

In which (i) h_t represents the daily variance, (ii) s_i is the diurnal variance for each intraday period, (iii) $q_{t,i}$ is the intraday variance component and (iv) $\varepsilon_{t,i}$ is an error term (or the standardized innovation) which follows a specified distribution. The daily component h_t can be estimated via standard GARCH methodologies. For our study, an Exponential Generalized Autoregressive Heteroscedastic ("EGARCH") methodology is chosen, as it addresses some of the shortcomings of a traditional GARCH methodology. These shortcomings include the restriction to non-negative values, which the EGARCH avoids through a log-linear formulation. This means that possible instabilities of optimization routines are reduced (Nelson, 1991). Further, the EGARCH specification permits differential impact from negative and positive innovations (as captured through its γ-coefficient), importantly allowing for an explicit leverage effect in the model:

$$\ln(\sigma_t^2) = \alpha_0 + \alpha_1 \frac{|\varepsilon_{t-1}| + \gamma_1 \varepsilon_{t-1}}{\sigma_{t-1}} + \beta_1 \ln\left(\sigma_{t-1}^2\right) \quad (5.4)$$

Indeed, when fitting both GARCH and EGARCH models on the S&P 500 returns, both the AIC and BIC point towards the EGARCH as the most appropriate model (please refer to Appendix B for an overview of the model fit). In terms of the intraday variance, the diurnal component (s_i) is estimated as the intraday variance in each 5-minute interval:

$$s_i = \frac{1}{T}\sum_{t=1}^{T}\frac{R_{t,i}^2}{h_t} \quad (5.5)$$

The returns on the S&P 500 are then normalized using the daily and diurnal variance:

$$z_{t,i} = \frac{R_{t,i}}{\sqrt{h_t s_i}} = \sqrt{q_{t,i}\varepsilon_{t,i}} \quad (5.6)$$

The stochastic intraday variance is modelled via a GARCH(p,q) process – for the purposes of this paper, a GARCH(1,1) process – and specified as:

$$q_{t,i} = \omega + \alpha\left(\frac{R_{t,i-1}}{\sqrt{h_t s_{i-1}}}\right)^2 + \beta q_{t,i-1} \quad (5.7)$$

In which $w \geq 0$, $\alpha \geq 0$ and $\beta \geq 0$. In this study, the innovation component $\varepsilon_{t,i}$ is modelled utilizing the Normal Inverse Gaussian distribution. This particular distribution allows the conditional distribution to be both skewed and leptokurtic (Stentoft, 2008) – a desirable feature considering the tendency for intraday returns to be fat tailed. Using this methodology, we gain the parameter estimates noted in Appendix B.

5.3.5 Measuring implied volatility

This study quantifies the risk-neutral implied variance measure via the square of the VIX index (post-2003 formulation[18]), following the approach in the Bollerslev et. al (2009) and Huang et al. (2018) studies among others. As mentioned, the VIX index calculation is based on highly liquid S&P 500 options with the model-free approach of pricing as a variance swap, specified to replicate the risk-neutral variance of a fixed 30-day maturity, with weighting applied to a portfolio of options to ensure an average of 30 days to maturity. It is important to note that the VIX is subject to some approximation error, but that it has generally emerged as the industry standard. Bollerslev et al. (2011) confirmed the applicability of the model-free formulation via a small-scale Monte Carlo simulation, which showed that using options with one month to maturity is superior to the estimates found utilizing Black-Scholes implied volatilities.

5.3.6 The issue of potential manipulation of the VIX

In mid-February, following the historically large observed spike in the VIX index days prior, an anonymous whistleblower urged the two financial regulatory bodies, the Securities and Exchange Commission (SEC) and Commodity Futures Trading Commission (CFTC), to investigate alleged large-scale manipulation of the VIX index. The issue underlying the allegation is the ability, given the structure of the VIX, to influence the level of the index without posting any capital in the process. The VIX is constructed using *the mid-price* of OTM options. However, for very DOTM options, trading tends to be limited and hence, many options will tend to have bids of zero and a non-zero ask (CBOE, 2015).

18 The CBOE formulated the VIX differently prior to 2003, where it was based on “S&P 100 options and Black-Scholes implied volatilities. The ‘new’ VIX index is based on S&P 500 options and model-free implied volatilities. Both indices calculations are still available from the CBOE web site. If more detail is needed, the authors kindly refer to the description in the CBOE VIX White Paper (CBOE, 2015)

Given this structure, along with the inverted strike-weight of the VIX, posting bids for DOTM options with 30 days left to maturity has the potential to move the VIX by a relatively large amount. Due to this phenomenon, "aggressive" buy orders may be posted in the open-auction period, driving up the clearing price of the options and with them, the VIX. Indeed, looking at trading behavior for S&P 500 options, Griffin & Shams (2017) find a large spike in trading in options with approximately 30 days to maturity in the window prior to 8:15am[19] with an upwards moving price trend. In the following 15 minutes, the price tends to ove downwards again implying that other traders put in orders to sell the overpriced options, adjusting the prices downwards. Griffin & Shams (2017) note that this behavior is only observed for OTM options, which count towards the VIX index, and not ITM options. They further conclude that this behavior cannot be perscribed to neither hedging or coordinated liquidity trading motivations.

While the VIX has come under increasing scrutiny, no agents have been convicted of market manipulation and the allegations from both the anonymous source and those put forward in the Griffin & Shams (2017) paper have not been endorsed by the CBOE. Naturally, such allegations pulls into question the validity of the VIX index and may confound the analysis of investor behavior. However, given the lack of a stronger model-independent measure of implied volatility, the authors of this paper choose to continue the use of the VIX index.

5.3.7 Creating a proxy for political events in the Trump era

In order to gain an understanding of how political events may affect the VRP and its components in the Trump era, this study takes a qualitative approach through the use of soft data points in the case study. The study thus defines a proxy for Trump's public activity, and how this creates political events. With the rise of the social-networking platform Twitter, which is seen and used by millions of users, it is possible to collect data directly on Trump's statements throughout his presidential period. With the dissemination of content via 140-character microblogs, known as 'tweets', Trump addresses the public directly, and expresses his opinions about companies and countries, as well as future US policies and other news, he may find relevant. Twitter has the extensive reach of 330 million active

19 From 8:15am to market open at 8:30am, only trading in options unrelated to VIX settlement is allowed. Note that our sample only uses data from trading hours, and thus will not capture this trend. However, the implication of this trend, i.e. potential manipulation of the index may have a profound effect on our results

monthly users and is thus a valuable communication tool for influencing the public for all types of politicians and celebrities (FXCM Market Insights (2017) and Statista (2018)). Trump's frequent use of Twitter has become an influential force: he has amassed more than 51 million followers (making his account the 19th most followed globally), has tweeted more than 37,000 times (Trump, 2018) and many of these tweets are reprinted in media across the world.

As Twitter comprises such a strong tool in terms of both (relatively) unfiltered opinions and good historical data storage, this study utilizes Twitter data in order to track the potential impact that Trump's tweets have on stock market return and volatility. To ease the data collection process and because Trump, in some instances, deletes Tweets, we downloaded a full archive of Trump's twitter feed from the third-party database Trump Twitter Archive (Trump Twitter Archive, 2018) over the time period stretching from November 8th 2016 (the day of the US election) till February 28th 2018. For each tweet, three data points are extracted: (i) date, (ii) time stamp and (iii) theme, which is a binary variable for seven different themes: Economic policy, politically themed tweets, tweets featuring 'Democrats', military policy, presidential duties, personal tweets and others. We further include a broad category called "fake news", as this is the most frequent combination of words across the entire sample.

Twitter supplies elements of both surprise and uncertainty, and as such one could expect the financial markets to be affected by sudden tweets from important political actors, such as Trump. As an example, one can consider a tweet by Trump right after the 2016 election, where he voiced his personal opinion about Boeing, saying "*Boeing is building a brand new 747 Air Force One for future presidents, but costs are out of control, more than $4 billion. Cancel order!*" (Trump, 2018). As a result, Boeing's stock immediately dropped 1%, as investors speculated if the company would lose favor with the new administration. Hence, not only have ethical questions about how President Trump uses Twitter been put forward, but history also shows that the tweets do indeed have the power to impact public (and financial market) opinion (FXCM Market Insights, 2017). With the current digitalized environment, market participants conduct trades very quickly, and as such information from the President can easily be expected to create unpredictable market fluctuations – and Twitter provides an outlet for data which has an unfiltered direct link to Trump and to investors.

Even fictitious news releases have been seen to affect the stock market; in 2013 a fake news report was released regarding the health of the President of the Unites States. It was falsely reported that President Obama and other White House members had been injured in explosions. When the tweet was posted, the equities markets plunged: Within minutes the DOW index dropped 143.5 points and the S&P 500 lost US$139bn in value (Prigg, 2015). This furthermore underlines the importance of gathering intraday data points for the market index and volatility, as the markets react within minutes, and then recover on the same day, confirming that the 2010 Flash Crash was not an isolated event in this respect (FXCM Market Insights, 2017).

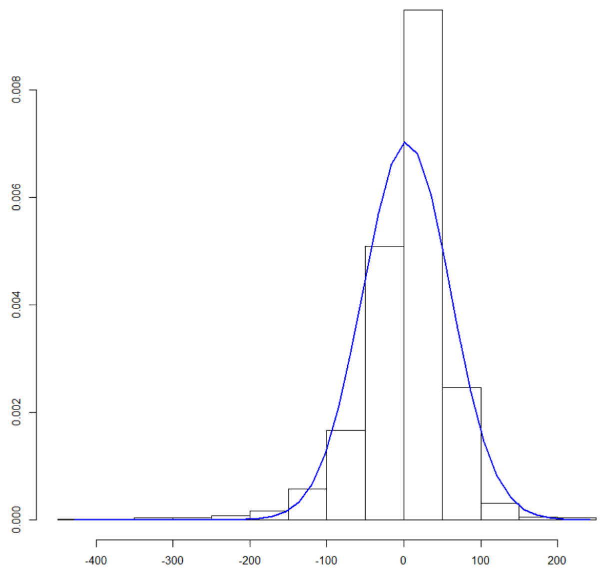
5.3.8 Other predictor variables as control variables

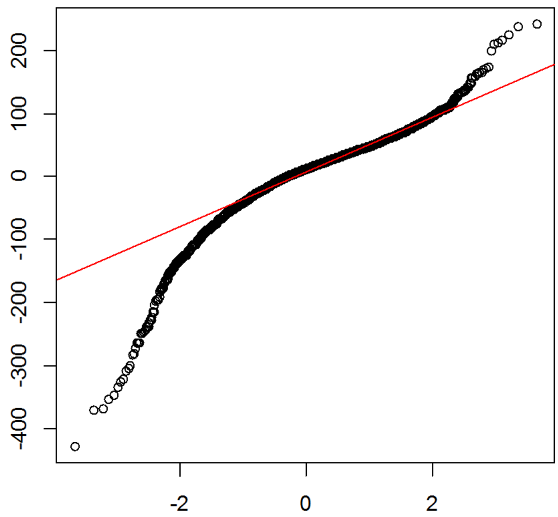
In order to gauge the strength of the VRP as a predictor variable, this study also includes several classical predictor variables. Inspired by several studies (Ang & Bekaert, 2007; Lamont, 1998; Lettau & Ludvigson, 2001; Bollerslev, et al., 2009), this study have chosen to include daily observations on i) the three-month T-bill rate ii) the default spread, which is the spread between Moody's BAA and AAA corporate bonds iii) the term spread, also referred to as the interest rate spread – the difference between interest rates at two different maturities (here the 10-year T-bond and the 3-month T-bill), iv) the stochastically detrended risk-free rate (three-month T-bill rate minus its backward twelve-month trailing average). These first four variables are all obtained from the St. Louis Fed. v) The Consumption-Wealth ratio (CAY) as defined by Lettau and Ludvigson (2001) and obtained from their website. The consumption wealth index is measured on a quarterly horizon, hence, following the approach in Bollerslev et al. (2009), we define each observation from the last quarterly observation vi) we further include two constructed price ratios; the price-dividend ("P/D") ratio and price-earnings ("P/E") ratio. Both are obtained from the database FactSet and are based the trailing 12-month averages on realized earnings or dividends as reported by brokers. Notably, this introduces some error margin as not all brokers update their estimates when a company announces earnings or dividends. However, overall, this methodology is empirically more stable relative to company reported figures in the database. Please refer to Appendix C for an overview of the included variables. Optimally, it would be preferable to have intraday data on all these variables in order to control the intraday regressions, however due to data limitations, this is not possible.

5.4 Statistical Properties of the Time Series

Over the sample period, the S&P 500 index had an average excess return of 3.71% (returns calculated as logarithmic returns in annualized terms, calculated on the monthly horizon), showing distinct departure from normality: As seen in the QQ-plot and histogram below, returns seem to exhibit negative skew with several extreme negative observations. At the same time, returns seem leptokurtic as evidenced by the distinct S-shape of the QQ-plot. Indeed, looking at summary statistics, we find kurtosis and skewness of 6.26 and -1.42 respectively (please refer to table 5.A below for a complete overview of summary statistics). As noted by Gençay, et al. (2001), fat tails are a common feature in stock returns in general, but especially on the intraday frequency. Since we construct daily returns from the sum of intraday returns, the high level of fat tails is not surprising.

Figure 5.B: Histogram and QQ-plot of daily excess returns on the S&P 500





Overview of distribution of daily excess returns on the S&P 500 (index returns less the US 3-month Treasury Rate) in the period from January 2002 to September 2018. Data sources: Thomson Reuters (2018) and (Federal Reserve Bank, 2018)

In terms of stationarity, an ADF test rejects the null hypothesis of a unit root at the 1% level, hence, stationarity is concluded for the returns. Testing for ARCH effects via Portmanteau-Q and Langrage-Multiplier tests, the null of independence is rejected at the 1% confidence level for both tests, concluding that the returns seem to exhibit ARCH effects (please refer to Appendix D for the output of the ADF and ARCH tests). This suggests the use of the ARCH/GARCH family of models for volatility modelling. Further looking at the correlogram of the returns (Appendix B) a clear pattern repeating at every 78 observations (1-day) is evident, showing increases in volatility at open and close of the market.

5.4.1 Variance estimates

Following the non-parametric method for estimating realized variance as described above, we find an average monthly variance of 24.27% over the full sample, for a volatility of 4.23%[20]. Comparatively, following the same methodology, Bollerslev et al. (2009) find an average monthly variance of 14.93% for their sample stretching from January 1990 to December 2007. Notably, this sample does not include financial crisis, and hence, it seems natural that the variance across our later sample is higher. For the MC-GARCH-modelled realized variance, we find an average monthly volatility of 4.13% for a variance of 26.77%. In Appendix B, the decomposition of the volatility is shown as the diurnal, daily and intraday volatility respectively with the last plot showing the total composite volatility for the time series. Between the two methodologies, we find a correlation of 0.65. For the implied variance, we find an average monthly value of 39.45, corresponding to an annual VIX value of 21.76.

5.4.2 Generating the variance risk premium

The variance risk premium is constructed as the difference between the ex-ante expected implied variance less the realized variance. Utilizing the ex-post realized variance methodology, the variance risk premium becomes:

$$VRP_t \equiv IV_{t,t+1} - RV_{t,t-1} \quad (5.8)$$

Notably, the two time series do not line up and further, the RV does not model the ARCH tendencies of the data directly. However, it does offer a model-free approach in which the VRP is directly observable at time *t*. Instead employing the MC-GARCH methodology for the realized variance allows the IV and RV to coincide and further models the volatility more accurately. However, by utilizing the MC-GARCH method, we sacrifice the model-free approach in order to gain the expected variance risk premium, formed as:

$$EVRP_t \equiv IV_{t,t+1} - RV_{t,t+1} \quad (5.9)$$

Using the two methodologies, we gain a VRP of 17.56 and an EVRP of 14.56. Thus, utilizing both methodologies, we find a positive variance risk premium in line with previous studies, however, slightly smaller than the one found in Bollerslev et al. (2009), who found an average VRP of 18.30.

20 Note that both the model-free and MC-GARCH-modelled realized variance are based on the pure, logarithmic returns, not the excess returns

5.4.3 The VRP from 2002 to 2018

During the sample period, the value of the VRP varies substantially, especially in the period during the eye of the storm of the financial crisis: In a period of just 48 trading days, the VRP ranged in values from a low of -283.815 to a high of 167.371, both representing in-sample extremes. The peak was observed on January 15th, 2009, generated from an implied variance of 233.230 and a realized variance of 65.859. During January 2009, both the implied and realized variance were in periods of cooling from having reached in-sample highs of 513.196 (on October 24th, 2008) and 475.704 (on October 31st, 2008) respectively. For the implied variance, it took 241 days to go from the highest point to its long-run average, while it took the realized variance 189 days. Hence, it seemed that investor fear mean-reverted slightly slower than the actual realized variance, implying that investors took longer to forget the strong volatility shock than the actual market. On average however, the IV mean reverts faster as evidenced by the slightly lower AR(1) process coefficient in table 5.A.

Throughout the sample, negative VRP values are rare; out of 3,956 observations, they occurred only 180 times, of which 59 occurred in the NBER-defined recession between December 2007 and July 2009 (NBER, 2018). Given previous studies, it is hardly surprising that the lowest value of the VRP occurs during the tumultuos period of the financial crisis: In particular, if market suppliers of liquidity are highly constrained, it may cause a switch in the identity of the net-buyers of DOTM puts, driving signage change of the VRP (Chen, et al., 2014). Indeed, we find the lowest point only a few months before the highest point on November 4th 2008. This trough in the VRP is the middle observation of 10 consecutive trading days of negative values, created by a mixture of the realized variance being slightly above the adjacent observations, while the implied variance was slightly below.

After the financial crisis, we observe the lowest value of the VRP on September 21st 2015 with a value of -48.574, following a pronounced spike in the VRP on August 24th 2015, when the Shanghai stock market fell 8.48%, causing stock markets to drop globally. The highest post-financial crisis value occurred on February 6th 2018, when the VIX-index performed the highest recorded jump in its history, increasing 115% in just one day to 37.32 (DeCambre, 2018), up from values of approximately 11 just a week prior. This spike was followed by a drop in the VRP to -16.40 on February 26th 2018. Interestingly, across the sample, we see a tendency for strong spikes in the VRP to be followed by pronounced negative values in a matter of days after. Hence, it seems that there is a tendency for the implied volatility to overshoot, with a market correction afterwards as a result. Whether this is due to the construction of the VRP, in which the implied variance runs 30 days ahead of the realized variance, or due to investors re-evaluating after fear spikes, is unknown.

5.4.4 The EVRP from 2002 to 2018

Overall, the EVRP sees much stronger spikes than the VRP, especially of the negative kind, primarily driven by the EGARCH-formulation of the daily variance, which yields a negative coefficient on the γ-parameter (-0.038 on average). Negative values in itself are rare in the EVRP, as it is for the VRP, occurring just 242 times out of the total of 3,965 observations (6.1%). However, the magnitude is much higher: The lowest value is recorded on August 8th, 2008 at a value of -2,155.49, driven by an extraordinarily pronounced spike in the MC-GARCH estimated variance. While the magnitude of the spike is surprising, the date on which it happened is not; called the "*the day the world changed*", August 8th, 2007 is widely recognized as the day the global financial crisis broke out, when banks across the US and Europe were brought to their knees in an unprecedented credit crunch. On this day, the FED and ECB felt compelled to inject approximately USD 90bn into the financial system in order to keep it afloat (Treanor, 2011). Hence, for the volatility to spike around such an event seems natural.

The MC-GARCH modelled realized variance generally mean-reverts quickly; the longest time from a negative spike to a return to the long-run mean was 178 days (following a spike on September 9th 2008), while the strong spike observed for August 8th, 2007 had evaporated just 9 days later. Given the overall tendency for excessive decay in intraday GARCH modelling (Goodhart & O'Hara, 1997), this hardly seems surprising. In terms of the expected variance risk premium, we observe the highest value on November 28th, 2008 with a value of 150.946, following just 24 trading days after a period of pronounced negative values in the EVRP. This seems like a general tendency in the EVRP; from strong negative spikes in the EVRP (driven by the MC-GARCH modelled realized variance), the EVRP also mean reverts quickly and often overshoots into periods of above-average values. Once again, the specific cause of this behavior is unknown, however, it seems natural that the EVRP and VRP would behave differently in terms of patterns, given the realignment of time periods – for more detail, please refer to table 5.A below.

Table 5.A: Summary statistics for key variables over the full test sample

	Summary statistics					Correlation matrix					
	Mean	Std. dev	Skew	Kurt.	AR(1)	$EGARCH_t$	RV_t	IV_t	VRP_t	$EVRP_t$	$r_{SPX} - r_f$
ERV_t	26.77	73.23	12.90	269.8	0.60	1					
RV_t	24.27	44.16	5.92	44.30	0.99	0.648	1				
IV_t	39.45	48.02	4.15	24.21	0.98	0.687	0.901	1			
VRP_t	15.39	21.01	-0.39	31.43	0.90	0.221	-0.026	0.410	1		
$EVRP_t$	13.31	53.27	-22.88	802.6	0.27	-0.751	-0.071	-0.035	0.069	1	
$r_{SPX} - r_f$	3.71	56.70	-1.42	6.26	0.94[21]	-0.461	-0.433	-0.500	-0.241	0.180	1

The sample period extends from January 1996 to the end of February 2018. All variables are reported in annualized percentage form whenever appropriate. Excess return (r_{SPX} - r_f) comprises the logarithmic return on the S&P 500 in excess of the 3-month US Treasury Rate. IV_t denotes the "model-free" implied variance – or the squared VIX-index. RV_t is the model-free realized variance, while ERV_t denotes the MC-GARCH derived realized variance. From this, the VRP_t denotes the spread between IV_t and RV_t, while $EVRP_t$ denotes the difference between IV_t and ERV_t. For a complete overview including control variables, please refer to Appendix E.

5.4.5 Trump tweets

Over the sample period stretching from the election (November 8th 2016) till February 28th 2018, Trump tweeted 2,903 times. Of these, the majority were outside trading hours: 26.67% occurred within NYSE trading hours, and 30.04% occurred within CBOE trading hours. Subtracting the tweets occurring outside trading hours leaves us with a sample of 774 tweets[22]. The bulk of the total number tweets were political in nature, accounting for 36.41% of the total sample and 32.43% of the within-NYSE trading hours sample. Most of these tweets occurred outside trading hours, 76.26% to be exact. The second largest group, "Personal", accounted for 25.53% of the total number of tweets. The group comprises a varied mix of tweets; from tweets regarding the "fake news press" to tweets on Christmas decorations in the White House. Like the political tweets, the lion's share of Personal tweets occurred after trading hours (77.87%). Across all categories, the most frequently used phrase was "*fake news*" occurring in 185 tweets or 6.37%. Most of these stemmed from personal tweets, in particular in regard to the US media. Not considering the "Other" category, fake news had the second lowest percentage of tweets written within trading hours at 19.46%. Please refer to Appendix F for a full overview of the Trump tweets sample.

21 AR(1) process for excess returns shows significant autocorrelation due to mechanical autocorrelation created by summing returns over the monthly horizon. The AR(1) process without summing returns shows a coefficient of -0.08. , which is not significant at the 5%-level.

22 Note that in terms of regressions, the sample is cut in accordance to NYSE trading hours (EST 9:30 a.m. to 16:00 p.m.) and hence the number of Tweets within trading hours follows the NYSE hours.

Leaving out the "Other" category, Military and Economic tweets were the rarest of the categories, accounting for just 4.17% and 9.30% of total tweets respectively. Economic tweets were slightly more represented in the sample covering within-trading hours, accounting for 10.08%, while only 7.49% of within-trading hours tweets were military in nature. Economic tweets cover a wide array of tweets that directly cover the US economy, including the Tax Cuts and Jobs Act of 2017, job creation and stock market performance. Notably most of these tweets occurred in November and December 2017 (31.85%), when the Tax Cuts and Jobs Act was being negotiated. Meanwhile, military tweets cover both tweets regarding military spending in the US and the conflict with North Korea, including the threat of nuclear war. A large share of the military tweets (19.01%) were written in November 2017, a month following the terrorist attack in New York on October 31st, 2017 (Mueller, et al., 2017) and further the escalation of the potential nuclear conflict between the US and North Korea.

5.5 Regression Methodology

In accordance with the overall structure of this paper, the four phases of this analysis attempt to uncover the two following broad areas: i) The relation between the variance risk premium and returns on the S&P 500 index and ii) the influence of political events on the variance risk premium, and its components, with a focus on the Trump Era. Based on the results from these regressions, it is attempted to formulate trading strategies in order to uncover the possibility of consistently profiting from these results.

5.5.1 The VRP and return predictability: Daily regressions

In order to gauge the return predictability of the VRP on the S&P 500 index, this study utilizes a series of simple regressions directly between the VRP and stock returns over varied return horizons stretching from 1 to 24 months. Returns are constructed as the annualized rolling sum of the intra-period daily logarithmic returns, yielding the following return regression:

$$\frac{12}{h}\sum_{j=1}^{h}\log(R_{t\to t+j}) = \beta_{0,h} + \beta_{1,h}VRP_{i,t} + \varepsilon_{t+h} \quad (5.10)$$

In order to test the parameter stability over time, this regression is run on the full sample, as well as for economically motivated subsamples; i) the period prior to the financial crisis, ii) the period during the financial crisis and iii) the period after. Furthermore, we test the period after the election of Trump separately, by making a pre- and a post-election sample for the second phase. Additionally, we formally test parameter stability by conducting rolling and expanding regressions as robustness checks. To further study the VRP's return predictability and interlinks with other predictors, we run multiple regressions in which we include lags of well-known predictors from the literature:

$$\frac{12}{h}\sum_{j=1}^{h}\log(R_{t\to t+j}) = \beta_{0,h} + \beta_{1,h}VRP_{i,t} + \beta_{2,h}\Gamma_{i,t} + \varepsilon_{t+h} \quad (5.11)$$

In which Γ denotes additional regressors, each with their unique coefficient $\beta_{2,h}$. As described above, these additional regressors include price ratios (price-earnings and price-dividends), the stochastically detrended risk-free rate, the term spread, the default spread and the consumption-wealth ratio. Furthermore, we run simple regressions on these predictors in order to test their individual predictive power relative to the VRP. As for the simple VRP-regressions, we test the multiple regressions over multiple time periods. However, for the samples pre and post the election of Trump, we test without the consumption-wealth ratio due to lacking data for the post-election sub-sample.

5.5.2 Intraday regressions and the influence of politics on the VRP

While the VRP has consistently been proven to have the strongest predictability over a quarterly horizon (Bollerslev, et al. (2009), Huang, et al. (2018) and Kilic & Shaliastovich (2017)), few (if any) papers have looked at very short-term predictive power of the VRP to the knowledge of the authors of this study. Hence, we run the same simple regression from the previous segment on an intraday sample covering the hourly, twice hourly, half daily and daily return horizons. As mentioned, while it would have been optimal to control the intraday regressions utilizing similar economic controls as described in the multiple regression, this has not been possible due to lacking intraday data on key macroeconomic variables.

In terms of uncovering the influence of politics on the variance risk premium, and its components, we run multiple regressions based on dummy variables as constructed from our dataset of Trump's Twitter feed. The dummy variables are constructed to have a value of 1 if a tweet of the category occurred in the previous 5 minutes, zero otherwise. The dummy then takes the next 5-minute value; that is, if a tweet occurred at 10:01 a.m., the tweet will be recorded for 10:05 a.m. We only consider tweets that have occurred within trading hours, as it becomes impossible to disentangle the individual effects of tweets outside trading hours as the effect of these will be pooled at market opening. As six of the seven categories are mutually exclusive, these do not cause concern regarding multicollinearity.

However, for the two categories “politically themed” and “mentioned ‘Democrats’”, we include an interaction term, as these are not mutually exclusive. Furthermore, as the category “fake news” has overlaps with multiple categories, we test this dummy variable in its own simple regression. From this, we run the following return regressions and variable regressions:

$$\frac{12}{h}\sum_{j=1}^{h}\log(R_{t\to t+j}) = \beta_{0,h} + \beta_{1,h} tweet_{i,t} + \varepsilon_{t+h} \quad (5.12)$$

$$\phi_{t+j} = \beta_{0,h} + \beta_{1,h} tweet_{i,t} + \varepsilon_{t+h} \quad (5.13)$$

In which *Φ* represents key variables, including the VRP, EVRP, realized variance and implied variance at time *t+j*. *h* is equal to the return horizon divided by the total number of daily observations (78) out of the number of days in a standard trading month (22). For a return horizon of 5 minutes, *j* takes the value of 1, 2 for 10 minutes and so on:

$$h = \frac{j}{78} \times \frac{1}{22} \quad (5.14)$$

We run this regression over multiple return horizons, spanning from 5 minutes to a full day. We further construct a daily regression which includes all Tweets occurring from market closing the previous day to market closing on the day in question. We then run regressions between the sum of the tweets and returns, as well as key variables:

$$\frac{12}{h}\sum_{j=1}^{h}\log(R_{t\to t+j}) = \beta_{0,h} + \beta_{1,h}\left[\sum_{m=1}^{n} tweet_m\right]_{i,t} + \varepsilon_{t+h} \quad (5.15)$$

$$\phi_{t+j} = \beta_{0,h} + \beta_{1,h}\left[\sum_{m=1}^{n} tweet_m\right]_{i,t} + \varepsilon_{t+h} \quad (5.16)$$

Following the calculation above, *h* takes the value 1⁄22 in these daily regressions. *Φ* represents the same key variables as described above.

5.5.3 Test-statistics and coefficient of determination

In the regression results noted below, all *t*-statistics are based on heteroscedasticity and autocorrelation consistent standard errors. For the regressions between the S&P 500 and the VRP, this paper employs Newey-West standard errors (which sums regressors in the past), following Huang, et al. (2018), Kilic & Shaliastovich (2017), Bollerslev, et al. (2015) and Chen, et al. (2017). However, as found by Hodrick (1992) and later studied in Ang & Bekaert (2007), long-horizon statistical inference with Newey-

West standard errors can be treacherous: While Newey-West standard errors are both autocorrelation and heteroscedasticity consistent, highly persistent predictors can cause a significant downwards bias in the standard errors. This downwards bias tends to cause results to be plagued by over-rejection of the null (type I error) and distorted R^2s. This is highly relevant for this study, considering both the inclusion of highly persistent predictors (such as price ratios and interest rates), as well as the introduction of persistence through the construction of variables; in particular, both realized variance and returns are constructed through rolling sums, which introduces mechanical autocorrelation in the sample. For our main results revolving around the quarterly to 4-month horizon, the choice of standard error is not considered as crucial, but when looking at longer horizons (one year and beyond), results should be interpreted with caution (Ang & Bekaert, 2007). For our intraday regressions based on dummy variables, we use Driscoll-Kraay (1998) standard errors. These standard errors apply a Newey-West type correction to the cross-sectional averages in order to account for cross-sectional or spatial dependence. For large samples, the Driscoll-Kraay standard errors are robust to both cross-sectional and serial correlation, and are further heteroscedasticity consistent (Hoechle, 2007).

Additionally, we report the ability of the predictors to explain the variability of the returns through the adjusted R^2. However, when looking at the variables noted above (along with the full overview of summary statistics in Appendix E including all control variables), persistence coefficients are very high, especially for the control variables. As noted throughout the literature (Stambaugh (1999) and Lewellen (2004) among others), this may cause serious issues with spurious and unbalanced regressions. Hence, the reported R^2 for regressions with overlapping multi-period returns should be interpreted with caution. This is especially true for the longer horizon: In their paper from 2008, Boudoukh, et al. show that despite a lacking increase in true predictive power, the value of the R^2s from regressions with highly persistent predictors and overlapping returns will, through sheer construction, increase approximately proportionally to the return horizon and the length of the overlap. Hence, this issue becomes of key concern for our long-horizon returns (one year and beyond) and in particular with regards to multiple regressions, which include strongly persistent predictors. However, as above, for the main results of this paper revolving around the quarterly horizon these issues are not as large in magnitude.

Lastly, as mentioned above, the VRP (along with returns) tend to deviate significantly from average values in periods of economic distress. As our sample covers a period of extraordinary economic conditions during the financial crisis, both the dependent and independent variables can take extreme values. In such a situation, even in samples with good volume, standard asymptotic inference becomes unreliable (Kilic & Shaliastovich, 2017). Hence, in order to alleviate concerns as to whether regressions are driven by outliers stemming from such deviation, we further conduct the daily and intraday regressions on winsorized samples.

6 Analysis of the VRP as a Predictor of Stock Returns

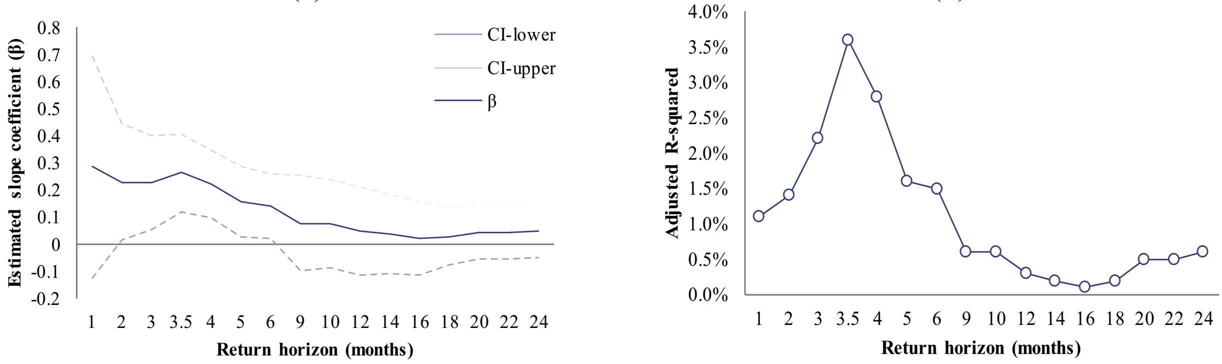
Based on the chosen methodology described in the previous section, the following analysis shows how these regressions may attempt to describe the predictive availability of the VRP and other variables from the literature. The ultimate goal of this analysis is to attempt to answer our two guiding research questions (no. 2 and 3); that is, whether the VRP remains a dominant predictor of stock returns on the short to intermediate return horizons, as well as two explore if and how the VRP and its components are affected by the political era of Trump. In order to uncover the highest degree of predictability, regressions are run over multiple return horizons, with interpretations of the empirical results focusing on the horizon with the strongest predictability in the full sample. As noted above, all reported *t*-statistics are based on robust Newey-West standard errors, however, given the long return overlaps especially the R^2s should be interpreted with caution.

6.1 Full Sample Regressions

Our full sample regressions cover a period stretching from January 2002 to September 2017. As our construction of the variance risk premium predictor variable is twofold, referred to as the 'VRP' and the 'EVRP', this paper naturally offers a dual-track analysis, which studies the coefficient size and explanatory power of both measures. However, the primary focus will be on the VRP measure, both in order to ease comparability with former papers, but also since the secondary EVRP metric can be viewed as a support of the non-parametric formulation of the VRP and thus as an inherent robustness check. This analysis begins with assessing the predictability of the VRP measure constructed identically to the BTZ paper's methodology, with *h* horizons spanning from 1 to 24 months. Figure 6.1.A below illustrates the plotted beta estimates for the VRP and adjusted R^2 for the stated return regression formula (5.10) at the different horizons:

Figure 6.1.A: VRP stock return predictability on the full sample

(a) (b)



Monthly return horizon	1	2	3	3.5	4	5	6	9	10	12	14	16	18	20	22	24
VRP_t	0.29	0.23	0.23	0.26	0.22	0.16	0.14	0.08	0.07	0.05	0.04	0.02	0.03	0.05	0.05	0.05
R^2	1.1%	1.4%	2.2%	3.6%	2.8%	1.6%	1.5%	0.6%	0.6%	0.3%	0.2%	0.1%	0.2%	0.5%	0.5%	0.6%

Overview of estimated β coefficients (a) and explanatory power (b) on a simple regression between the VRP for time *t*, against the return for time *t* to *t+1*

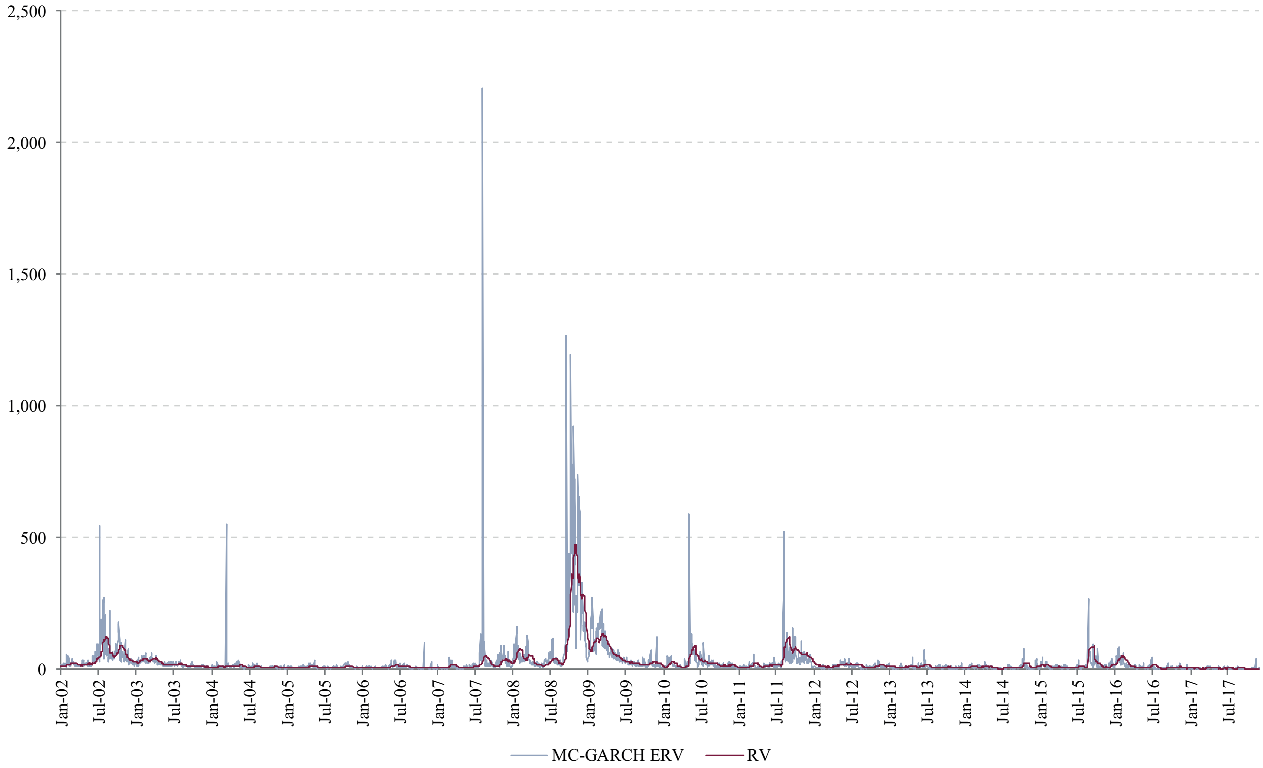
Considering figure (a) above, the slope is seen to peak both at the origin and at the 3.5-month horizon, followed by a downward-sloping pattern of the beta estimate, as the return-horizon increases. Relative to the BTZ study, which find a more consistently decreasing β-coefficient, our slightly hump-shaped beta development constitutes an interesting divergence to the earlier paper. However, taking the 95%-confidence intervals into account, it is clear that a positive relationship between the VRP and the expected excess return of the S&P 500 index can be confirmed. Additionally, due to the narrow confidence intervals, the accuracy of our model seems quite good until the return horizon surpasses 6 months and the lower bound moves below zero. Looking at the origin of the graph, while the beta estimate is quite high, the confidence interval is also quite wide and below zero on the lower bound. Hence, the return regressions' estimated β-coefficients do not provide evidence of rejection of the null of no predictability. Compiling these observations, our empirical findings seem to compliment earlier conclusions, as we detect the largest degree of predictability of the VRP at the intermediate return horizons between three to six months (Bollerslev, et al., 2009; Shaliastovich, 2015; Bollerslev, et al., 2015; Dreschler & Yaron, 2009; Du & Kapadia, 2012; Bollerslev, et al., 2014).

As the BTZ paper finds the largest degree of predictability at the 3-month horizon, while the more recent paper by Bollerslev, et al. from 2014 finds the largest degree of predictability of the 'global' VRP to be at the 4-month return regression horizon, we tested whether the predictability within our model peaked between these two horizons. Interestingly, a peak indeed exists between the two monthly return horizons at 3.5-months, where the VRP appears to offer the strongest degree of predictability as evident in the right-hand plot of the adj. R^2, which yields a maximum of 3.6% at the 3.5-month return horizon. This is backed by the 3.5-month return regression also offers the highest slope coefficient of 0.264. Both of these coefficients are slightly below those afforded by BTZ for the 3-month horizon.

Consequently, our findings confirm the predictive abilities of the VRP, and especially that the degree of predictability maximizes just past the quarterly horizon. Comparing to the theoretical model predictions in figure 2.D, our findings exhibit great similarity, in particular in terms of the shape of the adj. R^2 as well as the positive relationship between the VRP and returns. In accordance with the theoretical model, this may indicate how the VRP succeeds in isolating the systematic risk factor of time-varying volatility in consumption growth and persistence in volatility-of-volatility. Hence, the afforded predictability exists due to a mispricing of assets with respect to the specific risk characteristics, assuming a mean-reverting process driven by arbitrage. Thus, the VRP illustrates the market pricing of risk and is thus useful in gauging the current investor sentiment. The positive beta coefficients further validate the contemporaneous leverage effect, which cause asset prices to fall when volatility shocks occur. Following the shock, investors remain fearful, continuously paying heightened premiums for DOTM puts (driving up the VIX) and pricing with increased discount rates. As the memory of the shock diminishes, investors lessen their discount rates and prices slowly revert back upwards (Hull, 2012; Coval and Shumway, 2001).

When looking at the ERVP for the same regressions, we find supporting empirical results relative to our VRP simple regression (please refer to Appendix P for the regression output for the EVRP). Generally, the estimated slope coefficients are lower, and do not reveal the same 'peak', but in terms of explanatory power, we see a similar pattern to the VRP findings above. The largest degree of explanatory power is at the 4-months return horizon, after which the adj. R^2 tapers off. Looking across horizons, the betas tend to move towards zero with sub-zero lower bounds on the confidence intervals after the 6-months mark. That the EVRP results diverge from the VRP results is not surprising: As seen in figure 6.1.B below, the forecasted variance sees much stronger spikes relative to the non-parametric realized variance, driven by the EGARCH-modelled daily variance. This affects the EVRP, by potentially producing outliers, which can distort the regression outcome and predictability, resulting in lower β-estimates and explanatory power. Hence, the winsorized sample may yield interesting results in comparison. In terms of the shift in predictability to the 4-month mark, it seems indicative of a slightly stronger persistence in the volatility-of-volatility in the EVRP.

Figure 6.1.B: realized variance metrics over time



Overview of the MC-GARCH modelled realized variance (blue line) and the non-parametric realized variance estimate (red line). Shown for the full sample stretching from January 2002 to September 2017.

6.1.1 Multiple regressions

For the simple regressions, both measures yielded a peak in the degree of predictability just past the quarterly horizon: 3.5-month horizon for the VRP and the 4-month horizon for the EVRP. In order to study whether these findings are driven by unobserved variables, we further run multiple regressions including variables from the existent literature (following regression equation 5.11). Looking at the output in Appendix G, it is evident the VRP has the strongest *t*-statistic and further has the highest explanatory power across all simple regressions, except for the price-earnings ratio, which affords a similar R^2 (3.7%). However, the estimated β for the P/E ratio is insignificant, which may indicate that the R^2 is inflated by high persistence in the ratio.

In terms of significance, only the stochastically de-trended risk-free rate (RREL) yields a significant result, however, only at the 5% level compared to VRP, which is significant at the 1% level. It is further worth noting that the R^2 of the RREL is an impressive 8.8%, however, as for the P/E ratio, this may be due to high persistence. The rest of the predictor variables yield insignificant results with low explanatory power, even the P/D ratio, which should be one of the better predictors on shorter return horizons (Davis, et al., 2012). Overall, these findings support previous studies, which also find the VRP to be dominant in predicting returns on the intermediate horizon.

Considering the multiple regressions on the 3.5-months return horizon with the VRP and key economic variables (regressions numbers 10-15 in appendix G), we continue to find the VRP to be the superior predictor, in line with Bollerslev, et al (2009). Despite slightly lower β-coefficients and R^2s, the regression yield even higher t-statistics than in the BTZ paper, with the VRP predictor remaining significant at the 1%-level across all regressions as well. With the inclusion of the P/E ratio (reg. no. 10), the explanatory power increases to 7.6%, in excess of the sum of the individual adj. R^2's. Combining these two predictors thus contains predictive power in excess of the sum of the parts, with the significance of the P/E ratio increasing to the 10%-level as well. This is further consistent with the qualitative implications of the economic model put forward by Bollerslev, et al (2009), as the regression contain parameters explaining time-varying volatility and volatility-of-volatility, while also predicting the mean of consumption growth (Bollerslev, et al., 2009; Bansal & Yaron, 2004). However, it remains vastly dominated by the degree of predictability afforded by the VRP, of which the *t*-statistic becomes even more impressive. For the same multiple regressions with the EVRP on the 4-month return horizon, the P/E ratio becomes significant at the 5%-level, with the EVRP remaining significant at the 5%-level.

Looking at regression 11 in Appendix G, adding the CAY (consumption-wealth) ratio to the VRP in the predictive regressions yields a much higher adj. R^2 of 9.2%, compared to 3.6% and 2% for the VRP and CAY simple regressions, respectively. The *t*-statistic of the VRP is further increased, and greatly dominates the *t*-statistic of the CAY ratio. Interestingly, contrary to the BTZ findings, we find a negative signage of the CAY ratio. Comparing to the EVRP regression output in Appendix H, the CAY predictor variable coefficient is smaller and insignificant, while still carrying negative signage. The low predictive power is most likely due to the fact that the CAY ratio is expected to have larger explanatory power on longer horizons, much like the P/E ratio (Lettau & Ludvigson, 2001). If we compare our findings to Bollerslev, et al. (2011) regarding the volatility risk premium, we expect that adding the P/E ratio or the CAY ratio to the multiple regression would lower the adjusted R^2's, and only the VRP to remain significant in the predictive regressions (Bollerslev, et al., 2011). Thus, our findings support Bollerslev, et al. (2011), assuming that the square root process behaves akin to the VRP. While the massive increase in the constant may seem strange, it follows the empirical results presented in the BTZ, and it intuitively makes sense, as the β-coefficient for the P/E and CAY ratio are very large relative to the VRP.

As we find the simple regression on the de-trended risk-free rate (RREL) to have significant predictive powers on the intermediate return horizon, we further run the VRP and RREL together against excess returns (regression 12). This yields an even more impressive *t*-statistic of 5.346 for the VRP predictor, and the β-coefficient increases to 0.396 relative to the simple β-coefficient of 0.264. As noted above, the RREL was the only predictor variable that revealed some significance at the simple predictor regression level besides the VRP and EVRP, and this significance remains in the multiple regression at the 1%-level. Together, the two variables yield the highest R^2 yet at 16.3%, much higher than the sum of the individual R^2s. Comparing to the EVRP 4-month return regression in Appendix H, the RREL actually reveals higher predictive powers and more significance that the EVRP, however, overall the R^2 is lower at 12.2%. Nevertheless, the EVRP still provides support for the findings for the VRP.

Combining only the economic variables, we find consistent results to those above: both the P/E and the CAY ratio predictors are found to be insignificant, with low *t*-statistics and a lower adj. R^2 of 13% (and 14.2% for the 4-month regression), while only the RREL is significant. Intuitively, it makes sense that the adj. R^2 is higher for the excess return regression with the longest horizon, as the predictor variables, excluding the VRP, are known to have stronger explanatory powers over longer time periods. Furthermore, these are also more subject to inflation in the R^2 due to the high level of persistence.

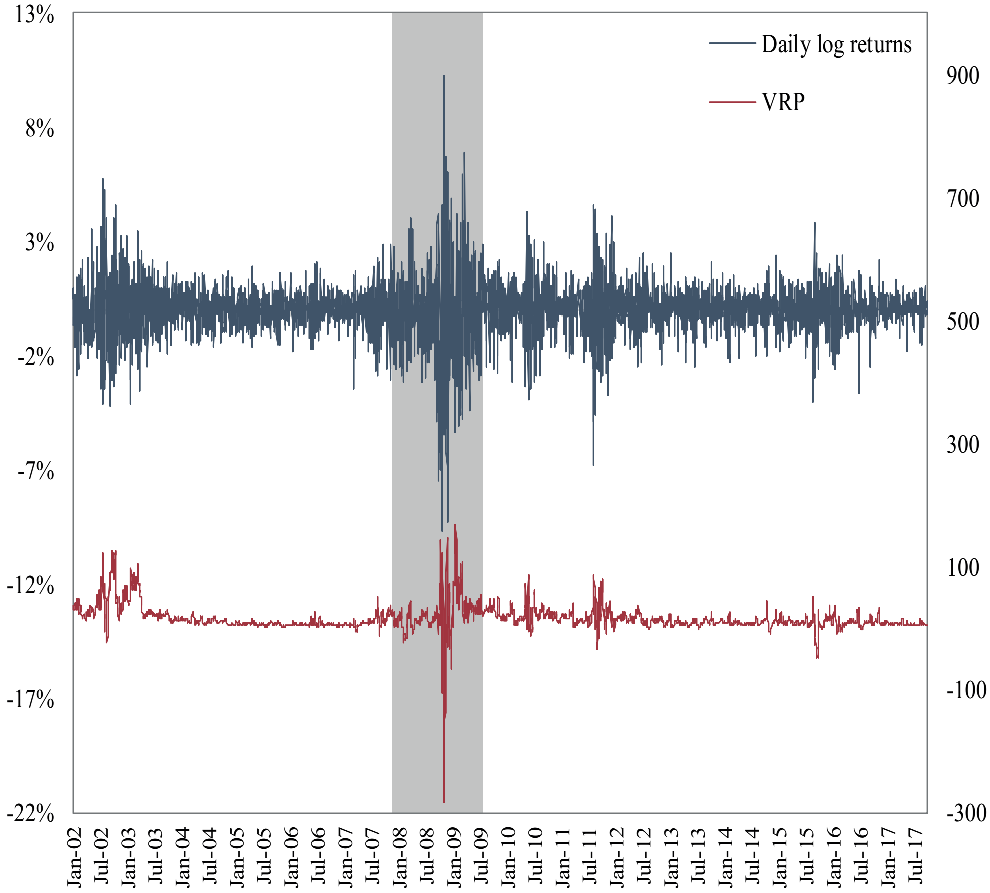
Adding back the VRP (reg. no. 14), results in largest explanatory power yet (adj. R^2 of 23%) and the highest slope coefficient for the VRP of 0.490. The multiple regression also reveals more significance for the P/E predictor variable, which becomes significant at the 5%-level. Furthermore, the VRP remains the dominant predictor on the 3.5-month return horizon, with a *t*-statistic of 5.235. The same pattern is evident in the 4-month EVRP return regression, also yielding the highest coefficient for the EVRP at 0.091. A possible driver of the higher explanatory power could be that adding long-term predictor variables enables the return regression to capture both short- and long-term risks in the market. Furthermore, by creating a more ceteris-paribus-environment, the VRP is perhaps more capable of truly isolating the risk factor associated with consumption growth volatility. Finally, including the last predictor variables, while omitting the CAY-ratio in line with Bollerslev, et al. (2009), the β-estimate for the VRP and the adj. R^2 deteriorates. This contrasts the findings in the BTZ paper, as they find the highest explanatory power in the full regression, albeit with only a marginal increase to the other regressions.

6.1.2 Regarding the intraday relevance of the VRP in the full sample

Besides the regressions conducted on a monthly return basis, we also investigated the intraday predictability of the VRP. As shown in Appendix I, all our findings are positive and significant for the VRP, with the strongest degree of predictability on an hourly basis, while controlling for realized variance. The estimated β-coefficient reaches 1.176 with significance at the 5%-level. Hence, the if the VRP increases by 1, the log-return will increase by 1.176 percentage points in the following hour. The risk of inflation of both significance and R^2s is not of key concern in these short-term regressions, and indeed the adj. R^2 remains small, indicating that the VRP is not a key driver of short-term return variation. However, a criticism of this result is that we are not able to add control variables to the regression to test the consistency and robustness of our findings due to limitation of high-frequency data points, which might cause omitted variable bias.

In summary, we confirm the VRP to be a dominant predictor over the intermediate horizon across simple, as well as multiple regressions. While we find higher adj. R^2s in the multiple regressions, relative to the BTZ study, we find overall lower slope coefficients and adj. R^2s in the simple regressions. Furthermore, it is quite interesting that relative to other studies (Bollerslev, et al., 2011; Bollerslev, et al., 2009), the variable based on the CAY ratio has opposite signage. Taking the development of the S&P 500 and the fear index (VIX) over the course of our sample period into consideration, one might consider how the global financial crisis (“GFC”) affects these findings, given the high level of volatility characteristic of this period. From figure 6.1.C below, the high level of return volatility is evident, as well as the strong spike in the VRP. As noted above, we see further observe a strong negative spike in the VRP, potentially indicative of an “overshooting” effect in the implied volatility.

Figure 6.1.C: S&P 500 returns and the VRP over the full sample period



Development of daily log returns on the S&P 500 and the VRP over the full sample period stretching from January 2002 to September 2017. The global financial crisis (December 2007 to July 2009) is denoted with a grey backdrop. Data source: Thomson Reuters (2018)

Given such radical change in both the independent and dependent variables, we further test the regressions above across three subsamples: i) the period prior to the financial crisis, ii) the period during the financial crisis, iii) the period after and lastly iv) the period prior to and after the recent US election. In addition to checking parameter stability, this dissection of samples further eases comparability to previous studies, which typically contain results from earlier dates (Bollerslev, et al., 2009; Bollerslev, et al., 2011; Shaliastovich, 2015; Bollerslev, et al., 2015; Dreschler & Yaron, 2009; Dreschler, 2013; Kelly & Jiang, 2014).

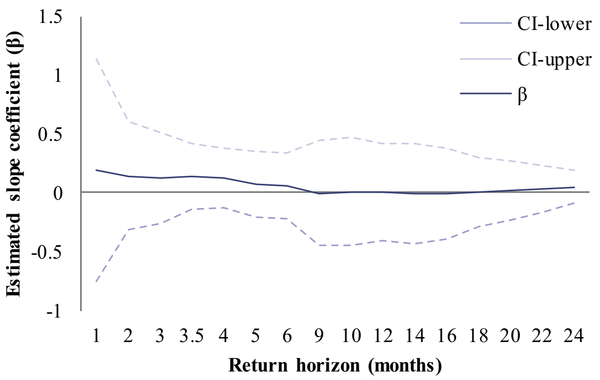
6.2 Pre-GFC Sample

We define the pre-GFC sample as the time period spanning from January 2002 until December 2007, which ends at the American National Bureau of Economics Research's definition of when the Global

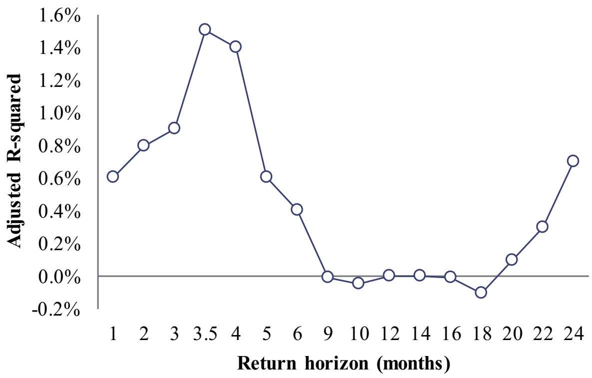
Financial Crisis (GFC) began (NBER, 2018). This sample period comprises the largest overlap with the BTZ paper, whose sample stretches from January 1990 to December 2007 and it is thus interesting to see whether we find (even) more comparable results than in our full sample findings. The most striking feature of our VRP regression results is the curvature observed for both *β*-coefficients and R^2 across return horizons. In terms of slope coefficients, we no longer see any significance across any of the return horizons and the *β*-estimate further remains flat throughout time. The right-hand side graph illustrating the explanatory power still exhibits a similar shape as for the full sample, which peaks at the 3.5-month return horizon, but the regressions exhibit much lower levels of adj. R^2 and further a tail at the very long horizons.

Figure 6.1.D: Estimated *β* and adj. R^2 for the pre-GFC sample

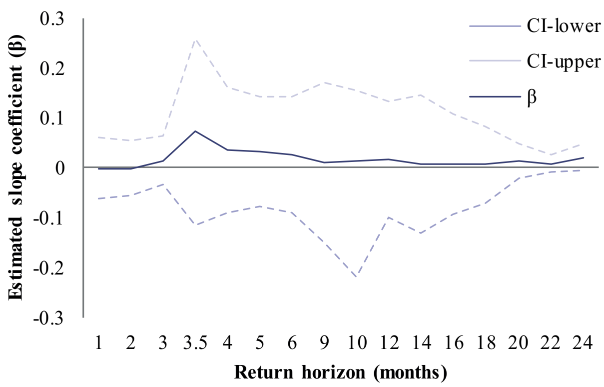
(a) VRP *β*-coefficient



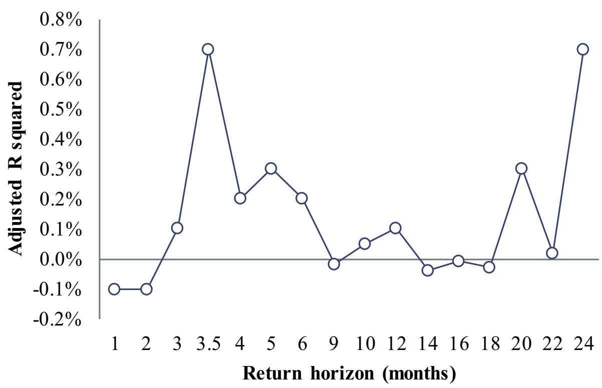
(b) VRP adj. R^2



(c) EVRP *β*-coefficient



(d) EVRP adj. R^2



In figure 6.1.D above, we also see drastic changes in the curvature for the EVRP's predictability. What is particularly interesting is that both the estimated slope coefficients (left) and the explanatory power (right) seems to peak at the 3.5-month return horizon rather than to the 4-month return horizon as evident for the full sample. Furthermore, the explanatory power remains low overall (maxing at

0.7%) and while it tapered off both for the VRP and EVRP regressions in the full sample, it shows a strong spike at 24 months, akin to the VRP results above. It is furthermore important to note how wide the 95%-confidence interval bands are across all horizons, thus implying an inability to reject the null at any of the return horizons. Hence, for both the VRP and EVRP, we can no longer claim the VRP to be a significant predictor of future index returns on our pre-GFC sample, when comparing only the simple return regression (please refer to Appendices J and K for a full overview of the outputs). On the intraday regressions (Appendix I), we likewise find no predictability, which may be due to less fear in the market, or slower reaction times in this sample period. In terms of the simple regressions on economic variables, not only is the RREL no longer a significant predictor, but the P/E ratio seems to have been a far stronger predictor prior to the GFC, as it is now significant at the 1% level.

In terms of multiple regressions for the 3.5-month horizon with the VRP (Appendix J), the VRP becomes a significant predictor at the 1% level in regression no. 10 and 12, which includes the P/E ratio and RREL, respectively. Again, one could argue that by including both a more long-term predictor (P/E or RREL) and the VRP, this regression captures different, important risk factors that affect the equity premium simultaneously. This observation is further supported by the fact that the explanatory power of the multiple regression (no. 10) outperforms the individual adj. R^2s, reaching 32.6%. However, when only including the traditional predictor variables, we find an even more impressive adj. R^2. The highest is found in the final (no. 15) regression, including all predictor variables: In this regression, we find an R^2 of 57.6%, despite the VRP remaining insignificant. However, we caution that this R^2 is likely inflated by the persistence of the predictors. A potential driver of the lack of predictability for the VRP may be a change in investor psyche, and that an increased fear of crashes has made the VRP a more significant predictor *after* the GFC compared to the precedent period. In the EVRP regressions on both the 3.5 and 4-month return horizons Appendix K, the EVRP actually proves to be a slightly significant predictor in the full multiple regression on the 4-month horizon, albeit on the 10%-level and with a switched signage on the β-estimate of -0.025. This regression result reveals the highest explanatory power yet – namely an astounding 63.1% in adj. R^2.

Some points can be made as to why the pre-GFC results for the VRP's and EVRP's predictive power are less encouraging than our own findings for the full sample size, and relative to those in Bollerslev, et al.'s (2009). Firstly, one should keep in mind that the time-periods do not completely overlap – in actuality, we are 12 years short of data-points, as their sample stretches from January 1990 to December 2007, making it unjust to draw direct parallels between the results. Secondly, looking at figure 6.1.C, plotting the VRP and the log returns on the index, we see that about a third of the sample period is characterized by a medium level of volatility, and this might also make it hard to predict returns – especially since it seems the VRP at that time did not spike as easily as it has done in recent years (it is quite narrow especially around late 2002 – early 2003). All in all, this opens up to several questions as to why the VRP proved to be the dominant predictor over the full sample size, as well whether the investor psyche or fear might have changed over time. In particular, how the VRP performs in a time period of the highest volatility seen since the Great Depression.

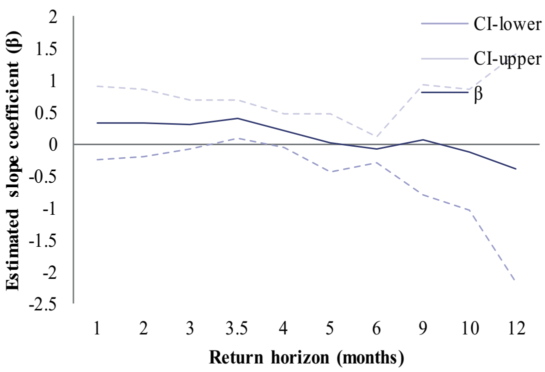
6.3 Global Financial Crisis Sample

The time period most deeply affected by the GFC stretches from December 2007 to July 2009 (NBER, 2018). As this time period comprises less than two years, it could create spurious results to run the regressions over 24 months, hence we have chosen to run the multi-period simple regression with horizons spanning up to 12 months. This subsample continues to support the fact that the VRP is a dominant predictor especially at the 3.5-month horizon. Looking at figure 6.1.E below, it is clear that the VRP as a predictor depends non-trivially on the return horizon: the explanatory power peaks at the 3.5-month return horizon yet again. The adj. R^2 is almost 12% for a simple regression – with quite a margin to the second highest which is below 6% in comparison. Despite relatively narrow confidence intervals, they are, for the most part, below zero, only allowing for 5%-significance at the 3.5-momth horizon. The confidence intervals widen significantly past the 5th month, where the adj. R2 further dips towards zero. Looking at the regression output in Appendix L, we see that the estimated beta coefficient of 0.395 is significant at the 1% level in the simple regression with VRP.

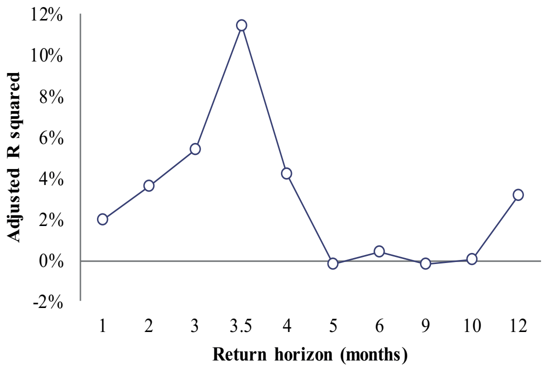
We know from the economic model presented that the persistence in volatility-of-volatility ("VOV") drives the VRP, reflecting the compensation for underlying, priced risk factors as known from the CAPM (Merton, 1973), which in turn also underlines why we see a positive relationship between the VRP as a risk compensation and the expected excess return. Based on the adj. R^2, it seems that the VOV became a significant driver of the excess stock returns in the highly volatile era of the GFC. Comparing our findings to the BTZ paper, we see that while our estimated coefficient and predictability is lower, our *t*-statistics are higher and we further find a higher level of explanatory power.

Figure 6.1.E: Estimated β and Adj. R^2 for VRP regressions in the GFC sample

(a) VRP β-coefficient



(b) VRP adj. R^2



One has to keep in mind that at that time the average VIX was about 22 points above its long-run average of 17, which was driven mostly by the beginning of the sample period. Volatility was the highest right after the crash, this was evident both in the implied variance, and in the realized variance measure: Right after the Lehman crash, the RV spiked much more than the VIX, underlining how the crash seemed to blindside the market. Hence, the highly volatile VRP seen in graph 6.1.C, contains multiple negative values. Such negative VRP values further indicate that options prices are expected to rise, as the investor fear incorporate the shocks to the realized variances in their expectations. Furthermore, the contemporaneous existence of a negative VRP and negative returns is an example of the leverage effect at work, with returns dropping simultaneously with upwards spikes to the volatility. As described earlier, with spikes to the RV and IV, we tend to see a relatively slower mean reversion of the IV from strong spikes, which creates a widened VRP-spread for a prolonged period of time. However, as noted, this tendency does not hold on average, as the RV has slightly lower autocorrelation across the sample.

A critical finding, which we also established in our main sample analysis, was that the traditional construction of the VRP is the strongest predictor, rather than the EVRP, which is again the case for this subsample: We find no significant results for the EVRP on any return horizon for the simple regressions, and only one significant result at the 10%-level for the multiple regressions at a 3-month return horizon. Looking at the plotted estimated slope coefficients for different horizons in Appendix P, as well as the adj. R^2 for the EVRP, this is not surprising – the confidence intervals are wide and only slightly above zero at the 3-month return horizon, with low β-coefficients. Given the tendency for the MC-GARCH to model very strong spikes, along with the fact that the GFC-subsample contains the largest outliers in the full sample, the lack of significance does not seem surprising. Hence, a winsorized EVRP sample may yield more compelling results, which indeed the case, as noted in our robustness checks below.

While we found no significant relationship between the VRP and returns intraday prior to the crisis, it is evident in Appendix I that we now discover a positive significant relationship on the 5% level even on an hourly basis. The VRP estimated β is 1.71 with no controls, with a *t*-statistic of 2.037, which could be interpreted as more fear to be driving the returns, even on an hourly basis. This intuitively makes sense, as the market in this time-period is the most volatile in our full sample, and both the VIX and especially the RV is seen to spike several times during a single day.

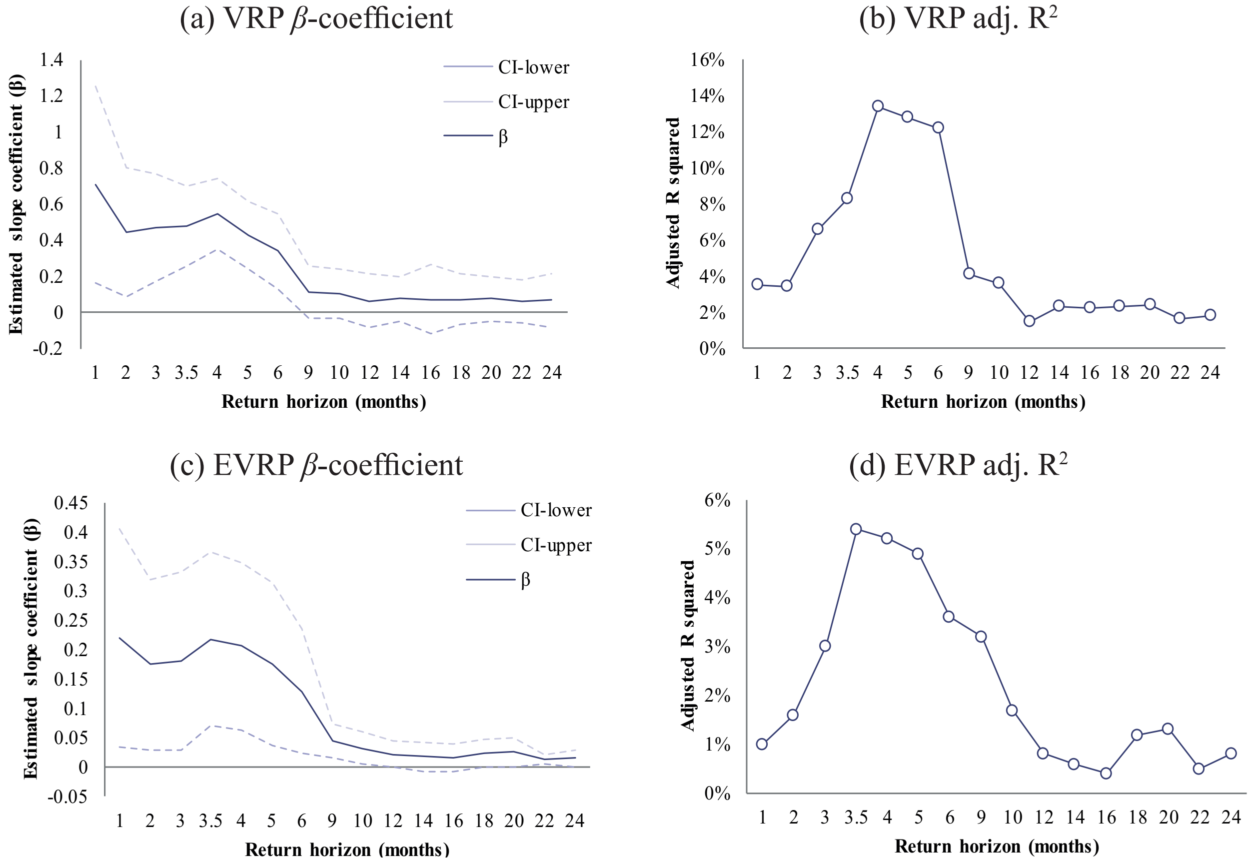
Isolated, none of the economic variables carry any predictability in the simple regressions. Meanwhile, in the multiple regressions, we see that including the P/E ratio increases the *t*-statistic, while maintaining an estimated β-coefficient at the same level. However, it actually reduces the explanatory power, as the sum of the individual adj. R^2's is larger than that of the multiple regression. The most significant regression output is regression number 15, including all predictors. This regression explains 70.8% of the variance of the excess returns in the financial crisis sample, while the estimated β-coefficient for the VRP falls to 0.268. Naturally, such high R^2 does raise concerns as to whether the R^2 may be inflated by the strongly persistent predictors and further the long overlap in returns relative to the length of the entire sample.

This subsample offers several key findings, which can be useful for both practitioners as well as researchers: While many consider the GFC as a time of uncertainty, unpredictability and drastically shrinking funds, these findings prove the VRP to be a reliable and dominant predictor of returns, even in the most volatile of times. One could pose that the predictive powers of the VRP is of particular importance in periods of heightened uncertainty, as it not only offers insights into the uncertain future, but does so on the very short-horizon, which may be of key concern in such tumultuous times.

6.4 Post-Global Financial Crisis Sample

Due to the data limitations in the CAY ratio, the post-GFC sample stretches over a time period of approximately eight years (July 2009 – September 2017). A representation of the computed multi-period return-regressions up to 24 months are shown below, again illustrating the development in the estimated slope coefficients and the explanatory power for both the traditional construction of the VRP as well as the MC-GARCH constructed EVRP. Contrary to the other samples, we now find coinciding curvatures for both the EVRP and VRP. Furthermore, we see a switch in the peak return horizon for the EVRP and the VRP: The EVRP now peaks at 3.5-month, while the VRP peaks at the 4-month return horizon. While the EVRP has been more unstable as to which horizon provides the highest degree of predictability, the VRP has, until this subsample, been stable at the 3.5-month return horizon. Nevertheless, while the curvature is now quite similar for the two metrics, the magnitude is vastly different: The VRP multi-period regression reveals a β-coefficient reaching 0.543 (with a narrow confidence interval) at the 4-month return horizon, while the EVRP reaches an estimated slope of 0.217 with wider confidence intervals. However, it is quite clear that both bands are above zero and looking at the regression outputs in Appendix N for the 4-month VRP return regression and Appendix O for the 3.5-month EVRP return regression it is clear that both regressors are strongly significant for their respective return horizons.

Figure 6.1.F: Estimated beta and Adj. R^2 for VRP regressions in the post-GFC sample



The increased coefficients and the switch in predictability horizon may be interpreted as a change in investor psyche in the aftermath of the GFC: The increased return predictability to 4 months may imply an increased persistence in the volatility-of-volatility, which causes the predictive horizon to be pushed outwards in line with the underlying economic model of this empirical study. Given the depth of the recent financial crisis, it seems natural that investors, rattled by the massive volatility spikes, would change their perception of risk, perhaps pushing them to demand more DOTM puts and to demand these for prolonged periods of time. Furthermore, the larger coefficients on both the VRP and EVRP indicate that fear has become a more pronounced factor in asset pricing, yielding greater predictive power to the two variables. In terms of the underlying economic model, the increased parameters may have been caused either by a change to the intertemporal elasticity of substitution (IES) or by a change to the volatility-of-volatility. As outlined earlier, a higher IES should theoretically cause the parameter estimate to increase as investors become more sensitive to uncertainty, amplifying changes to volatility-of-volatility. However, an increase in the persistence in VOV could likewise yield a higher β-coefficient. Thus, it is impossible to disentangle the individual effects of these two sources of change.

In terms of the EVRP, we see that the peak return-horizon predictability does not expand, but rather contracts, relative to the full sample findings. However, the β-coefficients for the 3.5 and 4-month horizon are very similar, hence, the decrease in predictive horizon for this variable is not as notable as the increase for the VRP, and does not necessarily imply a similar change in investor psyche. This is to be expected, as the MC-GARCH directly models the volatility persistency parameter, hence, the velocity of the volatility mean-reversion process may not change akin to the non-parametric VRP. For the overall curvature of the graphs, we once again find a hump-shaped pattern in both the β-coefficients and the adj. R^2s. However, these findings offer a higher estimated slope coefficient in our simple regression over a 4-month return horizon for the VRP (0.543, t = 5.422), relative to our full-sample findings. They also show superiority to the findings presented in the BTZ paper, which found a coefficient of 0.47 and a t-statistic of 2.86 on the quarterly return horizon. Hence, not only do we prove that the VRP still holds as a superior predictor, we also find evidence that while the return timing of the predictability has increased, the degree of predictability is even stronger than before. This confirms the argument stated above; investors are to a larger degree driven by fear when they invest and, as they dislike uncertainty and volatility, the risk premium assigned to the VRP increases.

In terms of the intraday horizons, we find the strongest predictability on the daily horizon, when controlling for realized variance, with significance at the 5%-level. The estimated slope coefficient is 1.504 with a Newey-West *t*-statistic of 2.024, while the explanatory power reaches 0.7%. Given the overall expectance of little to no explanatory power of the VRP on the very short horizons, this constitutes a relatively strong result. However, one has to recall the relatively smaller sample size when evaluating the explanatory power. Nevertheless, it is worth noting that the β-coefficient is above that of the 4-month horizon. Please refer to Appendix I for the intraday regressions.

In terms of the other variables, we generally find higher levels of significance in the post-GFC sample: relative to previous samples, we now find significant results on the 1%-level in the simple regressions for both realized and implied variances on the 4-month horizon, as well as for the expected realized variance on the 3.5-month horizon. Hence, it seems that not only is investor fear (in the form of the VRP) a significant predictor of stock returns in the post-GFC world, but so is the level of realized variance. This further supports the idea that the change in coefficient for the VRP may be driven by the combined effect of an increased persistence in the volatility-of-volatility as well as an increased intertemporal elasticity of substitution, as the RV offers insights into the volatility-of-volatility.

Furthermore, looking at the economic variables in the simple regressions for the 4-month horizon, both the P/E ratio and the RREL exhibit the expected negative relationship, also significant at the 1%-level. Furthermore, the default spread is now significant, with a positive relationship to excess returns, also at the 1%-level. Nevertheless, combining all of the economic variables removes the significance of the default spread and the RREL, and lowers the significance of the P/E ratio to the 10%-level. Hence, it seems that the simple regressions carried significant omitted variable bias. The only variable that does experience a dilutive effect is the VRP, which remains significant at the 1%, albeit with a lower coefficient (0.411). However, the multiple regression offers less explanatory power, as the sum of the predictor variables' simple regression adj. R^2s is much larger than 34.2% as noted in the multiple regression (or 23.1% for the EVRP 3.5-month return regression). Actually, none of the multiple regressions capture more predictability than the simple regressions, based on the sum of adj. R^2s. As such, it is easy to see that the VRP (and EVRP) still remains a dominant predictor in this subsample and indeed seems stronger than in previous samples.

6.5 Robustness Checks

While the subsampling of the data confirms the relative stability of the VRP as a predictor of returns across periods of both market turmoil and tranquility, it is further necessary to test these results for robustness. Thus, by changing certain regression specifications, we perform a series of robustness to confirm the structural validity of the results found above (White & Lu, 2010). In order to conserve space, the robustness checks discussed in this section only regard previously presented results in the analysis above, as these results were the most significant.

6.5.1 Inherent robustness checks

The methods applied in the analysis already contain several inherent robustness checkes, thus validating the dominance of the VRP as a return predictor. Given that the realized variance has been computed across two different measures (backward looking and forecasted), this acts as a robustness check in terms of realized variance modelling. As seen above, we generally find that the significance of the VRP holds in the expected form (EVRP) across subsamples (with few exceptions), albeit with lower beta coefficients and R^2s. Hence, it seems that while the significance and dominance of the VRP is relatively non-sensitive to the modelling, this has a non-trivial effect on coefficients and R^2s. In a similar test, the BTZ study find equally lower coefficients and explanatory power, but continue to find the EVRP to be the strongest predictor for the return horizons in question. They further argue that the similarity of results may imply that the fear of higher *future* volatility is priced in *today*, hence depressing prices and yielding higher future returns in line with the VRP.

Naturally, given this test of robustness to the realized variance measure, it may also have been relevant to check the robustness of the implied variance measure. This is especially true considering the allegations of potential manipulation of the VIX index. However, since previous studies (including Bollerslev, et al. (2009)) have conducted robustness checks in the form of computing Black-Scholes implied volatility, and overall argued that it was an inferior methodology, we do not consider it necessary to conduct such a test. Other testing methodologies would have required considerations outside the scope of this paper, and hence, we solely rely on the model-free variance swap computation of the VIX for implied variance.

The subsampling of the data further comprises a robustness test of the parameter estimates (Lamont, 1998). Comparing across subsamples, we continue to find the VRP (and in almost every subsample the EVRP), to be dominant, while only showing modest changes in the t-statistics and coefficients, but never a signage change. We only find the VRP to be insignificant in the pre-financial crisis sample in the simple regression, and otherwise it is significant at least at the 5%-level. Additionally, many papers argue that the multiple regressions they have conducted in similar capacity to ours, act as robustness check (Ang & Bekaert, 2007; Lettau & Ludvigson, 2001). Hence, we have inherently tested whether the VRP (and the investor sentiment it represents) is dominant relative to the included economic variables. Not only does the VRP prove to have better *t*-statistics across most samples; none of the other predictors are robust across all subsamples either. Hence, none of the economic variables shows a predictive capacity similar to the VRP.

6.5.2 Winsorized regressions

A typical approach when checking the robustness of regressions is to identify extreme values within the sample and remove them, if they can be characterized as genuine outliers (Ghosh & Vogt, 2012). As argued above, extreme outliers can cause asymptotic inference to become unreliable, which is especially true when both the independent and dependent variables can take extreme values, such as in our sample. One methodology for dealing with such issues is through winsorization, which either assigns a weight to the extreme value or modifies it to bring it closer to other sample values (ibid). For our purposes, we have winsorized at the 5%-level and utilized the second methodology, hence, observations falling below 5% or above 95% of the normal distribution are assigned the 5% or 95% value respectively. Naturally, one has to keep in mind that such winsorizing can produce poor estimates by introducing statistical bias and undervaluing the outliers. Hence, these winsorized results should be considered with respect to non-winsorized estimates.

We have winsorized all samples and subsamples for all frequencies utilized in the regressions, in order to check the robustness of our results. Below in table 6.A are examples of the OLS regression outputs versus the “robust regressions” based on the winsorized samples for the VRP regressions. The displayed regressions are the simple kind on the most significant return horizons, as well as the multiple regression including the logarithm of the price-earnigns ratio P/E. For a more detailed overview of all winsorized sample regressions, please see Appendix Q.

Table 6.A: Return predictability of the VRP (original and winsorized samples)

Sample	Dependent	Regressors		Original			Winsorized		
		X1	X2	β_1	β_2	Adj. R^2 (%)	β_1	β_2	Adj. R^2 (%)
Main sample	$r_{t+3.5}$	VRP		0.264***		3.6	0.211*		1.4
		(t -stat)		(3.602)			(1.839)		
Main sample	$r_{t+3.5}$	VRP	log (P/E)$_t$	0.279***	-40.738*	7.6	0.216**	-37.868*	6.0
		(t -stat)	(t -stat)	(3.978)	(-1.744)		(2.126)	(-1.645)	
Pre-GFC	$r_{t+3.5}$	VRP		0.140		1.5	0.070		0.3
		(t -stat)		(0.986)			(0.486)		
Pre-GFC	$r_{t+3.5}$	VRP	log (P/E)$_t$	0.396***	-133.112***	32.6	0.362***	-111.333***	30.1
		(t -stat)	(t -stat)	(3.475)	(-2.409)		(4.283)	(-3.671)	
During GFC	$r_{t+3.5}$	VRP		0.395***		11.4	0.599**		11.6
		(t -stat)		(2.524)			(2.196)		
During GFC	$r_{t+3.5}$	VRP	log (P/E)$_t$	0.358***	-71.171	15.1	0.557**	-21.689	11.8
		(t -stat)	(t -stat)	(3.935)	(-1.29)		(2.001)	(-0.481)	
Post-GFC	r_{t+4}	VRP		0.543***		13.4	0.638***		12.6
		(t -stat)		(5.422)			(4.365)		
Post-GFC	r_{t+4}	VRP	log (P/E)$_t$	0.334***	-55.297***	24.8	0.409***	-49.421***	23.1
		(t -stat)	(t -stat)	(3.796)	(-3.686)		(3.178)	(-2.975)	

Return predictability regressions for OLS and winsorized OLS regressions. The sample differs, and is defined in the first column. The t-statistics are Newey-West corrected. VRP is the Variance Risk Premium. *P/E* is the price-earnigns ratio of the S&P 500 index. The dependent variable is the excess log return on the S&P 500 Index over the periods indicated, streching from 3-4 months. The return series are overlapping.

The primary finding from these winsorized samples is that the VRP maintains significance across nearly all regressions. In fact, in both the GFC and post-GFC samples the simple regression and the multiple regression including the P/E ratio are stronger, both in terms of coefficient estimates and explanatory power. Considering that the largest spikes in the VRP happens during the GFC, and we later observe the flash crash in 2015, it seems that these extreme spikes negatively affected the predictability of the VRP for these samples. Interestingly, across the full sample, the significance of the VRP is strongly impacted when winsorizing, indicating that the full sample results were partly driven by outliers, some of which may stem from the abovementioned sub-periods.

When considering the regressions conducted on the winsorized samples for the EVRP (Appendix R), an even more solid picture emerges. All results across all subsamples and regressions become much stronger, which intuitively makes much sense: As described earlier, the EGARCH estimation of the daily variance tends to spike intensively, especially negatively, given our negative gamma parameter, much more so than the non-parametric estimate. Hence, outliers may very likely obscure the regression results for the EVRP and removing them creates a clearer picture.

While a limited significance was detected on the intraday frequencies for the VRP, the winsorized regressions prove to be even less persuasive, with a loss of nearly all significance. The only regression in which the VRP maintains 10% significance in a winsorized sample is for the pre-GFC period. This tendency for lower significance in the winsorized intraday results may be due to the tendency for fat tails in intraday returns, which may have been driving the regressions prior to winsorization.

6.5.3 Expanding and rolling regressions

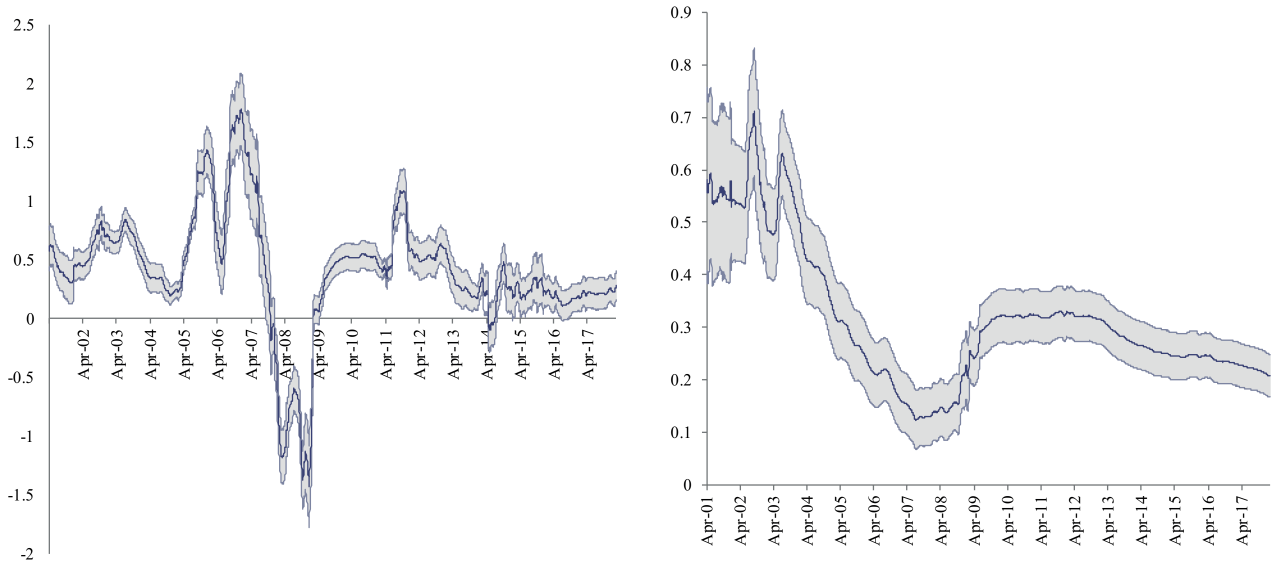
Another methodology within the sphere of robustness testing is to create recursive and rolling regressions over the sample period (Yu & Yuan, 2011). With respect to the scope of this paper, we conduct this test on the most robust of the full-sample regressions, which are the 3.5-month horizon for the VRP and the 4-month horizon for the EVRP. These robustness checks are not just statistically motivated, but also economically motivated as we expect pricing of risk to act differently in periods of booms or busts.

A rolling regression is based on a window of a fixed size that is "rolled" throughout the sample, where the earliest observation is dropped, and a new observation is added. When employing the methodology of a rolling window, the size of the estimation window is of key concern: If the window is too small, it potentially reduces the performance of the model, while a window too large adds little benefit compared to the full sample estimation. When conducting the rolling analysis, the sample repeatedly becomes split into estimation and prediction samples. Then model is then fitted on the estimation sample and rolled ahead in the given increments over the sample period. For our purposes, we utilize a training period of two years (1996 to 1998) to estimate the first window and roll the regression over 2-year windows from then onwards. In terms of the investor utilizing the VRP as a predictor, this rolling window regression assumes that the investor only regards the past two years and disregards any information prior to that on the day of investment. For the recursive regression, we increase the estimation window over time, and do not drop the oldest observation, when a new is added. Contrarily to the rolling regression, this assumes that the investor utilizes all available data up until the investment point.

These kinds of robustness checks seek to explore parameter stability over time, implying that a fully robust parameter will have little to no development. If the parameters change dramatically, the rolling and expanding windows will capture this instability, and hence question the validity, stability and predictive accuracy of the VRP. Figure 6.2.A illustrates estimated β-coefficient for the VRP on the 3.5-month return horizon for the rolling window regression (a) and the expanding window regression (b). For the 4-month horizon EVRP expanding and rolling window regressions, please refer to Appendix S.

Figure 6.2.A: Rolling and expanding window 3.5-month VRP return regressions

(a) (b)



As evidenced in the graphs above, while the recursive regression (b) seems robust, remaining above the zero mark throughout our full sample period, the rolling regression reveals inconsistencies around the financial crisis and slightly in the early summer of 2014. As we saw a change from insignificant to significant results for the VRP from the pre-GFC to the GFC sample, this is to be expected: Given the two-year window used for the rolling regression, the β-estimate in the rolling regression is the end-point of the two year estimation. Hence, negative β-coefficients in our pre-GFC sample would not be shown in the rolling regression until their end-point, which will be placed during the crisis. Likewise, the strong β-coefficients we find for the GFC sample will show with a delay in the rolling regressions, as evidenced by the sharp spike during early 2009. For the expanding window, we also see a decrease in the β-coefficient around the same time, however since the regression is computed on a larger amount of data, the data points right before the crisis are not extreme enough to cause the expanding window regression to move below zero. Hence, according to the recursive regression, our main sample regression is robust on the 3.5-month return horizon, while the rolling regression questions the robustness of our pre-GFC sample, in line with the subsampling conducted above.

For the EVRP (see Appendix S), we find the rolling regression on the 4-month return horizon to show a relatively different pattern: while the EVRP parameter seems more consistent over time, this consistency is relatively close to the zero-mark. Further the β-estimate sees a strong upwards spike in the period just prior to the GFC and further drops consistently below zero after April 2014. This finding post April 2014, makes sense, considering our finding of the 3.5-month return horizon to yield stronger predictability for the EVRP relative to the 4-month horizon in the post-GFC sample. In terms of the recursive estimation, we further find less encouraging results for the EVRP relative to the VRP: In line with the rolling window, the EVRP β-estimate consistently moves close to or below the zero mark. Hence, it seems that not only does the non-parametric VRP provide stronger β-coefficients and R^2s, the parameters also seem more robust.

6.6 Concluding Remarks On VRP-Regressions

From the analysis above, we find that from showing no significance in our pre-GFC sample, the VRP became a strong and dominant predictor of future stock returns in the tumultuous conditions during the financial crisis. However, this dominance was not contained to the GFC-sample: in the post-GFC recovery market, the VRP not only maintained its predictive prowess, but it did so in excess of previous sample periods, showing both stronger β-coefficients and R^2s. These findings are further confirmed by the EVRP, showing the robustness of the regressions towards the modelling of realized variance, as well as supporting that fear of *future* volatility is reflected in prices *today*.

In addition to the increased β-coefficients, we further find an outwards shift in the peak return predictability from 3.5 months to 4 months for the post-GFC sample. This combined change seems indicative of a change in the constituent parts of VRP predictability, the volatility-of-volatility and the intertemporal elasticity of substitution: Firstly, the increased peak predictability is indicative of an increased persistence in the volatility-of-volatility, hence, volatility shocks take longer to taper off in the post-GFC sample relative to earlier time periods. Such increased persistence may further be a driver of the increased β-coefficient, an effect which is amplified by potential increases in the intertemporal elasticity of substitution, which can be interpreted as an increased level of sensitivity in the investor sentiment. However, the exact disentanglement of these two effects is not possible with the current model setup. We could potentially have measured the persistence in an AR(1) process, however persistence will remain high due to the overlapping return calculations, and it is as such deemed inappropriate to conduct this analysis.

6.6.1 Creating a profitable trading strategy based on the findings for the VRP

To exemplify how the results above may be utilized by the interested practitioner, we further consider the possibilities of creating a profitable trading strategy based on the results. Given that the VRP shows stronger and more robust predictive power relative to the EVRP, we utilize the VRP for trading purposes. Furthermore, two things are clear: i) Firstly, as the relation between the VRP and future returns is positive, one should take a long position in the S&P 500, when the VRP is above a certain threshold. ii) Secondly, given that the coefficient on the VRP in the return regression is highest and most significant at the 3.5-month horizon in the full sample, a trading strategy should focus on holding the long position for this amount of time. As our strategy constitutes a market timing attempt, if the VRP is lower than the chosen threshold, the strategy rolls out of the market and takes a long position in the risk-free rate, proxied by the US 3-Month Treasury Bill.

In terms of technicality, we assume a notional of USD 100m with trading start on January 4th, 2000 and end on February 28th, 2018. We calculate percentiles of the VRP on a recursive window, allowing the investor to utilize all available information up until the investment decision. Further, we restrict the strategy to no short-selling and no leverage, however, to maintain simplicity, we do not consider any trading costs and assume that the investor can borrow and lend at the risk-free rate. In terms of the investment strategy itself, we assume that the investor re-weights 1/77 of the portfolio daily since, for a standard trading month of 22 days, a 3.5-month return horizon corresponds to 77 days. This further means that from the strategy start on January 4th, 2000, the portfolio is not fully invested until April 26th, 2000. At every re-weighting, the trader makes the following decision:

- If $VRP \geq \text{xth percentile}$, weight in the market for the 1/77 part of the portfolio is 1
- If $VRP < \text{xth percentile}$, weight for that part of the portfolio is 0

Given this structure, the trader may have a wide range of possible total exposure to the S&P 500, based on the weight assigned in any previous reweighting, as is made clear in figure 6.3.A below, in which the blue backdrop denotes the weight in the S&P 500 index. The highest cumulative weight for our strategy is reached on November 29th 2002, with a total weight of 98.701%, corresponding to having invested in the index for 76 consecutive reweights. At every reweight, the investor reinvests any profit for the past period into the new position taken.

In terms of evaluating the strategy, we benchmark to a strategy which also rebalances daily with a 77-day turnover, but it is restricted to only investing in the S&P 500 index. We then compare the two strategies across the three following key measurements: The total cumulative return, the Sharpe ratio and the Sortino ratio. The cumulative return simply considers the total dollar-wealth increase to the investor with no regard to the volatility exposure of the strategy. Meanwhile, the Sharpe ratio considers the unique return-volatility trade-off to the strategy and is calculated as follows:

$$Sharpe = \frac{r_p - r_f}{\sigma_p} \qquad (6.1)$$

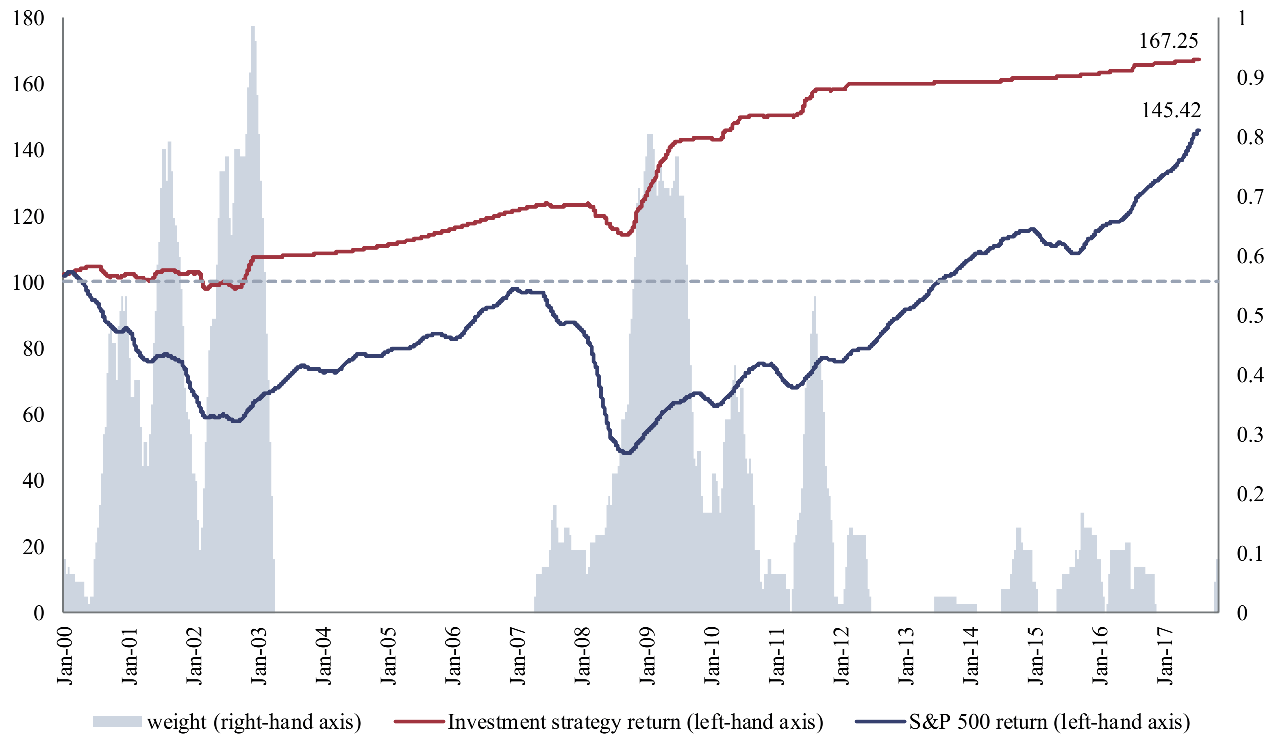
In which r_p reflects the return on the portfolio, r_f the risk-free rate as proxied by the US 3-month Treasury Bill and σ_p the standard deviation of the portfolio. As seen, engaging in a strategy with zero risk, i.e. investing in the risk-free rate, will yield a Sharpe ratio of exactly zero. However, while the Sharpe ratio is capable of taking into consideration the volatility of the portfolio, it does not distinguish between the downside and upside volatility. As an answer to this issue, the Sortino ratio, rather than considering risk tolerance, focuses on the investor's desired return. Similar to the Sharpe Ratio in calculation, rather than looking at the total standard deviation of the portfolio return, the Sortino ratio uses downsize deviation from the desired return as the denominator (Sortino & Price, 1994). Thus, the standard deviation then becomes the sum of downside deviations over the investment period, yielding the following ratio equation:

$$Sortino = \frac{r_p - r_f}{\sigma_{downside,p}} \qquad (6.2)$$

As our return requirement, we use the US 3-month Treasury Bill rate for the 3.5-month investment period. This is chosen as it is the most natural alternative to a market investment. An alternative could for example have been the long-run average equity premium, however, as this is not an investment available to the investor for each period, we find the risk-free rate to be a more viable choice. Naturally, by choosing the risk-free rate as the desired return, the Sortino ratio becomes biased, as the Sortino ratio will approach infinity as the portfolio becomes more and more heavily invested in the risk-free rate. Thus, we balance the Sortino ratio with the other metrics for completeness. With this in mind, we find the 65th percentile to be optimal as it balances a high Sharpe Ratio, a high cumulative return and a fairly high Sortino ratio (please refer to Appendix T for an overview of the three metrics at different percentiles).

Hence, based on this final strategy, in which the portfolio takes a long position in the market if the VRP is above its 65th percentile, we gain the cumulative return profile depicted in figure 6.3.A below:

Figure 6.3.A: Overview of cumulative returns from trading strategy vs. benchmark



Total return	Sharpe Ratio	Sortino Ratio
Strategy: 67.29%	Strategy: 20.03%	Strategy: 652.87%
S&P 500: 46.06%	S&P 500: 6.91%	S&P 500: 123.36%

Cumulative dollar-returns from an initial USD 100m investment in January 2000. The red line denotes the 65th-percentile investment strategy, while the blue line denotes a similarly rebalanced strategy, restricted to investing in the S&P 500 index. The blue bars in the background denote the total weight in the S&P 500 index at any given point in time. Price data from Thomson Reuters (2018).

A simple glance at the graph will reveal that the strategy outperforms the simple index strategy, especially when considering the effective cap of the large downturns in the S&P 500 index in 2000-2002 and 2007-2009. Notably, the strategy seems capable of timing the rebounds in the market fairly well, especially with the large portfolio weight invested during 2009. Out of the entire period, the strategy chose a long position in the S&P 500 index 723 times out of a 4,400 number of possible times. In terms of the metrics considered, the strategy is capable of generating a cumulative return of 167.25 (or 67.25%), while the index generated a return of 145.42 (45.42%)[23]. Meanwhile, the Sharpe ratio for the strategy was 20.03%, while it was only 6.91% for the index. Lastly, the strategy vastly outperformed the index on the Sortino Ratio with a ratio of 652.87% against 123.36%. Hence, it is clear that in addition to revealing information regarding the level of fear in the market, the VRP can also form the foundation of a profitable trading strategy by isolating the pricing of volatility-of-volatility.

7 The VRP in the Trump Era

Considering the instability of the political spectrum today, and how the world changed when Trump was elected in late 2016, the analysis progresses by investigating the potential effects the new president has had on stock market volatility. A wide array of opinions exist as to what impact Trump has actually had: some view the instability and unpredictability of Trump's personal character as a threat, leading to higher levels of volatility and potential tail risk in the market than during the GFC (Shen, 2017), some argue that Wall Street remains unsettled by Trump's policy moves (Bullock, et al., 2018), and some talk of the "Trump Rally" or "Trump Jump", as the stock market was up 26% by January 2018 since inauguration day (O'Grady, 2018). With respect to our earlier findings and our third guiding research question, it is thus interesting to consider, whether the VRP is still a dominant predictor in the Trump Era and further if it or its components are affected by the apparent political instability. In the following segment, we attempt to uncover the effect of Trump on the VRP via two avenues: By studying the VRP and its predictive ability in the subsample prior to and after the election of Trump and secondly, by directly examining the impact of political events on the VRP and its components by utilizing Trump's Twitter feed.

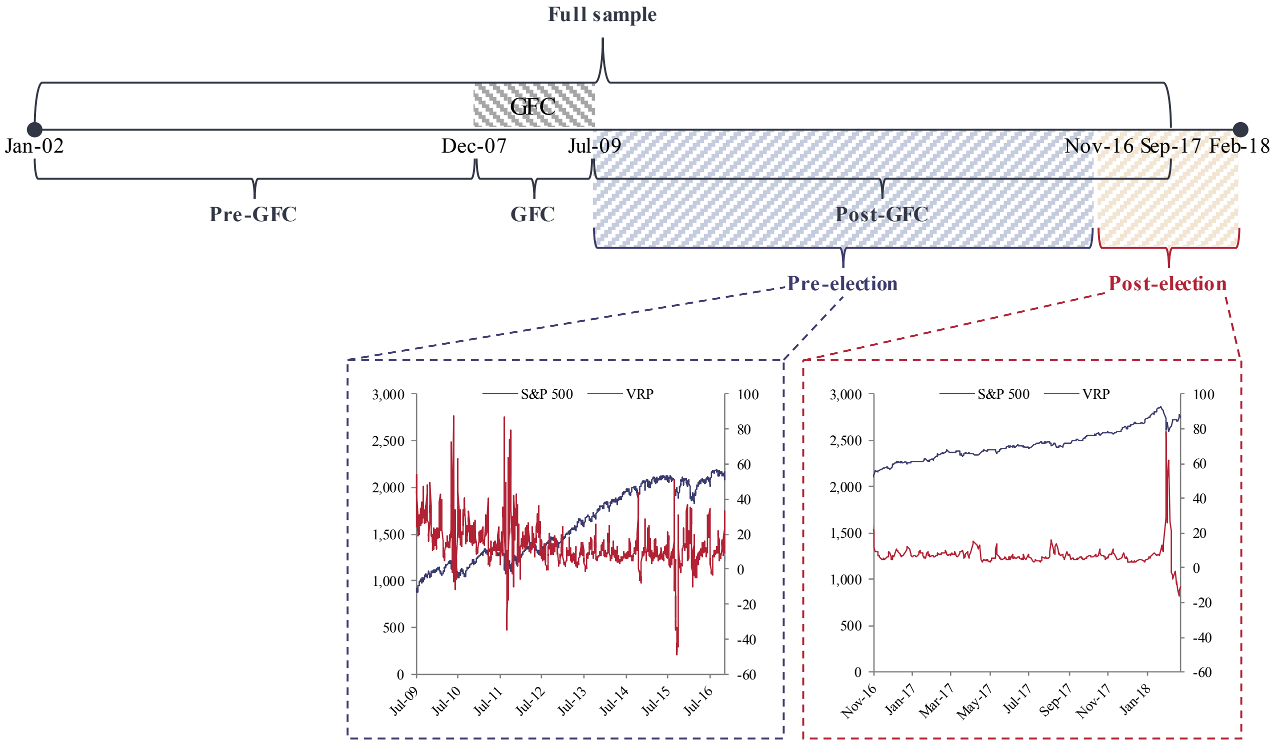
7.1 The VRP Return Regressions Prior to Trump

We define the period prior to the election of Trump as stretching from the end of the latest recession (July 2009) until the US presidential election on November 8th, 2016 – an overview of the samples is included in figure 7.1.A below. Given the large overlap to our post-GFC sample, we expect large

23 The authors would like to note that this comprises continuously rebalanced returns and does not correspond to the return from a simple buy-and-hold strategy. Over the entire investment horizon, such a strategy would have generated a return of 90.05%.

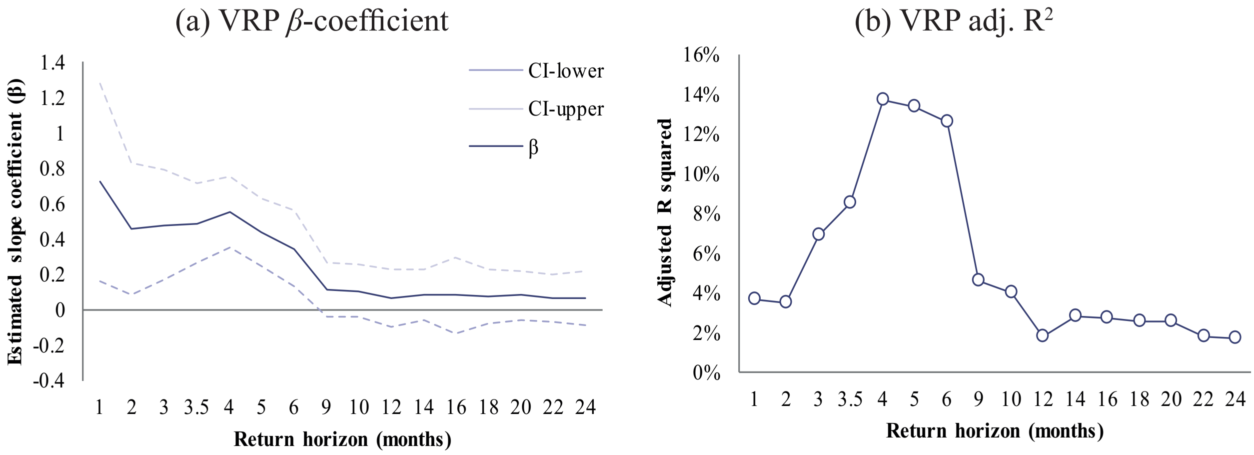
similarity in our findings for these two samples. Indeed, looking at figure 7.1.B we find the recognizable hump-like shape of both the estimated β and R^2.

Figure 7.1.A: Overview of samples



Overview of samples utilized. Pricing data for indices from Thomson Reuters (2018).

Figure 7.1.B: Estimated β-coefficient and R^2 for VRP return regression, pre-election sample



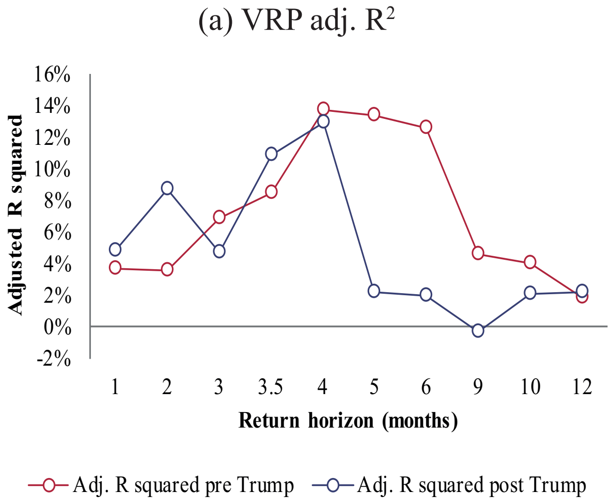
Relative to the post-GFC sample, we see the same degree of predictability, which peaks at the 4-month return horizon with an adj. R^2 around 14%. The estimated β for the VRP is significant at the 1%-level with a coefficient of 0.556. The pre-Trump sample thus exhibits a slightly higher degree of predictability compared to the post-GFC sample, which offered an estimated β-coefficient of 0.543. Not only are these results robust to winsorizing, they are strengthened with a β-estimate of 0.675 with significance at the 1%-level (see Appendix V). Notably, the highest t-statistic for the predictor variables for the simple regression is not for the VRP, but rather found for the price-earnings ratio. Even when combining the two predictors in a multiple regression, while they both remain significant at the 1%-level, it still seems to be the price-earnings ratio driving most of the predictability. Nevertheless, in the largest multiple regression, we again see the traditional predictor's crowding each other out, while only the VRP remains significant at the 1%-level.

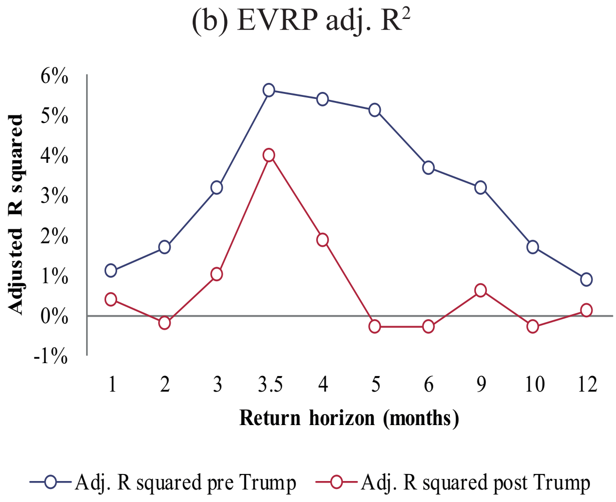
In terms of the EVRP, the adj. R^2 and β-coefficients both peak at 3.5 months, from which they taper off as the return horizon increases. The coefficient is again larger, just as we saw for the VRP, and the winsorized results (Appendix W) yields a tripled estimated β-coefficient, offering almost the same slope as the VRP ($VRP_{win,\ 4\text{-mo.}} = 0.675$ vs $EVRP_{win,\ 3.5\text{-mo.}} = 0.668$). For both the EVRP and the VRP, it is interesting that we once again find a hump-shaped development for both the β-coefficients and the explanatory power, unlike the findings in Bollerslev, et al. (2009), who found a gentler decrease in the β-coefficients from a peak at the 1-month horizon. For this pre-election subsample, this hump shape is even more pronounced than for our full sample and hence matches the post-GFC sample in this respect. Nevertheless, the increase in the degree of predictability for the VRP and EVRP in this subsample period might also imply that the last observations in the post-GFC sample could be negatively affecting the predictability. Hence, in the following we now study this remaining sample on its own to discover if the election may constitute a break in the predictive ability of the VRP.

7.2 The VRP in the Trump Era

We define the post-election sample as the period stretching from the election on November 8th, 2016 until the end of our sample on February 28th, 2018. Following the argumentation of our GFC sample, the multi-horizon return-regressions have been run only for one year, as the sample period is less than two years. We do caution that due to the shorter sample compared to the pre-election sample, the relative length of the return overlaps in the post-election sample may cause slight inflation in the R^2s. In the plotted graphs in Appendix U, the degree of R^2 and statistical significance of the VRP still maximizes at the 4-month horizon and 3.5 months for the EVRP. Notably, relative to the pre-election sample, both measures show significantly wider confidence intervals, most likely representative of the smaller sample size. Notably, the VRP no longer shows a smooth hump-shaped curvature, but rather strong jumps at 2 and 3.5 months. For the EVRP, the maximum at the 3.5-month return horizon is very pronounced, and likewise does not seem to follow a smooth development. Directly comparing the pre- and post-election R^2s (figure 7.1.C below) reveals, that for both the VRP and EVRP the explanatory power is lowered in the post-election sample.

Figure 7.1.C: Comparison of pre- and post-election R^2 for the VRP and EVRP





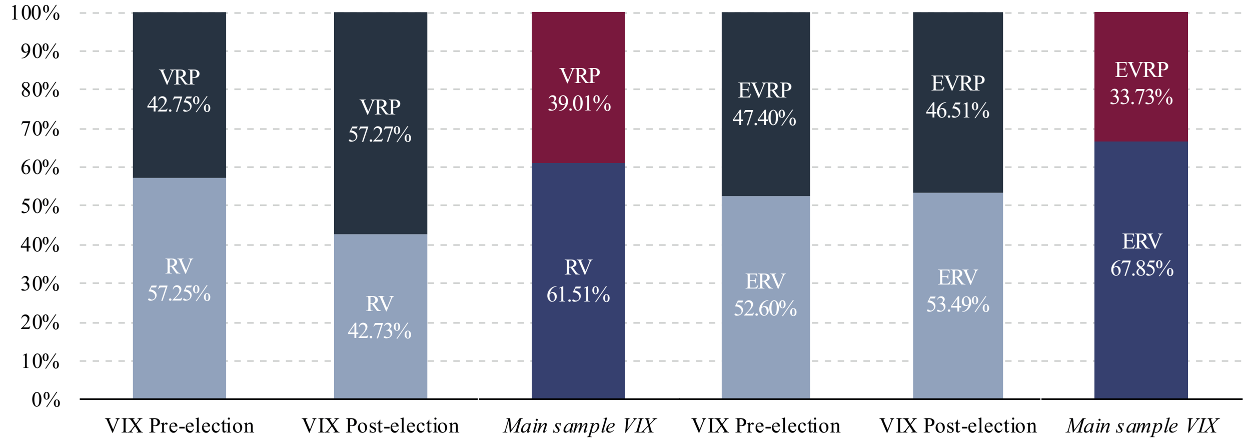
Turning to the regression outputs for the VRP and the EVRP simple regressions, we find contradicting results: Whereas the β-coefficient for the VRP reaches a new high of 0.692 (significant at the 1%-level), the EVRP with its relatively high β-estimate (0.527) carries no significance. This is contrary to previous samples, in which the VRP predictability was robust to the modelling of expected realized variance. Furthermore, when winsorizing the samples, all significance is removed; hence it seems that the predictive ability of the VRP in this period is primarily driven by outliers, such as the VIX-spike in February 2018. This constitutes a significant shift relative to previous samples, which found the opposite to be true. We note that the relatively low number of observations in the post-election sample may be a cause of this loss of significance, as it will tend to inflate the standard errors. However, considering the stronger results of the pre-election sample, relative to the post-GFC sample (in which the difference between these two samples is the post-election sample), it does seem that the VRP loses predictive power during the post-election sample – even in a larger sample setting.

The question as to why we experience such a drastic change in the predictive power of the VRP and EVRP remains to be answered. It seems that the time period during the Trump administration constitutes a significant change in the relationship between investor fear and stock returns. Hence, in figure

7.1.D below , we compare the mean of key variables in the pre- and post-election samples relative to the full sample statistics to attempt to solve the puzzle.

Figure 7.1.D: Comparison of means in the pre-election and post-election samples

	Pre-election	Post-election	*Main Sample*
VRP	13.45	7.23	*15.39*
EVRP	14.91	5.87	*13.31*
$r_{SPX} - r_f$	11.70	19.20	*3.71*
IV	31.46	12.63	*39.45*
RV	18.01	5.40	*24.27*
ERV	16.55	6.76	*26.77*



Graph showing the relative importance of the realized variance and variance risk premium as components of the implied variance.

Looking at the descriptive statistics above, a general picture emerges: there was much more volatility in the time period prior to the election of Trump relative to after – both in terms of implied and realized variance. However, the level of volatility for both samples can be characterized as lying below the full sample average. It is especially notable that despite the February spike in the VIX, the overall level of volatility in the post-election period is far below any previous sample studied. Furthermore, we see that the average excess return for both election samples are much larger than the full sample average – showing both the rebound in the stock markets following the GFC and perhaps evidencing the "Trump Rally".

The lack of predictability in the post-election Trump sample might be caused by a decreased relative importance of the RV compared to the VRP: In the pre-election sample, the VRP comprised 42.75% of the IV, while it accounted for 57.27% after the election. Considering that the IV is the sum of these two physical (RV) and perceived (VRP) risk measures, it seems that investors have become more

more fearful in the Trump Era with the perceived fear increasing in importance. As the underlying economic model explains, the VRP's predictive power stems from the pricing of the volatility-of-volatility and the intertemporal elasticity of substitution. Based on the findings above, the increased β-coefficient with lower significance may be indicative of a shift in the relative importance of the IES and persistence in the volatility-of-volatility ("VOV"). Given that perceived risk has increased in importance while the realized variance has decreased, it may be that investors have become more fearful and react more forcefully to changes in the VOV, demonstrating an increased IES. However, the persistence in VOV may have decreased as indicated by the lower realized variance. Together, these opposing model dynamics may cause the inflated β-estimates with little significance. Further noting the loss of significance when winsorizing, it seems that the VRP requires a more volatile environment to maintain its predictive ability.

With these results in mind, one may wonder if excess returns are driven by other factors than volatility. In the multiple regressions, both the P/E and P/D ratios, as well as the term spread, show strong t-statistics. Running these multiple regressions on both the original and winsorized sample offers predictive power to VRP, hence, it seems that the lack of significance for the VRP in the winsorized sample may also be caused by omitted variable bias. Indicating that overlap in long-run (economic) variables and short-run (VRP) has been introduced. Meanwhile, the EVRP remains insignificant in these multiple regressions, implying that the findings for the VRP are not robust to the realized variance modelling.

Nevertheless, the insignificance of the variance risk premium factor seems quite controversial relative to many medias' beliefs about Trump's character, as well as to the earlier empirical research and literature on uncertain policies and candidates' effects on the equity risk premium (Jensen & Schmith, 2005; Bittlingmayer, 1998; Beaulieu, et al., 2005). It is believed that a candidate, who is characterized as uncertain or with uncertain policies tends to spur uncertainty in the market, and thus increase the equity risk premium. However, as argued above, it seems that while investors are indeed more fearful in the Trump era as evidenced by the increased relative size of perceived risk, they have less to be fearful about in terms of realized volatility. While the cause of this change may be manifold, it cannot be rejected that it may be driven by the political climate during the Trump administration. Hence, in the following section, we seek to study how Trump may have affected investor sentiment in this extraordinary low-volatility world. In order to do so, we examine the effects of Trump tweets on the VRP and EVRP, along with their components, IV, RV and ERV, to detect if Trump tweets, as a proxy for the communication between Trump and the investors, may influence volatility and the pricing thereof.

7.3 Trump's Influence on Market Volatility

As described in the methodology section, we study the effect of Trump tweets on the stock market by running regressions between dummy variables representing these tweets[24] over various horizons spanning from the lowest possible intraday frequency (5 minutes) to a full day. In order to gain an overall image of the relation, we start with the full day regression between the sum of categorized tweets during the day against the chosen dependent variables.

On the daily horizon, we see a *negative* relation between the implied variance and economic tweets with a β-coefficient of -0.509 and significance at the 5%-level (please refer to Appendix X for the complete regression output). This result is robust to winsorizing, albeit with a slightly lower β-coefficient. Hence, it seems that the economic Tweets act as risk *relievers* in the market. An example of such a tweet is "*Jobless claims have dropped to a 45 year low!*" (Twitter, 2018), which Trump tweeted on February 10th, 2018. Based on the reassuring contents of such a tweet, it makes sense that this should decrease the implied variance – either via the perceived risk premium (VRP) or the realized volatility on the market. In addition to the effects of the economic tweets, we further find slight significance for political tweets on returns with a very low negative β-coefficient of -0.003, as well as for presidential duties with a β of 0.0003. As the economic impact of such results are very limited, we do not consider it cause for further investigation. Likewise, while we find some significance for the "Other" category, we do not find any economic intuition for this result and regard it as likely spurious, also due to the very limited amount of observations. Finally, we detect quite an impact between fake news tweets and the different variance measures – both the IV, the RV and the VRP. Hence, we see that variance and the fear premium is actually decreased by Trumps tweets on fake news – however, like before, the intuition behind this effect is hard to substantiate.

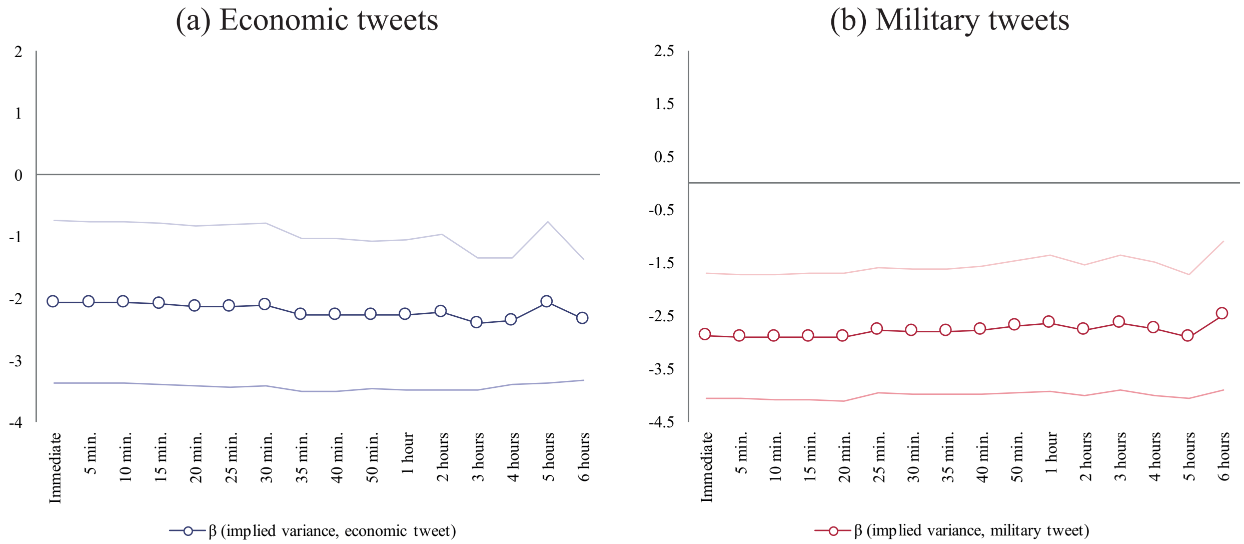
24 Relisting the categories as described in the methodology section: 1) Economic policy, 2) politically themed tweets, 3) tweets featuring 'Democrats', 4) military policy, 5) presidential duties, 6) personal tweets and 7) others. Additionally, we constructed a separate indicator variable on Trump's most frequently tweeted term; 8) fake news.

While we find only slight evidence of Trump affecting volatility on the daily frequency, the intraday regressions reveal quite different results: As noted, we test intraday frequencies ranging from the immediate market reaction to the daily reaction. Overall, it seems that Trump Tweets act as risk relievers across all frequencies and measures: While many coefficients are insignificant, they all share the characteristic of negative signage. The strongest relation is between the economic and military indicator variables against the implied variance. This result is consistent across almost all horizons and remains robust after winsorizing. Given the negative relation, both these types of tweets seem to act as risk relievers with a peak in the combined predictability at the 20-minute horizon. From an economic tweet occurs, the implied variance tends to *decrease* by 2.127 20-minutes later and by 2.906 for military tweets, both significant at the 1%-level (please refer to Appendix Y for the 20-minute regression output). Additionally, we see a significant decrease in the VRP, albeit with a lower β-coefficient. Given the lack of significance in the realized variance, it seems that the change in the VRP is driven by the effect of the tweets on the implied variance.

Based on this, it seems that on the intraday frequency, both military and economic tweets cause investors to be less fearful. In terms of the military tweets, an example includes "*North Korea disrespected the wishes of China & its highly respected President when it launched, though unsuccessfully, a missile today. Bad!*" (Twitter, 2016) tweeted by Trump on April 28th, 2016. However, other tweets include increased funding to the US military, which, given the existence of the military-industrial complex (Encyclopædia Britannica, 2018), should increase market confidence as this would imply higher economic activity.

While we experience a peak in predictability on the 20-minute horizon, we find little coefficient development in terms of continuous time. From our daily regressions, we know that in terms of discrete time, we find the coefficients to be much lower on the daily regressions, hence we expect a general tapering in the coefficients. However, looking at the coefficient development in the figure 7.2.A below, both variables remain significant up until the 6-hour mark, although the confidence intervals are not quite as stable at the greater time horizons. As the economic and military tweets also yield significant predictability towards the movement of the VRP, we also plotted the development of this relationship in Appendix Z. It is clear that the confidence intervals are much larger, and that the upper bounds for both variables are much closer to zero than for implied variance. The economic tweets maintain a significant, though less accurate, negative predictability towards the VRP throughout the 6-hour horizon, however the military tweets lose significance after the 40-minute mark.

Figure 7.2.A: β-coefficient development of economic (a) and military (b) tweets



Hence, we see that despite prior research and news outlets claiming a volatility-inducing effect of Trump, we find the opposite effect: Overall, we see that the Trump Era is characterized by an extraordinarily low level of volatility, in which Trump tweets act as further risk relief, diminishing investor fear on the intraday horizon. We further see that the market reacts rapidly to Trump tweets with significant immediate reactions and greatest absorption at the 20-minute horizon. Given that the number of economic and military tweets are low relative to the overall number of tweets, we cannot conclude that this is representative of an overall investor reaction pattern to Trump's character. However, it seems that, at least his communication regarding military and economic matters have a reassuring effect on the market.

7.4 Concluding Remarks on the VRP in the Trump Era

As seen in the analysis above, relative to both of the full sample and the pre-election sample, the VRP maintains its significance and has increased β-coefficients in the Trump era, with the greatest return predictability at the 4-month horizon. However, these results are not robust to winsorizing or the modelling of realized variance. Despite this apparent loss of robustness, we find that the VRP accounts for a relatively higher part of the implied variance, compared to both the pre-election and full sample. Thus, given that we see increased β-coefficients, but a loss of robustness, it may be that the two constituent parts of the VRP have changed in opposite directions in this time period: Given the low overall volatility in the time period, but ability of shocks to drive the regression results, it may be that shocks, despite their size, no longer permeate the rest of the sample to the same degree. Hence, it may be that the persistence of volatility-of-volatility has decreased, which would dilute the efficacy of the VRP as a return predictor.

Meanwhile, this ability of shocks to drive the regression results, combined with the evidence of increased β-coefficients, may reflect an increased intertemporal elasticity of substitution: An increased IES would cause investors to become highly sensitive to changes in the volatility-of-volatility and would thus inflate the importance of shocks. Based on this argumentation, it can be theorized that the investor sentiment has become more uneasy, as evidenced by the increased weight of the VRP in the implied variance, however, not due to increased underlying volatility, but rather the fear of changes in the volatility-of-volatility. Together, this may cause the VRP to lose its predictability, when we disregard the effect of shocks.

It cannot be disregarded that part of the roots for this state of the market is described by Trump. Indeed, looking at the reaction of the VRP and its components to Trump tweets, we find that tweets of economic and military nature have significant *negative* impacts on especially the implied variance as well as a milder (but still negative) effect on the VRP. We furthermore find that the market reacts quickly to these tweets with the largest news absorption seeming to occur at the 20-minute horizon. Hence, it seems that the tweets act as a risk relief in the market – despite the many news outlets proclaiming Trump as a risk inducer. While such a finding carries important information regarding the investor sentiment in the Trump Era, it further contains information that may be of interest for the trader attempting to create a profitable trading strategy. Hence, in the following segment, we outline how these results may be used in intraday trading.

7.4.1 Utilizing Trump tweets as a key input to a trading strategy

While we find significance in both the implied variance and the VRP for economic and military tweets, for trading purposes, we only utilize the results for the implied variance. This is due to the impossibility of trading directly in the VRP: to utilize the negative relation for the VRP would require a short position in the implied variance and a long position in the realized variance. However, as the realized variance is a mere estimate of the variance on the S&P 500 index, it does not constitute a directly tradeable entity. Hence, it is not possible to create the required spread to follow such a strategy. As an alternative, one may use a chained trading strategy, using tweets as a predictor for the VRP, which is in turn a predictor for future returns on the S&P 500. However, as the VRP has the strongest predictive power at the quarterly horizon, while the tweets have intraday power, the chain strategy becomes hard to implement given the vastly different time horizons at play.

Instead, we build the strategy around the implied variance, using the VIX index as the invested entity. We do recognize, however, that the VIX is also not directly tradable and a trading strategy would have to make use of VIX futures instead. While we would have wished to base the strategy results below on such futures instead, this was not possible due to a lack of intraday prices. Hence, we use the VIX as a *proxy* for the futures' prices, cautioning that these can diverge as there is no arbitrage opportunity between the VIX index and its futures value: while a portfolio of options could be created to replicate the VIX index value, as the VIX is created from *mid-prices*, in practice this becomes impossible (CBOE, 2018). In terms of predictor values, we utilize both economic and military tweets in order to create a strategy with as many event dummies as possible. As for the signage of these dummies, the negative relation between both types of tweets implies that a trading strategy should optimally take a *short* position in the VIX following either type of tweet. As we find the strongest effect on the 20-minute horizon, we choose this as the exit point. However, given the relatively slow tapering in the effect of the tweets, exact exit-timing is not critical. As before, this constitutes a market timing strategy, in which the market is now the short VIX and the alternative investment is comprised of a risk-free investment (3-Month US Treasury Bill).

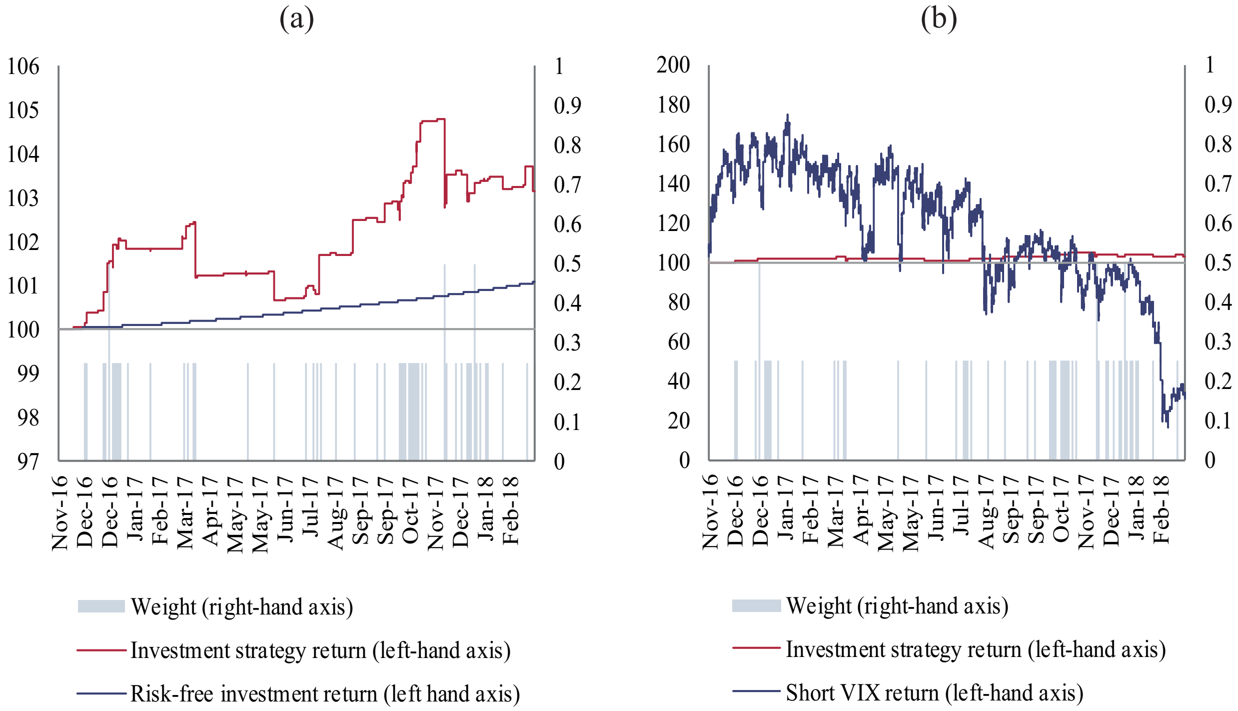
As in the VRP-based strategy, we assume a rebalancing portfolio, however, we now assume that one-fourth of the portfolio is rebalanced every five minutes, for a full turnover of at the 20-minute mark. Naturally, such frequent rebalancing would in practicality require the use of a trading algorithm, however, with the rise of topic modelling within machine learning, this does not seem far-fetched[25]. We assume trading start on November 8th, 2016 (the day of the US-election) with strategy-end on

25 If the reader is interested in some of the possibilities with machine learning, we would recommend "Automatic Donald Trump" by Filip Hráček (https://filiph.github.io/markov/), which generates fake Trump-tweets based on the existent Twitter feed.

February 28th, 2018. In terms of restrictions, we assume that short-selling is allowed, however, we do not allow for leverage. As before, we assume that the investor can borrow and lend at the risk-free rate and further faces no trading costs. As the constituent parts of the strategy are a short-VIX position and long risk-free position, we benchmark the strategy against two similarly rebalanced portfolios that are restricted to holding only either type of asset. As before, the key performance metrics are the total return, the Sharpe ratio and the Sortino ratio.

Over the course of the strategy, we have 67 within-trading hour tweets[26]. Thus, out of 21,547 available re-balances, the strategy only takes a short 0.31% of time. The highest weight observed is 50%, which occurs 8 times, evidencing a relatively low degree of clustering in the tweets, which can further be seen in the overview of the weights in figure 7.2.B below. In terms of key performance metrics, the strategy generated a cumulative return of 3.14%, while the risk-free and short-VIX portfolios generated returns of 1.07% (a) and -68.81% (b) respectively. Naturally, this loss in the short-VIX portfolio permeates through to the Sharpe and Sortino ratios, which are both negative for the short-VIX portfolio. For the tweet-driven strategy, the Sharpe ratio was 35.159%, while the Sortino was 921.773.

Figure 7.2.B: Cumulative returns on investment strategy vs. alternative investments



26 Note that this is lower than the recorded amount in Appendix F due to the data availability on the utilized price indices.

Total return	Sharpe Ratio	Sortino Ratio
Strategy: 3.140%	Strategy: 35.159%	Strategy: 921.773
Short-VIX: -68.808%	Short-VIX: -0.697%	Short-VIX: -0.663
Risk-free: 1.069%	Risk-free: n.m.	Risk-free: n.m.

Cumulative dollar-return from an initial USD 100m investment over the investment horizon (from November 8th, 2016 The red line denotes the tweet-driven short-VIX investment strategy, while the blue line in (a) denotes a similarly rebalanced strategy, restricted to investing in the risk-free rate. Meanwhile the blue line in (b) denotes a similarly rebalanced portfolio, restricted to only holding a short position in the VIX. The blue bars in the background denote the total weight of the short-position in the VIX index at any given point in time.

This very high Sortino ratio is primarily driven by a large weight in the risk-free asset; as mentioned, our choice of the risk-free rate as the return requirement, causes the Sortino ratio to approach infinity as a larger weight is invested in the risk-free asset. Furthermore, while the strategy outperforms the short-VIX portfolio across all three metrics, the poor performance of said portfolio is primarily driven by the large spike in the VIX in February 2018. Given the very low R^2 found for the regression between the tweets and the VIX, it seems unlikely that the trading strategy would consistently be capable of avoiding such detrimental spikes in the future. Hence, while Trump's Twitter feed seems to have some effect on the development of the VIX, it is a stretch to call it a true driver. This saturates this trading strategy as well: if measured against the broad market portfolio, it does not outperform a similarly rebalanced S&P 500 investment across any of the metrics. Hence, while these results seem to reveal interesting insights regarding the reaction of investor fear to Trump communication, it is no simple feat to formulate a trading strategy around these results.

8 Discussion and Potential Implications for Current Investor Sentiment

Over the course of time, across multiple subsamples, studies, methodologies and presented analyses, the variance risk premium has proven a dominant predictor of future stock returns. However, in the wake of the global financial crisis, market dynamics changed considerably: Extraordinarily low interest rates have caused bond yields to plunge towards zero, pushing investors into massive equity purchases, yielding extraordinary returns on the stock markets in the western world. Despite increasing political instability with the surge in populist movements, which culminated in the election of the Donald J. Trump as the 45th president of the US, market volatility has followed the bond yields to historically low levels. Hence, while economists and international newspapers, within and without the US, have criticized Trump repeatedly for his seemingly unpredictable and irrational character, the American market stock market has, undeniably, flourished in recent years. This development is in spite of an increasing interest rate during the Trump presidency, which may have been expected to otherwise depress stock returns.

Interestingly, a new market state in the Trump Era has yielded a decline in the predictability offered by the VRP – a perplexing result, given the parameter's stability throughout the financial crisis and the subsequent period leading up to the election. Hence, the following section seeks to answer the fourth guiding research question, and thus interpret and discuss the potential sources of the lesser degree of predictability of the VRP, including the potential influence of the current uncertain political setting. Additionally, we seek to discuss how we may derive key insights regarding investor sentiment and how this affects the VRP.

In order to determine the sources of the decreased predictability, we turn to the key components of the VRP: Overall, the VRP is considered to be driven by two major dynamics directly and indirectly - the persistence in the volatility-of-volatility ("VOV") and the intertemporal elasticity of substitution ("IES") (Bollerslev, et al., 2009). As described in the economic underpinnings of this empirical study, the IES intuitively models the market agent responsiveness – or rather sensitivity – towards changes in the growth of consumption. Further, given the Epstein-Zin-Weil recursive preferences behind this model, a preference for early resolution of uncertainty will cause agents to change their consumption patterns based on the persistence in VOV. In particular, with increased persistence in the VOV of consumption growth, market agents will prefer to hold safer assets and hence the price of riskier assets, such as stocks, will fall (the leverage effect) (Bansal & Yaron, 2004). As prices drop, future returns are likely to increase, exactly as predicted by the VRP. Given such interdependency, it is natural to view the VRP as a pure volatility bet, in which the realized variance is risk-neutralized away (Bollerslev, et al., 2009).

The IES will further enhance these findings: for a given level of VOV, the IES will increase the estimated slope coefficient of the VRP – implying that investors are more sensitive to the VOV. However, it is clear from this line of argumentation that the persistence of VOV unanimously and directly influences the VRP: With a more persistent VOV, the isolated variance premium increases in importance to investors, as uncertainty becomes a more integral part of the market, hence permeating the asset pricing decision to a greater degree. Together, the IES and VOV represent a composite effect: If the persistence of VOV is high, volatility represents a central part of asset pricing decisions for prolonged periods, while a higher IES will further compound this effect by intensifying the sensitivity to the given level of uncertainty. However, as these terms are interlinked in the economic model, their effects cannot be directly separated. Hence, in the following paragraphs we study the clues in our findings attempting to disentangle the two effects and how they might separately affect the VRP, considering the current market characteristics and change in investor sentiment.

8.1 The VRP, Investor Sensitivity and Difference Between Risk and Uncertainty

In attempt to explain the lack of predictability, the amplifying effect of consumption growth sensitivity of investors to the volatility risk premium is key. Hence, in order to determine whether such sensitivity has decreased or increased in recent times, it is essential to consider the underpinning effects at work. According to Drechsler (2013), an important explanatory factor of the predictive power of the VRP may arise from the Knightian distinction of risk and uncertainty. In particular, the ability of the VRP to predict future stock returns derives from the risk of jumps in the economy, while this effect is compounded by the market agents' uncertainty in assessing the odds of such jumps. Even in a world of rational market agents, this can result in overestimation of the risk of crashes, as the uncertainty regarding the assigned odds inflates the odds themselves.

After the financial crisis, we have seen an increase in the relative size of the VRP, with a particular inflation after the US election, implying that investors are demanding DOTM puts to a larger degree, driving up the VIX relatively more than the development in the realized variance would entail in terms of actual potential tail risk. The divergence of the VRP and the RV follows the line of arguments presented by Chen, et al. (2014), who also find that investor perceived crash risk may be higher than the actual crash risk in the market and that the difference may contract or expand over time. As the original formulation of the VRP does not separate risk and uncertainty, the lack of significance might be caused by a divergence in these two factors: while the current perceived uncertainty is high, the actual crash risk is low given the apparent market tranquility. Thus, investors seem unable to assign probabilities with certainty, perhaps because investor psyche remains affected by the GFC, or because it has become stirred by the new unstable political sphere. Regardless of such high uncertainty, with a low actual crash risk, the product of these two will continue to be limited. Contrarily, in a highly volatile market, we see an amplified effect: in the GFC subsample, where both the RV and the VRP are high, we expectedly find strong predictability for the VRP.

In terms of understanding investor sentiment in relation to Trump and his influence on the economy, this distinction between actual risk and investor perceived uncertainty may offer further insight: As we pointed out within the analysis, Trump's economic and military tweets seem to act as risk relievers. This effect might be due to investors regarding the uncertainty of Trump's overall political agenda and the manner in which this is conducted to be worse than the policies actually proposed and approved. Such fear of political instability follows the findings on the German and Pakistani markets (Bittlingmayer, 1998; Nazir, et al., 2014). Furthermore, as Jensen & Schmith (2005) argued in their "Candidate Uncertainty" hypothesis, uncertainty regarding the policies of a popular presidential candidate can be a key driver for market volatility. Hence, by utilizing the distinction of risk and uncertainty (Drechsler, 2013), we may be better equipped to explain how the seemingly irrational and unpredictable Trump does not generate higher volatility in the market with his tweets:

It may be that, in the era of Trump, investors assign some non-zero probability to the implementation of policies, however, due to the unpredictable nature of the current president, this probability becomes assigned with higher uncertainty. This higher uncertainty causes investors to become fearful, spurring demand for DOTM puts, and skewing the volatility surface into a more pronounced smirk, inflating the VIX. The tweets then act as a relief of the uncertainty, as investors can now more accurately place odds on the policies in question. Since the compounding effect of uncertainty is reduced, the VIX index drops – in our empirical findings, 20 minutes following the tweet. The detected drop in implied volatility following a tweet is then not a relief of overall uncertainty, but rather the uncertainty induced by the Trump administration itself.

8.2 Behavioral Finance Within the World of Trumponomics

While Dreshler's (2013) distinction explained how rational agents in the post-Trump world may overestimate crash risk, the field of behavioral finance offers a similar justification based on the actions of *irrational* agents, namely through the idea of prospect theory (Driessen, et al., 2014). A key feature of prospect theory is the ability to capture how strong shocks continue to permeate investor psyche: Given that investors have a combination of strong loss aversion and a tendency for distorted probability assessment, it seems likely that an old and severe shock, such as the GFC, continues to affect investor preferences nearly a decade later. Hence, investors continue to have a heighted fear of potential crashes today.

Our finding of a relatively larger VRP thus may lend support to this argument: In prospect theory, when the probability of an extreme event changes, as above, perception and probability enters multiplicatively. Hence, while investors continue to overestimate the risk of crashes following the financial crisis, the actual crash risk is low. Thus, the multiplicative effect of these two factors is not strong enough to afford the VRP significant predictability. This may also explain the importance of the volatility spikes in the post-election sample – and hence why winsorization causes the significance of the VRP to disappear: If we effectively cap extreme tail risks (of which there are very few in the post-election sample), the remaining magnitude of the shocks is not large enough to drive VRP predictability.

Considering the risk relieving effect of Trump Tweets, a similar argument applies as in the world of rational agent assumptions (Drechsler, 2013): The tweets can be seen to reduce the distorted probability assessments, as they offer some degree of certainty about the future development of the US economy and military. Not only does this carry important implications regarding how the market perceives Trump, but it can also form the basis of a profitable trading strategy – both in terms of augmenting understanding of the drivers of the VRP, but also as a direct, intraday trading strategy in VIX futures as seen above.

8.3 Volatility-of-volatility and Changes in Crash Risk

Persistence in VOV is assumed to be the sole 'direct' driver of a positive VRP, which is particularly true in terms of jump risk in the left tail (Bollerslev, et al., 2009; Bollerslev, et al., 2015). The general market recovery period after the GFC, including the Trump era, has been described as constituting a stable market setting, however it is especially tranquil during the post-election sample. Hence, the sample shows low probability of crashes and persistence of these, with the exception of the jump in volatility in February 2018. As mentioned above, it is thus not surprising that we lose significance for the post-election sample, contrary to other samples, when we apply winsorization techniques, as this removes the large spike, which is assumed to drive at least some of the predictability.

Given the political focus of this paper, it is important to note that the volatility jump was, to a large degree, not politically driven or motivated. One could argue that the representation of Trump as a person and a politician throughout this paper may have been affected by the European mindset of the authors, and that the detected results for the VIX are not as surprising, as they might otherwise seem. Arguably, many of Trump's policies are good for the US stock market; examples cover tax cuts for firms, more military spending (increasing economic activity through the military-industrial complex), and protection of US-based steel producers among others.

If Trump is not the facilitator of risk or perceived uncertainty, the lack of significance must be triggered by some other factor(s). Another theory that may explain the lacking predictability of the VRP, is that it seems to fail in periods of low volatility. Like the Trumponomics subsample, the pre-GFC subsample was generally characterized by more peaceful market conditions. However, in previous periods of high instability (GFC) or relatively normal levels of volatility (post-GFC/pre-election) the VRP seems to be a successful and dominant predictor. What these last-mentioned periods seem to have in common, is the larger persistency of the VOV, as well as having the compounded effect of VOV and IES moving in the same 'direction'. Hence, not only is the risk higher with some probability, the uncertainty regarding the reference model is also higher (Drechsler & Yaron, 2009).

Nevertheless, whether the VRP simply is not modelled towards capturing low persistence in VOV or that the VOV dynamics have changed, it seems that model modifications could potentially yield better results in terms of predictability and insight into the current investor sentiment. One such solution can be found in the idea of a decomposed VRP as presented by Kilic & Shaliastovich (2017) and Segal, et al. (2015). The decomposition makes it possible for the model to capture upside and downside volatility differently, which is of utmost relevance as they carry relationships of opposite signage with regards to expected return. Investors like good uncertainty, as it increases the potential for substantial gains, whereas bad uncertainty carries an increased probability of extreme losses. Given that we, during the Trumponomics sample, see at least one large negative spikes, and few strong positive spikes, a decomposed VRP may more accurately capture investor perception of risk for the subsample.

Another potential modification, could be direct modeling of risk jump-diffusion (Pan, 2002; Eraker, 2008; Broadie, et al., 2007; Drechsler & Yaron, 2009), which might seem appropriate for this subsample in particular. Given the aim of constructing a VRP variable that accurately depicts investor sentiment and further can form the basis of a profitable trading strategy viable across multiple economic cycles, it is important that a model does not simply apply to the world of today, but also the world of tomorrow. Hence, the inclusion of model modifications, such as those suggested, may be of help to the investor going forward.

8.4 Final considerations

As evidenced by the increased importance of the VRP as a constituent part of the VIX, it seems that, despite a relatively tranquil market, investors continue to fear potential crashes: they seem to react very strongly to potential changes in the future volatility of consumption growth, even more so than in previous periods. This is not simply a factor in our theoretically based discussion above; in terms of more empirical evidence, the historical spike in the VIX index in February 2018 followed a job report, which due to the increasing employment in the US economy, may translate into rising wages and hence inflation in the future (Varathan, 2018). While such factors should naturally be considered in asset prices today, it may be argued that the reaction in the VIX was surprisingly strong considering the overall positive news. Given the discussion above, such a strong reaction might have several foundations, including that investors face a high level of uncertainty in the decision-making process (in line with the argument of Drechsler (2013)) or that investors have strongly distorted probability assessments, following a prospect theory argument.

In similar manner, the finding of Trump as a risk reliever in the market, could be an expression of cautionary optimism towards Trump in either of two ways: Firstly, the unpredictable nature of the US president may cause uncertainty regarding his policies to be build up in the market, which is then relieved when the tweet is posted. Thus, in either a Knightian uncertainty argument, or through distorted probability assessment, the strength of the multiplicative effect of uncertainty is lessened. Alternatively, investors could simply find the content of the tweets to be beneficial to the US economy, and that the increased relative importance of the VRP in implied variance is due to a lack of faith in the existence of a greater political agenda. Naturally, in the middle of the presidential term it is difficult to accurately determine the full effect of Trump on the market. Hence, such conclusions are perhaps better made in the future with the benefit of hindsight.

A disconnect between the actual crash risk and the level of fear of these crashes could be an underlying reason of why the predictive power of the VRP is not as robust in the post-election world: The general level of risk in the market is simply not large enough to drive predictability on a robust foundation without a greater volume of spikes or stronger persistence of these spikes. Overall, it seems that investors are in a relatively calm market with both low volatility and persistence of VOV, but do not expect this market state to continue forever. Model modification to the VRP, such as a decomposition of the volatility or direct inclusion of jump risk, may provide a VRP estimate capable of capturing these specific market dynamics, yielding a more robust predictor in this subsample and beyond.

9 Conclusion

As evidenced by the scope of previous literature, along with the poor track record of market timing efforts, it seems that the enigma of the equity premium remains to be decoded. This is especially true for the short to intermediate term horizons, in which it seems that investment decisions are opaque. As agents are known to be risk averse, which seems to cause the volatility smirk via demand for insurance-like strategies in states of market uncertainty, the VRP gains predictive power in the short-medium term horizon through the leverage effect or a fear of crashes, or a combination of the two.

Over the past two decades, the world has weathered all stages of the economic cycle: from the expansion of the 00's creating the housing bubble, which culminated with the Lehman crash and credit crunch of 2007, resulting in the contraction known as the Global Financial Crisis ("GFC"), to the economic recovery beginning in Q3 2009. The GFC was the most severe crash since the Great Depression, wreaking havoc and creating highly volatile markets within and without the US, making the road to recovery from the trough of the cycle long and winding. Nevertheless, the economy has now reached a new, expansionary market state, characterized by tranquility: low volatility and interest rates have spurred investors to search for yield, driving stock markets to soar to new highs. For the first time since the end of the recession, the economy is now outperforming most predictions including a positive gap between realized and potential GDP (Federal Reserve Bank, 2018), which is only expected amplified throughout 2018 (Hatzius, et al., 2017). Given the uniqueness of the financial markets post-GFC, it seems even more appropriate to test the VRP's predictability throughout this time period, as the variable seeks to capture the potential manifestation of perceptions of uncertainty in asset prices. Moreover, the thesis is further motivated by the relatively small body of literature published after the GFC, and through its systemized, deductive methodological approach it aims to fill the void within academia of whether the dominant predictive prowess of the VRP remains today and what information it may carry regarding investor sentiment.

On a model-free formulation, the VRP provides robust evidence of dominant predictability relative to traditional variables on a 3.5-month return horizon on the S&P 500 index for the entire sample period, stretching from January 2002 to September 2017. The thesis furthermore presents robust results for an outward shift in predictability of the VRP towards a 4-months return horizon after the GFC, and stronger predictability and explanatory power than the findings in the BTZ paper for this time period. Hence, the natural behavior of uncertainty avoidance permeates through our findings, confirming the importance of risk aversion in investment decisions as suggested by Adam Smith (1776 / 1997) and Menger (1871 / 2007). Following the period of high volatility in the GFC, where consumer confidence and the financial markets hit rock bottom, the results of this thesis suggest that a shift in investor sentiment occurred. Put simply, the VRP predictability seems to be driven by two dynamics – persistence in volatility-of-volatility ("VOV") and the elasticity of intertemporal substitution ("IES"). While the general volatility is lower post-GFC, it seems that a combined effect of higher persistence of VOV and higher IES created this shift in the VRP predictability. In this post-GFC world, shocks to volatility take longer to die out and furthermore, as the IES can be seen as the level of sensitivity to shocks, investors remain even more fearful of potential shocks, that is, it seems as if they have tightened the seat belts in fear of what lies ahead.

Viewing the VRP as a pure volatility bet, this illustrates how the investors' fear of tail risk has increased, and how investor sentiment is hyper-sensitive to changes in the volatility-of-volatility, inflating the importance of volatility spikes. The significance of these results is not just relevant within the sphere of academia but could also be of use for practitioners. Understanding investor sentiment thus seems key if one seeks to understand the riddle of future stock yields. Hence, this thesis proves that it can be profitable to trade on fear, by following a market timing strategy utilizing our findings, which follows the mantra of Warren Buffett, "*We simply attempt to be fearful when others are greedy and to be greedy only when others are fearful.*" (Buffett, 2018).

Not only did the recovery from the GFC result in tranquility of financial markets – the new world also brought on a tumultuous political epoch, including the Brexit and the inauguration of President Donald J. Trump. While politically driven volatility has been scrutinized in earlier literature, never before have the dots between political uncertainty and the VRP been connected. The Trump Era has yielded less volatility and higher returns, but more importantly, the composition of the implied variance has been altered; the VRP makes up much more of the implied variance relative to the realized variance after the election. Subsequently, the otherwise proven dominant predictability of the VRP is found to be unrobust, although yielding higher coefficients than before at the 4-month return horizon. In an attempt to elucidate these findings, Trump's tweets are analyzed to test whether he is at fault for the relative increase in investor uncertainty. Contrarily to popular beliefs of both the authors and media, Trump's economic and military tweets act as risk *relievers* in a significant manner in terms of implied variance as well as the VRP, most strongly 20 minutes after a tweet.

Many possible explanations for the evolvement of the VRP's predictability – or lack thereof – exist, as well as to why the investors seem to be relieved 20 minutes after Trump tweets. As the IES seems to be inflated, even compared to the pre-election period, this entails that the prevalence of fear seems intensified in the investor sentiment after the election of Trump, the latest evidence seen with the extreme spike of the VIX in February 2018. While this might be driven by Knightian uncertainty regarding Trump's political agenda, the persistence in VOV also seems to have decreased in the Trump Era, and as such the multiplicative effect of risk and uncertainty is lessened, yielding the VRP's significance and robustness to be inferior relative to earlier samples or other predictors. However, while Trump tweets prove to be risk relievers, it might be from uncertainty that Trump has induced himself. As to whether he is following a Madman theory strategy (Thompson, 2018) or is rather driven by spontaneous urges towards action rather than inaction, one can only speculate.

Nevertheless, the weakening of the VRP's predictive prowess towards returns poses a conundrum. Intuitively, as well as economically, it makes sense that if one understands the current volatility setting and investors sensitivity towards that level of uncertainty, it should convey some information about future asset prices – which is also a key conclusion of this thesis. However, although the new market has yielded higher stock prices while realized and implied variances have reached new lows, investors seem more sensitive to potential tail risk than ever before, triggering a disconnect between the VRP and excess returns. Hence, the BTZ proposed model-free formulation of the VRP as a predictor may require modifications, in order to capture the true essence of what lies ahead. Whether that is distinguishing between good and bad volatility or the inclusion of a jump-diffusion parameter, is for future research to determine. With continued economic expansion and a potential risk of overheating, we may also face different market characteristics in terms of higher interest rates and inflation sooner rather than later. This only makes the modifications more important both within the field of academia and practice, as it can aid agents in understanding future investor sentiment, predicting asset prices and determining political impact on market volatility in the Era of Trumponomics and beyond.

10 Further Research

From our discussion above it becomes clear that, while our analysis has helped expand the knowledge base of the VRP and investor sentiment in the post-GFC and Trump Era markets, several questions remain, especially regarding the underlying drivers of the observed tendencies. While we have attempted to outline possible reasons, we remain limited by the scope of this paper. Hence, in the following, we seek to outline areas, which may be of interest for future research.

A particular issue made clear in both in our interpretation of results and our discussion is the inability to disentangle the separate effects of the persistence in VOV and IES. Given that the IES is difficult to estimate, the most viable route seems to be the study of persistence in VOV, however, due to our variance construction from rolling returns, this becomes unstable, while additional measures would muddle the analysis with an overabundance of metrics. Future studies may thus focus on studying the persistence through other avenues, either through a different construction of the realized variance or by a proxy - an example of an approach could be through the persistence in implied volatility from options on the VIX (the VVIX index). Additionally, the distinct impacts of the leverage effect and the fear of crashes is unclear, hence, future studies could also focus on studying these more separately. One could do so by looking at the CBOE SKEW index, which measures the probabilities of extreme outlier returns from options data and is further indicative of a steepening or flattening of the implied volatility surface (CBOE, 2018b). Lastly, model improvements that directly include a decomposition of the VRP and jump risk may further yield interesting insights into the predictability of the VRP and investor sentiment.

This paper's study of political impact on the VRP and its components took the form of a case study of the Trump Era, however, it may of interest to study whether our findings hold in both a broader temporal, spatial and methodological sense. Hence, future research may apply our methodology to other geographical markets looking at the impact of political leaders in these geographies. Alternatively, studies could examine the impact of other political leaders in the US, for example President Obama during his presidency, or Hillary Clinton during the presidential candidacy. Additionally, other methodological approaches are available, for example by quantifying political risk through the use of such metrics as Caldara and Iacoviello (2018)'s Geopolitical Risk Index. Not only would this broaden the spatial scope of the study, it would also provide a timeframe stretching back to 1985 (for daily data) or 1899 (for monthly data), hence allowing for a very broad study of the effect of politics on the VRP and investor sentiment in both a spatial and temporal sense.

Through our analysis, we find that Trump seems to act as a risk reliever and theorize that this relief may stem from uncertainty that the President has induced himself. However, to draw conclusions from such considerations, further studies are required. A potential approach could be to study the development in the VRP and its components *prior* to a Tweet (contrarily to our methodology, which studied the development after). Doing so would allow the researcher to study whether the Tweets seem to cause relief from pent-up uncertainty or whether they constitute a true positive event. In a likewise manner, we have discussed the possibility of whether our surprise at the results are due to a European mind-set: in an American view, many of Trump's policies should, at least in the short term, lead to more stable markets given the general pro-business content. From this, it may be interesting to study both whether European markets react to Trump tweets at all and whether a reaction has similar signage to the US. Lastly, the recent thaw in the relationship between North and South Korea may be an early indication of a change in the political calculus: Perhaps, Trump's apparent unpredictability is not a measure of his character, but rather a Nixon-like 'Madman' theory strategy (Thompson, 2018). However, given the novelty of the development, such considerations and their potential impact on the financial markets, are better to left future research, which may benefit from greater retrospection.

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Appendices

A

Overview of Appendices:

Appendix A: Glossary

Abbreviation	Full denotation
ARCH	Autoregressive Conditional Heteroscedasticity
ATM	At-the-money (regarding options)
BS	Black-Scholes(-Merton) option pricing model
BTZ	Bollerslev, et al. (2009) study
CAPM	Capital Asset Pricing Model (Merton, 1973)
CAY	Consumption-Wealth Ratio
CBOE	Chicago Board of Exchange
DOTM	Deep-out-of-the-money (regarding options)
EGARCH	Exponential Generalized Autoregressive Conditional Heteroscedastic (model)
ERV	Expected realized variance (modelled with MC-GARCH)
GARCH	Generalized Autoregressive Conditional Heteroscedastic (model)
GBM	General Brownian Motion
GFC	Global Financial Crisis
IES	Intertemporal Elasticity of Substitution
ITM	In-the-money (regarding options)
IV	Implied variance
LRR	Long Run Risks model (Bansal & Yaron, 2004)
MC-GARCH	Multiplicative Component Generalized Autoregressive Conditional Heteroscedastic (model)
MN	Moneyness
OTM	Out-of-the-money (regarding options)
P/D	Price-dividend ratio
P/E	Price-earnings ratio
RREL	Relative risk-free rate (stochastically de-trended risk-free rate)
RV	Realized variance
SPX	S&P 500 index
SPX VIX	Volatility index constructed from S&P 500 options (CBOE, 2018)
VIX	Volatility index constructed from S&P 500 options (CBOE, 2018)
VOV	Volatility-of-volatility
VRP	Variance risk premium
vrp	Volatility risk premium
VVIX	Volatility-of-volatility measure constructed from options on the VIX (CBOE,2018)

Appendix B: Overview of MC-GARCH modelled output

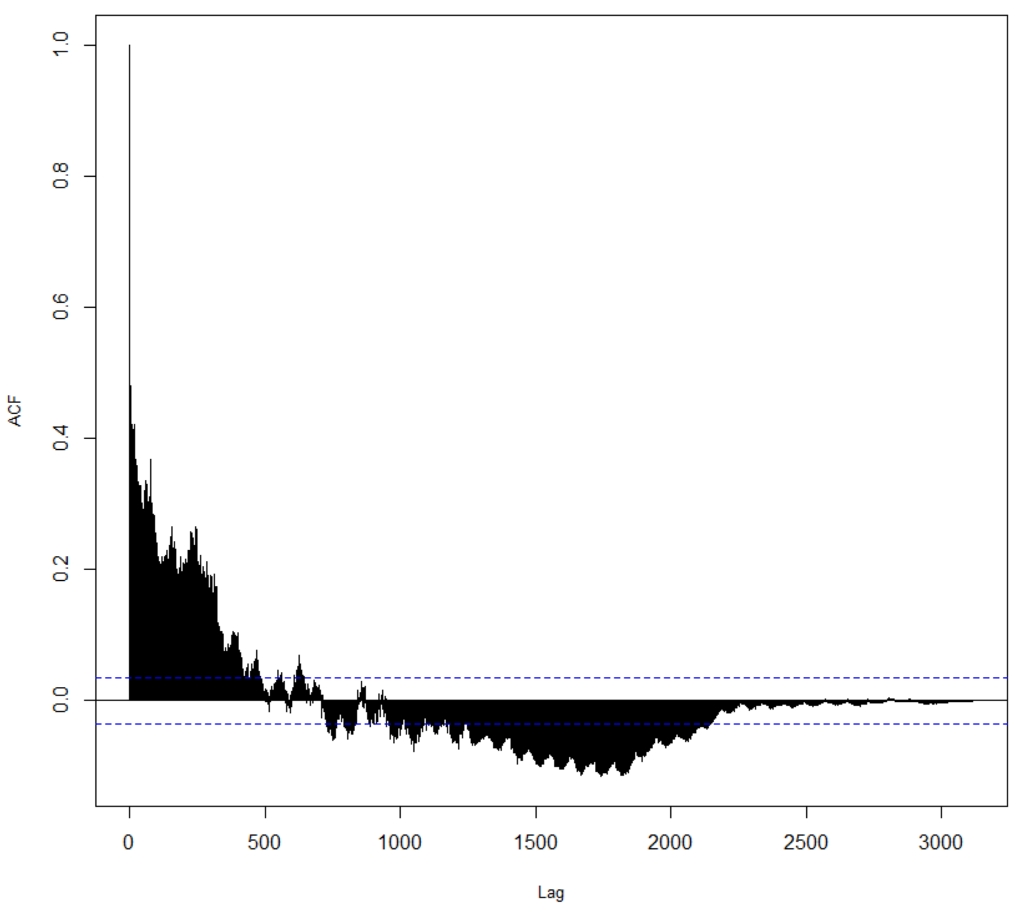
Table B.1: Overview of information criteria for *daily* variance

Information criterion	GARCH (1,1)	EGARCH(1,1)
AIC (Akaike)	-6.5354	-6.5676
BIC (Bayesian)	-6.5262	-6.5573
Shibata	-6.5354	-6.5676
Hannan-Quinn	-6.5322	-6.5640

Table B.2: Parameter estimates from MC-GARCH model

	μ	$AR(1)$	$MA(1)$	ω	α	β	γ	Skew	Shape
Mean	0.00005	-0.04892	0.01084	-0.85544	0.23469	0.91082	-0.03792	0.25013	7.39760
Std. Dev	0.00088	0.60291	0.62295	1.26432	0.12398	0.12870	0.14960	0.24410	8.59474

Figure B.1: Correlogram of 5-minute absolute returns on the S&P 500 Index for the period stretching from January 1st 2018 to February 28th 2018



Appendix B: Overview of MC-GARCH modelled output (continued)

Figure B.2: Overview of components of MC-GARCH model, for the period stretching from January 1st 2018 to February 28th 2018

Appendix C: Overview of included control variables

Variable	Description	Source
US 3-month Treasury Bill		Federal Reserve Bank of St. Louis (2018)
Default spread	Spread between Moody's BAA and AAA bond indices	Federal Reserve Bank of St. Louis (2018)
Term spread	The difference between the rates on the US 10-year Treasury Bond the US 3-Month Treasury Bill	Federal Reserve Bank of St. Louis (2018)
Relative Risk-free Rate (RREL)	Stochastically detrended risk-free rate; the US 3-month minus its backward twelve-month trailing average	Federal Reserve Bank of St. Louis (2018)
Consumption-Wealth Ratio (CAY)	Log of consumption wealth ratio is defined as: $cw_t \equiv log\left(\frac{C_t}{W_t}\right) = c_t - w_t$, in which W_t denotes the total wealth, while C_t denotes the aggregate consumption.	As empirically defined in Lettau & Ludvigson (2001) and retrieved from their website
Price-earnings ratio (P/E)	The price of the S&P 500 index divided by an index of last year's earnings for the constituent firms: ${}^{P}/_{E} = \frac{P_{SPX}}{E_{SPX}}$ Based on trailing 12-month averages on realized earnings as reported by brokers.	FactSet (2018)
Price-dividend ratio (P/D)	The price of the S&P 500 index divided by an index of last year's dividends for the constituent firms: ${}^{P}/_{E} = \frac{P_{SPX}}{D_{SPX}}$ Based on trailing 12-month averages on realized dividends as reported by brokers.	FactSet (2018)

Appendix D: Output from ADF tests and ARCH tests

Table D.1: Augmented Dickey-Fuller Test

Variable	Test-statistic	Critical values 1%	5%	10%
r_{SPX}	-17.057	-3.43	-2.86	-2.57
$(r_{SPX} - r_m)$	-11.513	-3.43	-2.86	-2.57
RV_t	-6.637	-3.43	-2.86	-2.57
IV_t	-3.9114	-3.43	-2.86	-2.57
VRP_t	-10.127	-3.96	-3.41	-3.12
ERV_t	-5.935	-3.43	-2.86	-2.57
ERP_t	-8.849	-3.43	-2.86	-2.57
$\log(P/E)_t$	-2.306	-3.43	-2.86	-2.57
$\log(P/D)_t$	0.688	-3.43	-2.86	-2.57
$DFSP_t$	-2.412	-3.43	-2.86	-2.57
$TMSP_t$	-1.940	-3.43	-2.86	-2.57
CAY_t	-3.141	-3.96	-3.41	-3.12
$RREL_t$	-2.607	-3.43	-2.86	-2.57

Table D.2: ARCH heteroscedasticity test for residuals, 5-minute returns on the S&P 500

Portmanteau-Q test

Order	PQ	P-value
4	54,864	0.00
8	82,085	0.00
12	90,951	0.00
16	99,244	0.00
20	106,636	0.00
24	112,052	0.00

Langrange-Multiplier test

Order	LM	P-value
4	374,516	0.00
8	160,916	0.00
12	105,121	0.00
16	77,725	0.00
20	61,491	0.00
24	50,986	0.00

Appendix E: Overview of summary statistics

Summary statistics

	Mean	Std. dev	Skew	Kurt.	AR(1)
$r_{SPX} - r_f$	3.712	56.701	-1.418	6.261	0.937[1]
ERV_t	26.770	73.236	12.896	269.786	0.602
RV_t	24.268	44.157	5.917	44.302	0.997
IV_t	39.453	48.019	4.150	24.208	0.979
VRP_t	15.389	21.013	-0.393	31.432	0.900
$EVRP_t$	13.308	53.274	-22.879	802.562	0.269
CAY_t	-0.008	0.015	0.290	-0.442	0.997
$(P/E)_t$	16.351	2.334	0.128	0.396	0.996
$(P/D)_t$	0.039	0.012	0.273	-0.779	0.997
$RREL_t$	-0.063	0.631	-1.066	2.579	0.996
$DFSP_t$	1.094	0.463	2.779	9.402	0.999
$TMSP_t$	2.054	1.062	-0.623	-0.270	0.998

[1] AR(1) process for excess returns shows significant autocorrelation due to mechanical autocorrelation created by summing returns over the monthly horizon. The AR(1) process without summing returns shows a coefficient of -0.08, which is not significant at the 5%-level.

Appendix E: Overview of summary statistics

Full correlation Matrix

	$(r_{SPX}-r_m)_{t-t+1}$	ERV_t	RV_t	IV_t	VRP_t	$EVRP_t$	CAY_t	$(P/E)_t$	$(P/D)_t$	$RREL_t$	$DFSP_t$	$TMSP_t$
$(r_{SPX}-r_m)_{t-t+1}$	1											
ERV_t	-0.461	1										
RV_t	-0.433	0.648	1									
IV_t	-0.500	0.687	0.901	1								
VRP_t	-0.241	0.221	-0.026	0.410	1							
$EVRP_t$	0.180	-0.751	-0.071	-0.035	0.069	1						
CAY_t	-0.203	0.282	0.397	0.532	0.391	0.095	1					
$(P/E)_t$	0.066	-0.240	-0.370	-0.344	-0.016	0.017	-0.122	1				
$(P/D)_t$	-0.052	0.052	0.070	0.205	0.325	0.114	0.747	0.276	1			
$RREL_t$	0.204	-0.322	-0.448	-0.492	-0.191	-0.004	-0.373	0.161	-0.054	1		
$DFSP_t$	-0.203	0.463	0.733	0.766	0.224	0.060	0.381	-0.497	0.062	-0.535	1	
$TMSP_t$	-0.018	0.127	0.203	0.283	0.225	0.082	0.312	0.105	0.281	-0.361	0.222	1

Appendix F: Summary statistics of Trump Tweets

Month	Total no. of tweets	Economics	Political	Featured Democrats*	Military	Presidential Duties	Personal	Other	Fake News*
Nov-16	98	1	49	9	2	17	28	1	0
Dec-16	132	16	36	12	9	35	36	0	1
Jan-17	207	12	85	20	6	31	72	1	11
Feb-17	152	5	47	10	9	38	53	0	18
Mar-17	133	15	54	13	3	28	30	3	7
Apr-17	138	7	52	22	7	31	40	1	3
May-17	146	9	51	19	1	45	38	2	12
Jun-17	175	5	92	25	8	29	41	0	12
Jul-17	228	18	77	26	8	57	67	2	16
Aug-17	197	9	68	10	5	68	46	1	18
Sep-17	234	9	64	12	4	92	56	4	9
Oct-17	257	35	83	43	8	71	51	3	25
Nov-17	250	38	80	18	23	51	58	3	13
Dec-17	190	48	56	16	12	26	49	1	22
Jan-18	206	31	95	40	14	33	34	2	9
Feb-18	160	12	68	16	2	37	42	1	9
Total	**2,903**	**270**	**1,057**	**311**	**121**	**689**	**741**	**25**	**185**
Inside trading hours (NYSE)	774	78	251	58	34	244	164	3	36
Outside trading hours (NYSE)	2,129	192	806	253	87	445	577	22	149
Inside trading hours (CBOE)	811	82	260	61	35	261	170	3	37
Outside trading hours (CBOE)	2,092	188	797	250	86	428	571	22	148

Appendix G: VRP 3.5 month return regressions, full sample from Jan. '02 to Sep. '17

	Dependent variable: $(r_{SPX} - r_m)_{t \to t+3.5}$														
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
VRP_t	0.264***									0.279***	0.413***	0.396***		0.490***	0.457***
	(3.602)									(3.978)	(4.603)	(5.346)		(5.235)	(5.997)
IV_t		-0.016													
		(-0.203)													
RV_t			-0.085												
			(-1.147)												
$\log(P/E)_t$				-38.656						-40.738*			-41.069	-46.561**	-50.882**
				(-1.269)						(-1.744)			(-1.416)	(-2.563)	(-2.054)
$\log(P/D)_t$					-7.862										-9.340
					(-0.648)										(-1.522)
$DFSP_t$						-2.936									-5.628
						(-0.224)									(-0.775)
$TMSP_t$							-1.562								2.049
							(-0.469)								(0.873)
CAY_t								-2.873			-5.307**		-0.688	-3.300	
								(-0.816)			(-1.989)		(-0.242)	(-1.482)	
$RREL_t$									13.181**			16.390***	12.867**	14.518***	16.118***
									(2.368)			(4.288)	(2.530)	(3.462)	(2.589)
Constant	-0.200	4.760	6.238	111.846	-21.652	7.330	7.356	1.864	5.597	113.114*	-6.742	-0.481	119.502	124.996**	111.662
	(-0.050)	(1.007)	(1.213)	(1.297)	(-0.522)	(0.606)	(1.349)	(0.273)	(1.426)	(1.714)	(-1.241)	(-0.162)	(1.462)	(2.497)	(1.480)
Observations	3,850	3,850	3,850	3,850	3,850	3,850	3,850	3,850	3,850	3,850	3,850	3,850	3,850	3,850	3,850
R^2	0.036	0.001	0.015	0.037	0.006	0.002	0.003	0.020	0.088	0.077	0.093	0.164	0.130	0.231	0.226
Adjusted R^2	0.036	0.0004	0.015	0.037	0.006	0.002	0.003	0.020	0.088	0.076	0.092	0.163	0.130	0.230	0.225

Note: *Parentheses denote t-statistics* $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Appendix H: EVRP 4-month return regressions, full sample from Jan. ‘02 to Sep. ‘17

	Dependent variable:														
	$(r_{SPX} - r_m)_{t\to t+4}$														
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
$EVRP_t$	0.079**									0.083**	0.087**	0.085**		0.091**	0.088**
	(2.201)									(2.147)	(2.260)	(2.312)		(2.319)	(2.185)
IV_t		-0.008													
		(-0.098)													
ERV_t			-0.065												
			(-0.808)												
$\log(P/E)_t$				-39.644						-40.835**			-41.086	-42.570**	-45.301*
				(-1.348)						(-2.059)			(-1.389)	(-2.271)	(-1.912)
$\log(P/D)_t$					-7.848										-1.961
					(-0.673)										(-0.292)
$DFSP_t$						-1.382									-1.197
						(-0.110)									(-0.129)
$TMSP_t$							-1.295								2.566
							(-0.405)								(1.246)
CAY_t								-2.529			-2.862		-0.1269	-0.640	
								(-0.723)			(-1.286)		(-0.096)	(-0.306)	
$RREL_t$									13.026*			13.256***	12.981**	12.900***	14.377**
									(1.947)			(3.263)	(2.041)	(3.080)	(2.515)
Constant	2.979	4.435	5.735	114.595	-21.595	5.607	6.786	2.144	5.639	116.745**	0.667	4.480	119.956	122.524**	120.399
	(0.829)	(0.948)	(1.071)	(1.378)	(-0.533)	(0.482)	(1.286)	(0.307)	(1.468)	(2.086)	(0.139)	(1.416)	(1.447)	(2.307)	(1.525)
Observations	3,850	3,850	3,850	3,850	3,850	3,850	3,850	3,850	3,850	3,850	3,850	3,850	3,850	3,850	3,850
R^2	0.022	0.0002	0.010	0.043	0.007	0.0005	0.002	0.017	0.096	0.068	0.044	0.122	0.142	0.172	0.178
Adjusted R^2	0.022	-0.0001	0.009	0.043	0.007	0.0002	0.002	0.017	0.096	0.067	0.044	0.122	0.142	0.171	0.177

Note: *Parentheses denote t-statistics* $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Appendix I: Intraday regressions between S&P 500 returns and key variables,

Table I.1: VRP, full sample from January 2002 till February 2018

	Dependent variable:											
	Hourly return			Return per 2 hours			Half day returns			Daily returns		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$VRP_{t-1hour}$	1.104**	1.176**	1.027**									
	(2.474)	(2.572)	(2.135)									
$RV_{t-1hour}$		0.149										
		(0.639)										
$IV_{t-1hour}$			0.149									
			(0.640)									
$VRP_{t-2hours}$				1.064**	1.044**	1.085**						
				(2.310)	(2.128)	(2.197)						
$RV_{t-2hours}$					-0.041							
					(-0.147)							
$IV_{t-2hours}$						-0.041						
						(-0.151)						
$VRP_{t-half\ day}$							1.120**	1.114*	1.127**			
							(2.053)	(1.944)	(1.996)			
$RV_{t-half\ day}$								-0.013				
								(-0.040)				
$IV_{t-half\ day}$									-0.013			
									(-0.040)			
VRP_{t-1day}										1.270**	1.282**	1.258**
										(2.232)	(2.107)	(2.272)
RV_{t-1day}											0.024	
											(0.058)	
$IV_{t-1\ day}$												0.024
												(0.058)
Constant	-10.895*	-15.78**	-15.78**	-10.190	-8.858	-8.858	-9.650	-9.227	-9.227	-10.697	-11.475	-11.475
	(-1.657)	(-1.964)	(-1.961	(-1.505)	(-0.961)	(-0.987)	(-1.231)	(-0.840)	(-0.840)	(-1.299)	(-0.853)	(-0.858)
Observations	265,588	265,588	265,588	265,588	265,588	265,588	265,588	265,588	265,588	265,588	265,588	265,588
R^2	0.002	0.002	0.002	0.002	0.002	0.002	0.004	0.004	0.004	0.009	0.009	0.009
Adjusted R^2	0.002	0.002	0.002	0.002	0.002	0.002	0.004	0.004	0.004	0.009	0.009	0.009
Note:	*Parentheses denote t-statistics*									*p<0.1; **p<0.05; ***p<0.01		

Table I.2: Intraday VRP, pre-financial crisis sample, January 2002 till December 2007

	Dependent variable:											
	Hourly return			Return per 2 hours			Half day returns			Daily returns		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$VRP_{t-1hour}$	0.463	0.106	-0.566									
	(0.865)	(0.181)	(-0.547)									
$RV_{t-1hour}$		0.672										
		(1.052)										
$IV_{t-1hour}$			0.672									
			(1.052)									
$VRP_{t-2hours}$				0.322	0.121	-0.258						
				(0.523)	(0.181)	(-0.235)						
$RV_{t-2hours}$					0.379							
					(0.589)							
$IV_{t-2hours}$						0.379						
						(0.590)						
$VRP_{t-half\ day}$							0.233	0.049	-0.296			
							(0.301)	(0.061)	(-0.212)			
$RV_{t-half\ day}$								0.345				
								(0.403)				
$IV_{t-half\ day}$									0.345			
									(0.401)			
VRP_{t-1day}										0.200	0.023	-0.311
										(0.204)	(0.022)	(-0.171)
RV_{t-1day}											0.334	
											(0.304)	
$IV_{t-1\ day}$												0.334
												(0.300)
Constant	-6.969	-13.519	-13.519	-2.864	-6.550	-6.550	0.160	-3.198	-3.198	1.099	-2.139	-2.139
	(-0.867)	(-1.418)	(-1.421)	(-0.32)	(-0.644)	(-0.645)	(0.015)	(-0.245)	(-0.244)	(0.082)	(-0.134)	(-0.133)
Observations	96,414	96,414	96,414	96,414	96,414	96,414	96,414	96,414	96,414	96,414	96,414	96,414
R^2	0.0003	0.001	0.001	0.0002	0.0005	0.0005	0.0002	0.0005	0.0005	0.0002	0.001	0.001
Adjusted R^2	0.0003	0.001	0.001	0.0002	0.0005	0.0005	0.0002	0.0005	0.0005	0.0002	0.001	0.001
Note:	*Parentheses denote t-statistics*									*p<0.1; **p<0.05; ***p<0.01		

Table I.3: Intraday VRP, financial crisis sample, December 2007 till July 2009

	Dependent variable:											
	Hourly return			Return per 2 hours			Half day returns			Daily returns		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$VRP_{t-1hour}$	1.710**	2.279*	1.756*									
	(2.037)	(1.766)	(1.875)									
$RV_{t-1hour}$		0.523										
		(0.879)										
$IV_{t-1hour}$			0.523									
			(0.891)									
$VRP_{t-2hours}$				1.526*	1.840*	1.551*						
				(1.873)	(1.767)	(1.878)						
$RV_{t-2hours}$					0.289							
					(0.613)							
$IV_{t-2hours}$						0.289						
						(0.610)						
$VRP_{t-half\ day}$							1.579	1.973	1.610			
							(1.458)	(1.418)	(1.551)			
$RV_{t-half\ day}$								0.363				
								(0.584)				
$IV_{t-half\ day}$									0.363			
									(0.585)			
VRP_{t-1day}										1.806*	2.312	1.846*
										(1.748)	(1.404)	(1.763)
RV_{t-1day}											0.467	
											(0.518)	
$IV_{t-1\ day}$												0.467
												(0.514)
Constant	-25.594	-85.744	-85.744	-47.20*	-80.40*	-80.402*	-48.712	-90.424	-90.424	-49.661	-103.24	-103.24
	(-0.934)	(-1.498)	(-1.518)	(-1.69)	(-1.783)	(-1.782)	(-1.31)	(-1.517)	(-1.523)	(-1.101)	(-1.276)	(-1.268)
Observations	26,076	26,076	26,076	26,076	26,076	26,076	26,076	26,076	26,076	26,076	26,076	26,076
R^2	0.006	0.008	0.008	0.007	0.008	0.008	0.011	0.013	0.013	0.025	0.031	0.031
Adjusted R^2	0.006	0.008	0.008	0.007	0.008	0.008	0.011	0.013	0.013	0.025	0.031	0.031
Note:	*Parentheses denote t-statistics*											*p<0.1; **p<0.05; ***p<0.01

Table I.4: Intraday VRP, post-financial crisis sample, July 2009 till February 2018

	Dependent variable:											
	Hourly return			Return per 2 hours			Half day returns			Daily returns		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$VRP_{t-1hour}$	0.452	0.456	0.375									
	(1.008)	(0.978)	(0.794)									
$RV_{t-1hour}$		0.081										
		(0.270)										
$IV_{t-1hour}$			0.081									
			(0.274)									
$VRP_{t-2hours}$				0.947	0.957	0.764						
				(1.619)	(1.644)	(1.209)						
$RV_{t-2hours}$					0.193							
					(0.493)							
$IV_{t-2hours}$						0.193						
						(0.489)						
$VRP_{t-half\ day}$							1.245	1.261*	0.970			
							(1.568)	(1.740)	(1.151)			
$RV_{t-half\ day}$								0.291				
								(0.550)				
$IV_{t-half\ day}$									0.291			
									(0.543)			
VRP_{t-1day}										1.487**	1.504**	1.180
										(2.106)	(2.024)	(1.286)
RV_{t-1day}											0.324	
											(0.476)	
$IV_{t-1\ day}$												0.324
												(0.503)
Constant	2.248	0.763	0.763	0.313	-3.239	-3.239	-1.466	-6.810	-6.810	-2.964	-8.922	-8.922
	(0.437)	(0.104)	(0.106)	(0.048)	(-0.361)	(-0.358)	(-0.16)	(-0.604)	(-0.593)	(-0.363)	(-0.695)	(-0.719)
Observations	143,098	143,098	143,098	143,098	143,098	143,098	143,098	143,098	143,098	143,098	143,098	143,098
R^2	0.0002	0.0002	0.0002	0.001	0.001	0.001	0.002	0.003	0.003	0.006	0.007	0.007
Adjusted R^2	0.0002	0.0002	0.0002	0.001	0.001	0.001	0.002	0.003	0.003	0.006	0.007	0.007

Note: *Parentheses denote t-statistics* $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table I.5: Intraday VRP, post-election sample, November 2016 till February 2018

	Dependent variable:											
	Hourly return			Return per 2 hours			Half day returns			Daily returns		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$VRP_{t-1hour}$	1.108	0.925	-0.819									
	(0.229)	(0.198)	(-0.181)									
$RV_{t-1hour}$		1.743										
		(0.690)										
$IV_{t-1hour}$			1.743									
			(0.690)									
$VRP_{t-2hours}$				1.230	0.964	-1.411						
				(0.266)	(0.207)	(-0.385)						
$RV_{t-2hours}$					2.375							
					(0.817)							
$IV_{t-2hours}$						2.375						
						(0.832)						
$VRP_{t-half\ day}$							1.024	0.804	-1.048			
							(0.179)	(0.140)	(-0.239)			
$RV_{t-half\ day}$								1.852				
								(0.605)				
$IV_{t-half\ day}$									1.852			
									(0.610)			
VRP_{t-1day}										2.439	2.253	0.877
										(0.474)	(0.480)	(0.233)
RV_{t-1day}											1.377	
											(0.381)	
$IV_{t-1\ day}$												1.377
												(0.365)
Constant	1.151	-7.116	-7.116	8.216	-2.876	-2.876	11.684	3.167	3.167	2.312	-3.780	-3.780
	(0.037)	(-0.199)	(-0.199)	(0.286)	(-0.072)	(-0.073)	(0.332)	(0.067)	(0.068)	(0.076)	(-0.090)	(-0.085)
Observations	21,317	21,317	21,317	21,317	21,317	21,317	21,317	21,317	21,317	21,317	21,317	21,317
R^2	0.001	0.002	0.002	0.002	0.005	0.005	0.002	0.004	0.004	0.016	0.018	0.018
Adjusted R^2	0.001	0.002	0.002	0.002	0.005	0.005	0.002	0.004	0.004	0.016	0.018	0.018
Note:	*Parentheses denote t-statistics*									$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$		

Appendix J: VRP 3.5-month return regressions, pre-financial crisis sample (January ‘02 to December ‘07)

	Dependent variable:														
	$(r_{SPX} - r_m)_{t \to t+3.5}$														
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
VRP_t	0.140									0.396***	0.220	0.386**		0.133	0.123
	(0.986)									(3.475)	(1.640)	(2.444)		(1.141)	(1.581)
IV_t		0.045													
		(0.497)													
RV_t			-0.023												
			(-0.153)												
$\log(P/E)_t$				-103.987**						-133.112**			-187.349***	-180.616***	-307.105***
				(-1.992)						(-2.409)			(-3.064)	(-3.045)	(-6.280)
$\log(P/D)_t$					-18.157										91.050*
					(-0.477)										(1.670
$DFSP_t$						-34.611									-58.799***
						(-0.980)									(-3.033)
$TMSP_t$							-3.002								3.775
							(-0.574)								(0.825)
CAY_t								0.768			-1.821		6.713***	5.332*	
								(0.232)			(-0.624)		(2.663)	(1.884)	
$RREL_t$									6.144			12.156*	-7.360	-5.955	-18.942***
									(0.955)			(1.915)	(-1.290)	(-1.194)	(-4.555)
Constant	-0.171	0.890	2.995	303.076**	-51.626	36.253	7.925*	2.644	2.132	379.437**	-1.872	-5.919	544.995***	522.704***	1,211.335***
	(-0.034)	(0.172)	(0.493)	(2.040)	(-0.433)	(1.202)	(1.723)	(0.432)	(0.331)	(2.439)	(-0.269)	(-0.911)	(3.115)	(3.086)	(4.309)
Observations	1,440	1,440	1,440	1,440	1,440	1,440	1,440	1,440	1,440	1,440	1,440	1,440	1,440	1,440	1,440
R^2	0.015	0.004	0.0003	0.222	0.013	0.076	0.027	0.002	0.038	0.327	0.020	0.119	0.368	0.374	0.578
Adjusted R^2	0.015	0.004	-0.0004	0.221	0.013	0.075	0.026	0.001	0.038	0.326	0.019	0.117	0.367	0.373	0.576

Note: *Parantheses denote t-statistics* $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Appendix K: EVRP return regressions, pre-financial crisis sample (January ‘02 to December ‘07)

Table K.1: EVRP, 4-month return horizon , pre-GFC

	Dependent variable: $(r_{SPX} - r_m)_{t \to t+4}$														
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
$EVRP_t$	0.036									0.095^{**}	0.025	0.085^{*}		-0.017	-0.024^{*}
	(0.557)									(2.023)	(0.747)	(1.715)		(-0.753)	(-1.945)
IV_t		0.040													
		(0.478)													
ERV_t			-0.024												
			(-0.183)												
$\log(P/E)_t$				-102.421^{*}						-107.823^{*}			-185.267^{***}	-186.420^{***}	-319.079^{***}
				(-1.829)						(-1.935)			(-2.931)	(-2.816)	(-7.379)
$\log(P/D)_t$					-16.937										107.563^{**}
					(-0.397)										(2.420)
$DFSP_t$						-33.095									-55.045^{***}
						(-0.937)									(-3.646)
$TMSP_t$							-2.836								3.349
							(-0.504)								(0.903)
CAY_t								0.974			0.690		6.908^{**}	7.090^{**}	
								(0.287)			(0.250)		(2.440)	(2.521)	
$RREL_t$									6.245			7.383	-6.888	-7.060	-19.949^{***}
									(0.746)			(1.058)	(-1.032)	(-1.073)	(-4.647)
Constant	1.972	1.094	3.031	298.767^{*}	-47.907	34.765	7.684	2.663	2.209	312.707^{**}	2.198	0.639	539.157^{***}	542.817^{***}	$1{,}295.234^{***}$
	(0.354)	(0.187)	(0.456)	(1.872)	(-0.360)	(1.151)	(1.524)	(0.383)	(0.318)	(1.972)	(0.341)	(0.109)	(2.973)	(2.859)	(6.028)
Observations	1,440	1,440	1,440	1,440	1,440	1,440	1,440	1,440	1,440	1,440	1,440	1,440	1,440	1,440	1,440
R^2	0.003	0.004	0.0004	0.246	0.013	0.080	0.027	0.003	0.047	0.267	0.004	0.063	0.416	0.416	0.632
Adjusted R^2	0.002	0.003	-0.0003	0.245	0.012	0.079	0.027	0.002	0.046	0.266	0.003	0.061	0.415	0.415	0.631

Note: *Parentheses denote t-statistics* $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table K.2: EVRP, 3.5-month return horizon, pre-GFC

	Dependent variable:														
	$(r_{SPX} - r_m)_{t\to t+3.5}$														
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
$EVRP_t$	0.073									0.184**	0.075	0.165*		0.019	-0.021
	(0.763)									(2.187)	(1.255)	(1.894)		(0.521)	(-1.035)
IV_t		0.045													
		(0.497)													
ERV_t			-0.023												
			(-0.153)												
$\log(P/E)_t$				-103.987**						-116.038***			-187.349***	-186.192***	-319.691***
				(-1.992)						(-2.612)			(-3.064)	(-2.994)	(-6.300)
$\log(P/D)_t$					-18.157										117.534**
					(-0.477)										(2.382)
$DFSP_t$						-34.611									-59.570***
						(-0.980)									(-2.961)
$TMSP_t$							-3.002								2.114
							(-0.574)								(0.496)
CAY_t								0.768			-0.098		6.713***	6.514***	
								(0.232)			(-0.039)		(2.663)	(2.661)	
$RREL_t$									6.144			8.601*	-7.360	-7.152	-20.969***
									(0.955)			(1.665)	(-1.290)	(-1.253)	(-5.078)
Constant	1.285	0.890	2.995	303.076**	-51.626	36.253	7.925*	2.644	2.132	334.619***	1.236	-1.004	544.995***	541.281***	1,333.438***
	(0.265)	(0.172)	(0.493)	(2.040)	(-0.433)	(1.202)	(1.723)	(0.432)	(0.331)	(2.656)	(0.214)	(-0.208)	(3.115)	(3.041)	(4.769)
Observations	1,440	1,440	1,440	1,440	1,440	1,440	1,440	1,440	1,440	1,440	1,440	1,440	1,440	1,440	1,440
R^2	0.008	0.004	0.0003	0.222	0.013	0.076	0.027	0.002	0.038	0.266	0.008	0.071	0.368	0.369	0.573
Adjusted R^2	0.007	0.004	-0.0004	0.221	0.013	0.075	0.026	0.001	0.038	0.265	0.006	0.070	0.367	0.367	0.572

Note: *Parentheses denote t-statistics* *p<0.1; **p<0.05; ***p<0.01

Appendix L: VRP return regressions, financial crisis sample (December ’07 to July ‘09)

	Dependent variable:														
	$(r_{SPX} - r_m)_{t \to t+3.5}$														
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
VRP_t	0.395***									0.358***	0.406*	0.432**		0.340***	0.268***
	(2.524)									(3.935)	(1.895)	(2.299)		(4.191)	(4.203)
IV_t		0.096													
		(1.119)													
RV_t			0.021												
			(0.173)												
$\log(P/E)_t$				-88.91						-71.171			-238.154	-215.224**	-433.671***
				(-0.542)						(-1.29)			(-1.487)	(-2.140)	(-5.563)
$\log(P/D)_t$					1,218.12										1,071.76***
					(0.764)										(2.730)
$DFSP_t$						14.278									-5.161
						(0.532)									(-5.161)
$TMSP_t$							-9.948								-53.153***
							(-0.539)								(-7.448)
CAY_t								-12.525			-13.150		-32.112**	-30.3464**	
								(-0.579)			(-1.036)		(-2.099)	(-2.330)	
$RREL_t$									-11.694			-17.905	-9.922	-14.616	-57.433***
									(-0.259)			(-0.653)	(-0.447)	(-0.820)	(-7.693=
Constant	-42.95***	-46.12*	-38.095	198.040	4,011.82	-60.922*	-17.316	-31.494	-52.455	145.239	-38.108***	-68.340	589.931	516.596*	4,694.674***
	(-2.806)	(-1.910)	(-1.157)	(0.449)	(0.757)	(-1.681)	(-1.102)	(-1.444)	(-0.565)	(0.951)	(-3.191)	(-1.292)	(1.292)	(1.802)	(3.216)
Observations	389	389	389	389	389	389	389	389	389	389	389	389	389	389	389
R^2	0.117	0.037	0.002	0.062	0.135	0.053	0.030	0.065	0.015	0.155	0.188	0.151	0.346	0.427	0.713
Adjusted R^2	0.114	0.035	-0.001	0.059	0.133	0.051	0.027	0.063	0.012	0.151	0.184	0.146	0.340	0.421	0.708

Note: *p<0.1; **p<0.05; ***p<0.01

Appendix M: EVRP return regressions, financial crisis sample (December ’07 to July ‘09)

Table M.1: EVRP, 3-month return horizon, GFC

	Dependent variable:														
	$(r_{SPX} - r_m)_{t \to t+3}$														
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
$EVRP_t$	0.093**									0.097***	0.071	0.098***		0.048*	0.052*
	(2.539)									(3.459)	(1.161)	(3.128)		(1.901)	(1.706)
IV_t		0.097													
		(0.977)													
ERV_t			0.037												
			(0.513)												
$\log(P/E)_t$				-117.986						-119.587			-293.476**	-290.387***	-633.914***
				(-0.990)						(-1.216)			(-2.518)	(-2.589)	(-4.299)
$\log(P/D)_t$					1,510.362										1,379.117***
					(1.045)										(2.988)
$DFSP_t$						16.011									-43.325*
						(0.751)									(-1.668)
$TMSP_t$							-5.149								-44.675***
							(-0.392)								(-4.601)
CAY_t								-15.515			-14.468		-40.603***	-39.500***	
								(-0.859)			(-0.894)		(-3.525)	(-3.450)	
$RREL_t$									-9.375			-11.106	-8.632	-9.748	-56.600***
									(-0.176)			(-0.257)	(-0.309)	(-0.369)	(-4.914)
Constant	-35.452*	-45.530	-38.640	274.265	4,984.564	-63.990*	-25.319	-28.542**	-48.344	278.439	-29.028**	-50.759	741.005**	730.855**	6,299.190***
	(-1.884)	(-1.631)	(-1.360)	(0.865)	(1.036)	(-1.735)	(-1.620)	(-2.008)	(-0.469)	(1.070)	(-2.230)	(-0.624)	(2.213)	(2.271)	(3.858)
Observations	389	389	389	389	389	389	389	389	389	389	389	389	389	389	389
R^2	0.027	0.030	0.005	0.094	0.145	0.055	0.006	0.077	0.008	0.123	0.092	0.037	0.441	0.448	0.602
Adjusted R^2	0.024	0.028	0.002	0.092	0.143	0.053	0.003	0.074	0.005	0.119	0.087	0.032	0.437	0.442	0.595
Note:	*Parentheses denote t-statistics*														$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table M.2: EVRP, 3.5-month return horizon , GFC

	Dependent variable:														
	$(r_{SPX} - r_m)_{t\to t+3.5}$														
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
$EVRP_t$	0.028									0.030*	0.023	0.027		0.019	0.015
	(1.239)									(1.665)	(0.671)	(0.706)		(1.262)	(0.933)
IV_t		0.096													
		(1.119)													
ERV_t			0.021												
			(0.173)												
$\log(P/E)_t$				-88.914						-89.535			-238.154	-237.672	-518.878***
				(-0.542)						(-0.605)			(-1.487)	(-1.594)	(-3.489)
$\log(P/D)_t$					1,218.124										882.422*
					(0.764)										(1.898)
$DFSP_t$						14.278									-13.672
						(0.532)									(-0.652)
$TMSP_t$							-9.948								-60.829***
							(-0.539)								(-5.811)
CAY_t								-12.525			-12.341		-32.112**	-31.929**	
								(-0.579)			(-0.623)		(-2.099)	(-2.157)	
$RREL_t$									-11.694			-11.472	-9.922	-9.800	-58.112***
									(-0.259)			(-0.274)	(-0.447)	(-0.477)	(-7.427)
Constant	-36.115	-46.124*	-38.095	198.040	4,011.816	-60.922*	-17.316	-31.494	-52.455	199.860	-31.422	-51.983	589.931	588.875	4,323.024**
	(-1.504)	(-1.910)	(-1.157)	(0.449)	(0.757)	(-1.681)	(-1.102)	(-1.444)	(-0.565)	(0.502)	(-1.532)	(-0.610)	(1.292)	(1.388)	(2.423)
Observations	389	389	389	389	389	389	389	389	389	389	389	389	389	389	389
R^2	0.007	0.037	0.002	0.062	0.135	0.053	0.030	0.065	0.015	0.069	0.070	0.021	0.346	0.349	0.668
Adjusted R^2	0.004	0.035	-0.001	0.059	0.133	0.051	0.027	0.063	0.012	0.064	0.065	0.016	0.340	0.342	0.662

Note: *Parentheses denote t-statistics* *p<0.1; **p<0.05; ***p<0.01

Table M.3: EVRP, 4-month return horizon , GFC

	Dependent variable:														
	$(r_{SPX} - r_m)_{t \to t+4}$														
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
$EVRP_t$	0.034									0.035	0.030	0.032		0.027	0.015
	(1.104)									(0.972)	(0.950)	(0.932)		(1.058)	(1.082)
IV_t		0.078													
		(0.803)													
ERV_t			0.035												
			(0.295)												
$\log(P/E)_t$				-53.609						-54.716			-177.770	-177.437	-350.538***
				(-0.321)						(-0.470)			(-1.169)	(-1.393)	(-3.053)
$\log(P/D)_t$					1,017.147										846.101***
					(1.371)										(3.622)
$DFSP_t$						11.691									10.509
						(0.575)									(0.679)
$TMSP_t$							-12.064								-56.887***
							(-0.892)								(-7.219)
CAY_t								-10.635			-10.401		-24.787	-24.549	
								(-0.586)			(-0.697)		(-1.338)	(-1.629)	
$RREL_t$									-12.850			-12.560	-11.174	-10.942	-55.908***
									(-0.527)			(-0.466)	(-0.599)	(-0.588)	(-10.613)
Constant	-37.755**	-45.626**	-40.911	103.928	3,341.298	-57.544*	-15.937	-34.566*	-55.502	107.106	-34.435*	-54.884	425.377	424.923	3,711.342***
	(-1.972)	(-2.218)	(-1.484)	(0.231)	(1.364)	(-1.729)	(-1.315)	(-1.687)	(-1.025)	(0.345)	(-1.922)	(-0.969)	(0.975)	(1.160)	(4.985)
Observations	389	389	389	389	389	389	389	389	389	389	389	389	389	389	389
R^2	0.013	0.032	0.007	0.026	0.147	0.045	0.064	0.064	0.027	0.040	0.073	0.038	0.257	0.265	0.755
Adjusted R^2	0.010	0.029	0.005	0.023	0.145	0.043	0.061	0.061	0.024	0.035	0.069	0.033	0.252	0.258	0.751

Note: *Parentheses denote t-statistics* $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Appendix N: VRP return regressions, post-financial crisis sample (July '09 to September '17)

Table N.1: VRP, 3.5-month return horizon, post-GFC

	Dependent variable:														
	$(r_{SPX} - r_m)_{t\rightarrow t+3.5}$														
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
VRP_t	0.479***									0.292***	0.409***	0.361***		0.351***	0.405***
	(4.275)									(2.991)	(3.312)	(3.425)		(3.281)	(3.535)
IV_t		0.316***													
		(5.422)													
RV_t			0.332***												
			(3.231)												
$\log(P/E)_t$				-62.889***						-53.570***			-82.576**	-84.508**	-57.356
				(-3.698)						(-3.397)			(-2.040)	(-2.211)	(-1.389)
$\log(P/D)_t$					8.063										-16.567
					(0.529)										(-0.766)
$DFSP_t$						19.130***									5.520
						(6.211)									(0.675)
$TMSP_t$							-3.477								-4.087
							(-0.630)								(-0.705)
CAY_t								3.333			1.960		-2.832	-3.783	
								(1.617)			(0.992)		(-0.825)	(-1.169)	
$RREL_t$									-32.946***			-23.652***	-0.957	6.358	-6.937
									(-3.502)			(-2.777)	(-0.060)	(0.422)	(-0.346)
Constant	6.426**	2.564	6.586	185.513***	40.970	-7.536	21.107*	17.984***	12.855***	155.960***	10.335**	7.955**	235.269**	234.365**	110.881
	(2.279)	(0.672)	(1.638)	(3.973)	(0.747)	(-1.393)	(1.846)	(3.346)	(3.569)	(3.589)	(1.970)	(2.430)	(2.212)	(2.349)	(1.430)
Observations	2,022	2,022	2,022	2,022	2,022	2,022	2,022	2,022	2,022	2,022	2,022	2,022	2,022	2,022	2,022
R^2	0.083	0.176	0.127	0.157	0.010	0.136	0.013	0.043	0.076	0.184	0.096	0.118	0.172	0.208	0.264
Adjusted R^2	0.083	0.175	0.126	0.157	0.010	0.136	0.013	0.043	0.076	0.184	0.095	0.117	0.171	0.207	0.261

Note: *Parentheses denote t-statistics* $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table N.2: VRP, 4-month return horizon , post-GFC

	Dependent variable:														
	$(r_{SPX} - r_m)_{t \to t+4}$														
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
VRP_t	0.543***									0.334***	0.473***	0.395***		0.386***	0.411***
	(5.422)									(3.796)	(4.095)	(4.207)		(3.695)	(4.211)
IV_t		0.331***													
		(7.824)													
RV_t			0.367***												
			(3.211)												
$\log(P/E)_t$				-68.320***						-55.297***			-84.045**	-85.981***	-59.981*
				(-3.962)						(-3.686)			(-2.487)	(-2.912)	(-1.903)
$\log(P/D)_t$					8.169										-18.527
					(0.546)										(-1.148)
$DFSP_t$						21.089***									6.149
						(5.831)									(1.007)
$TMSP_t$							-3.537								-3.564
							(-0.621)								(-0.690)
CAY_t								3.763			1.942		-2.888	-3.947	
								(1.546)			(0.991)		(-0.930)	(-1.444)	
$RREL_t$									-38.546***			-25.681***	-5.778	4.703	-5.109
									(-3.328)			(-2.753)	(-0.399)	(0.346)	(-0.297)
Constant	5.610**	2.016	5.980	200.469***	41.598	-9.601*	21.558*	18.837***	12.852***	160.076***	9.465*	7.420**	239.216***	237.621***	109.197*
	(2.192)	(0.608)	(1.544)	(4.213)	(0.762)	(-1.657)	(1.912)	(3.021)	(3.842)	(3.837)	(1.756)	(2.396)	(2.711)	(3.109)	(1.904)
Observations	2,022	2,022	2,022	2,022	2,022	2,022	2,022	2,022	2,022	2,022	2,022	2,022	2,022	2,022	2,022
R^2	0.134	0.246	0.181	0.206	0.011	0.195	0.014	0.060	0.120	0.249	0.148	0.177	0.225	0.277	0.344
Adjusted R^2	0.134	0.245	0.181	0.205	0.011	0.195	0.014	0.059	0.119	0.248	0.147	0.176	0.224	0.276	0.342

Note: *Parentheses denote t-statistics* *p<0.1; **p<0.05; ***p<0.01

Appendix O: EVRP return regressions, post-financial crisis sample (July ’09 to September ‘17)

Table O.1: EVRP, 5-month return horizon , post-GFC

	Dependent variable:														
	$(r_{SPX} - r_m)_{t \to t+4}$														
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
$EVRP_t$	0.206***									0.102***	0.162***	0.132***		0.108**	0.100***
	(2.838)									(3.011)	(2.762)	(2.712)		(2.481)	(2.650)
IV_t		0.331***													
		(7.824)													
ERV_t			0.367***												
			(3.211)												
$\log(P/E)_t$				-68.320***						-63.636***			-84.045**	-82.914***	-54.644
				(-3.962)						(-3.792)			(-2.847)	(-2.724)	(-1.544)
$\log(P/D)_t$					8.169										-11.846
					(0.546)										(-0.602)
$DFSP_t$						21.089***									7.818
						(5.831)									(1.013)
$TMSP_t$							-3.537								-4.180
							(-0.621)								(-0.656)
CAY_t								3.763			3.091		-2.888	-3.119	
								(1.546)			(1.346)		(-0.930)	(-1.085)	
$RREL_t$									-38.546***			-34.135***	-5.778	-3.387	-11.680
									(-3.328)			(-3.040)	(-0.399)	(-0.242)	(-0.616)
Constant	10.059***	2.016	5.980	204.763***	40.834	-9.601*	21.558*	18.837***	12.852***	185.045***	15.318**	10.850***	239.216***	234.128***	121.562
	(3.290)	(0.608)	(1.544)	(4.213)	(0.762)	(-1.657)	(1.912)	(3.021)	(3.842)	(3.962)	(2.549)	(3.422)	(2.711)	(2.952)	(1.617)
Observations	2,022	2,022	2,022	2,022	2,022	2,022	2,022	2,022	2,022	2,022	2,022	2,022	2,022	2,022	2,022
R^2	0.053	0.246	0.181	0.206	0.011	0.195	0.014	0.060	0.120	0.218	0.091	0.139	0.225	0.238	0.299
Adjusted R^2	0.052	0.245	0.181	0.205	0.011	0.195	0.014	0.059	0.119	0.217	0.090	0.139	0.224	0.237	0.29

Note: *Parentheses denote t-statistics* *p<0.1; **p<0.05; ***p<0.01

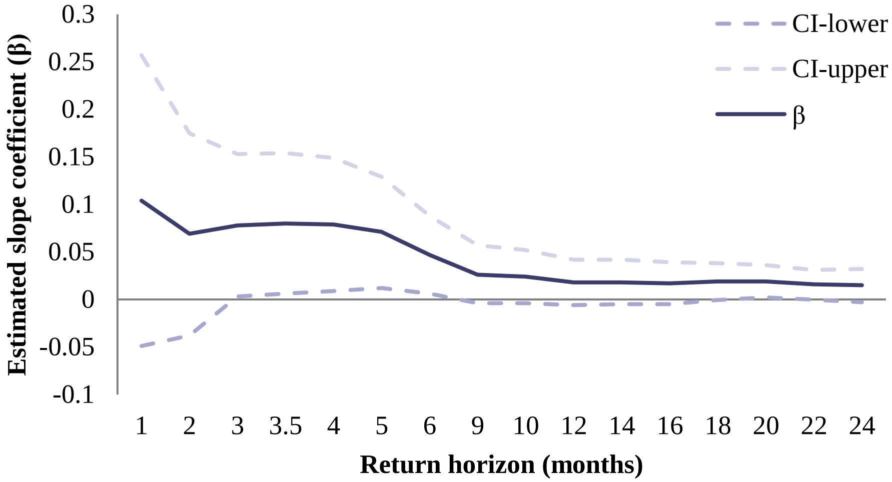
Table O.2: EVRP, 3.5-month return horizon , post-GFC

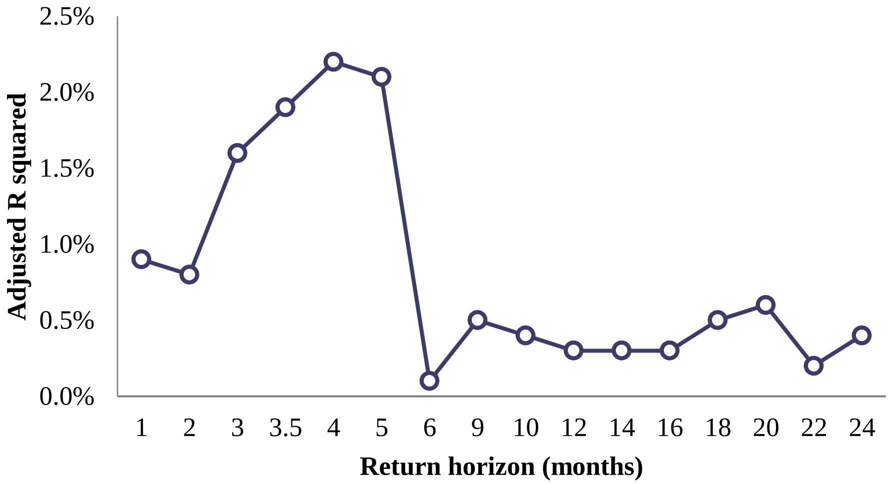
	Dependent variable:														
	$(r_{SPX} - r_m)_{t \to t+3.5}$														
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
$EVRP_t$	0.217***									0.123***	0.181***	0.157***		0.132***	0.120***
	(2.884)									(3.060)	(2.820)	(2.800)		(2.727)	(2.954)
IV_t		0.316***													
		(5.422)													
ERV_t			0.332***												
			(3.231)												
$\log(P/E)_t$				-62.89***						-56.99***			-82.576**	-81.11***	-51.169
				(-3.698)						(-3.799)			(-2.040)	(-2.638)	(-1.351)
$\log(P/D)_t$					8.063										-9.230
					(0.529)										(-0.462)
$DFSP_t$						19.130***									6.303
						(6.211)									(0.774)
$TMSP_t$							-3.477								-4.646
							(-0.630)								(-0.760)
CAY_t								3.333			2.566		-2.832	-3.117	
								(1.617)			(1.345		(-0.825)	(-1.126)	
$RREL_t$									-32.95***			-27.24***	-0.957	2.367	-10.509
									(-3.502)			(-3.311)	(-0.060)	(0.181)	(-0.553)
Constant	9.615***	2.564	6.586	185.51***	40.970	-7.536	21.107*	17.984***	12.855***	167.42***	14.040***	10.455***	235.269**	228.78***	123.515
	(3.226)	(0.672)	(1.638)	(3.973)	(0.747)	(-1.393)	(1.846)	(3.346)	(3.569)	(4.021)	(2.842)	(3.210)	(2.212)	(2.812)	(1.467)
Observations	2,022	2,022	2,022	2,022	2,022	2,022	2,022	2,022	2,022	2,022	2,022	2,022	2,022	2,022	2,022
R^2	0.054	0.176	0.127	0.157	0.010	0.136	0.013	0.043	0.076	0.173	0.078	0.102	0.172	0.190	0.233
Adjusted R^2	0.054	0.175	0.126	0.157	0.010	0.136	0.013	0.043	0.076	0.172	0.077	0.101	0.171	0.188	0.231

Note: *Parentheses denote t-statistics* *p<0.1; **p<0.05; ***p<0.01

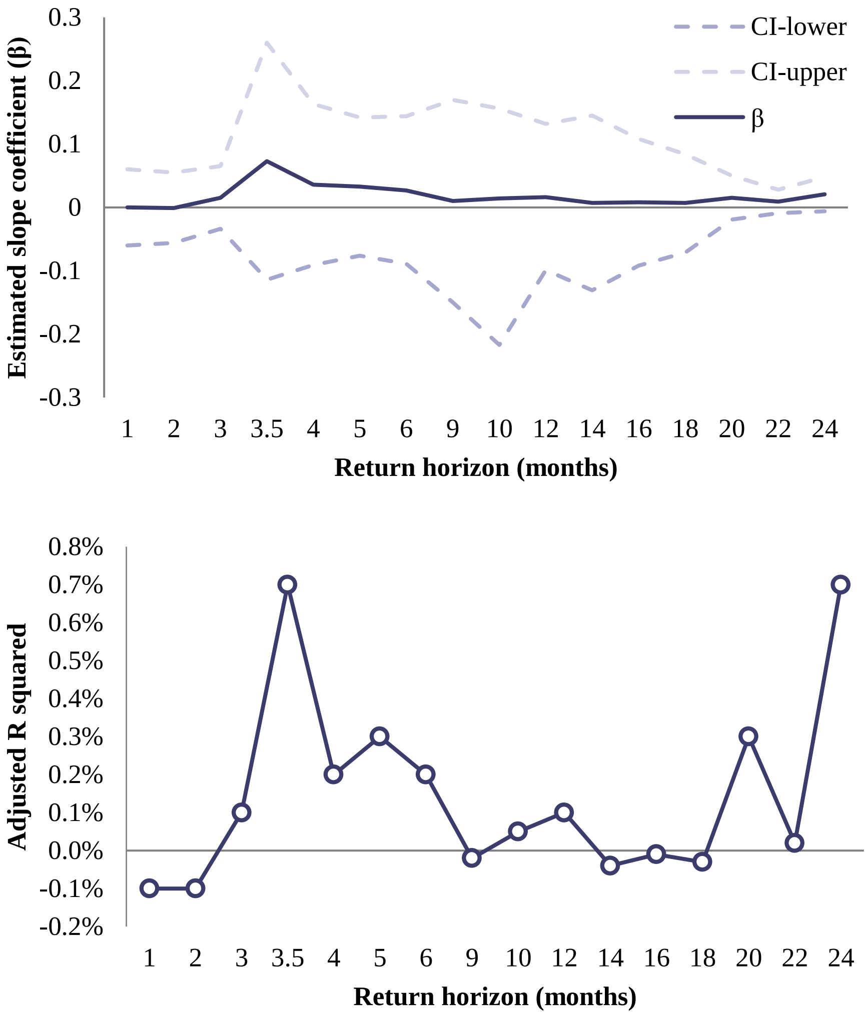
Appendix P: Overview of EVRP slope coefficients (with 95% confidence intervals) and adj. R squared for studied time samples

Figures P.1: Expected Variance Risk Premium (EVRP) for the full sample

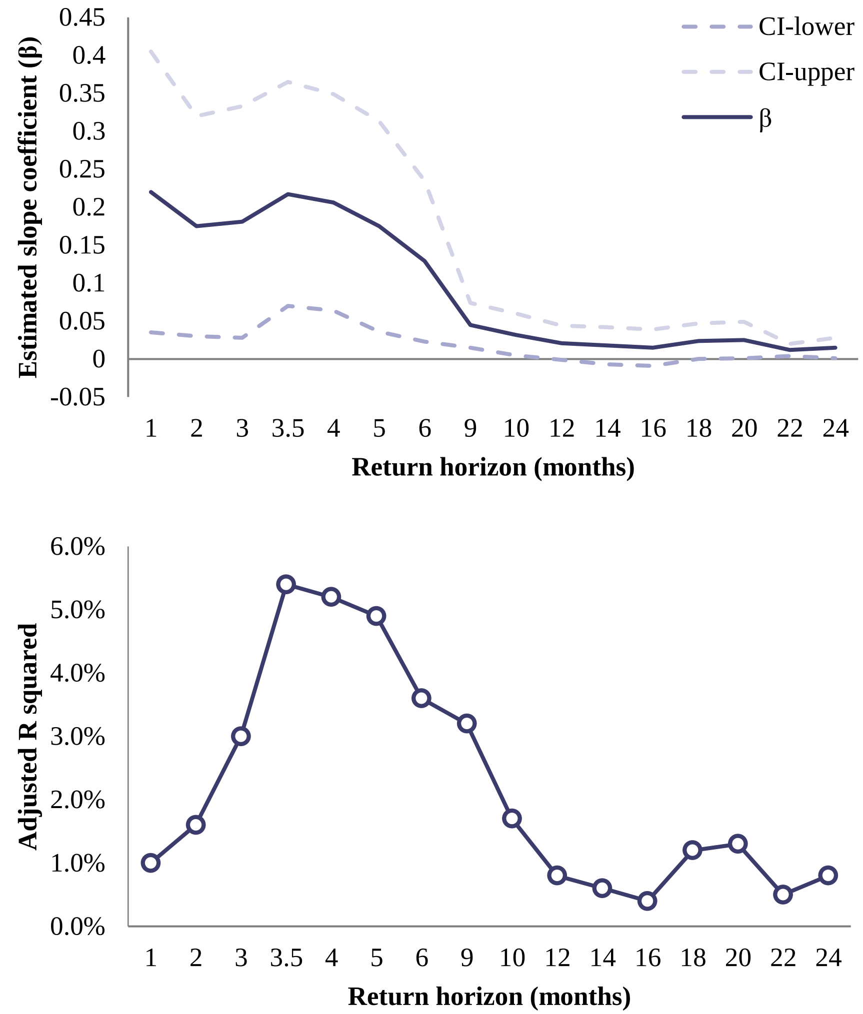




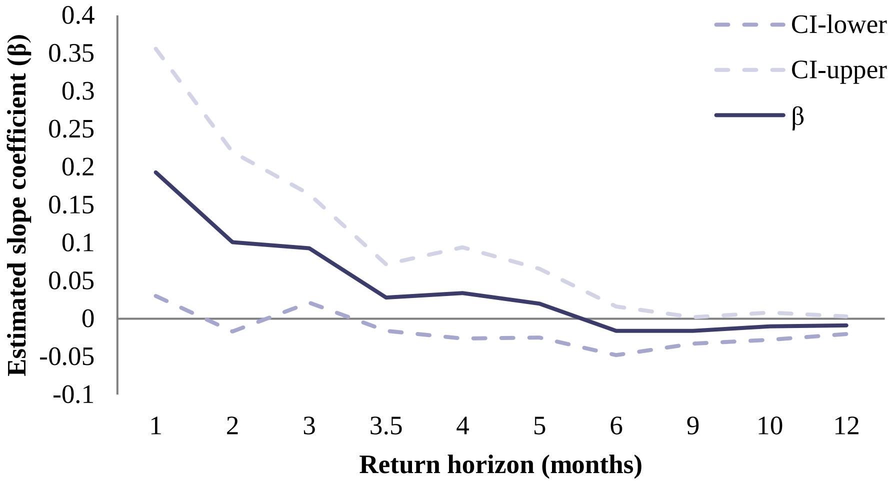
Figures P.2: EVRP for the pre-financial crisis sample (January 2002 to December 2007)

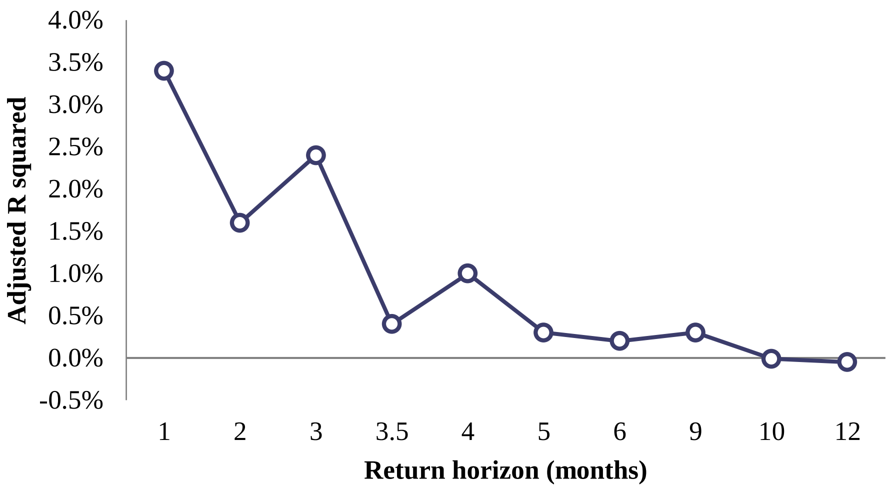


Figures P.3: EVRP for the post-financial crisis sample (July 2009 to March 2018)



Figures P.4: EVRP for the financial crisis sample (January 2002 to December 2007)





Appendix Q: VRP winsorized samples

Table Q.1: VRP 3.5 month return regressions, winsorized full sample from January 2002 to September 2017

	Dependent variable:														
	$(r_{SPX} - r_m)_{t\to t+3.5}$														
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
VRP_t	0.211*									0.216**	0.446***	0.538***		0.685***	0.679***
	(1.839)									(2.126)	(3.622)	(4.980)		(5.967)	(6.119)
IV_t		0.042													
		(0.495)													
RV_t			0.022												
			(0.144)												
$\log(P/E)_t$				-37.596						-37.868*			-42.692**	-47.580***	-50.074***
				(-1.447)						(-1.645)			(-2.124)	(-3.514)	(-2.852)
$\log(P/D)_t$					-7.197										-11.188**
					(-0.735)										(-2.119)
$DFSP_t$						-5.289									-8.714
						(-0.358)									(-0.840)
$TMSP_t$							-0.847								2.085
							(-0.282)								(0.888)
CAY_t								-1.963			-4.182**		0.115	-2.651*	
								(-0.869)			(-2.236)		(0.058)	(-1.796)	
$RREL_t$									11.847***			16.793***	12.780***	16.370***	17.593***
									(2.938)			(5.610)	(3.214)	(5.005)	(4.564)
Constant	2.114	3.862	4.986	110.240	-18.121	11.019	7.220	3.915	6.554**	107.589*	-4.864	-1.488	125.725**	126.705***	104.117*
	(0.752)	(1.019)	(1.184)	(1.506)	(-0.542)	(0.787)	(1.310)	(0.870)	(2.129)	(1.657)	(-1.127)	(-0.591)	(2.234)	(3.366)	(1.679)
Observations	3,850	3,850	3,850	3,850	3,850	3,850	3,850	3,850	3,850	3,850	3,850	3,850	3,850	3,850	3,850
R^2	0.014	0.003	0.0004	0.046	0.009	0.004	0.001	0.014	0.096	0.061	0.060	0.173	0.155	0.256	0.267
Adjusted R^2	0.014	0.003	0.0001	0.045	0.009	0.004	0.001	0.014	0.096	0.060	0.060	0.173	0.154	0.255	0.266

Note: *Parentheses denote t-statistics* $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table Q.2: VRP 3.5 month return regressions, winsorized pre-GFC sample from January 2002 to September 2017

	Dependent variable:														
	$(r_{SPX} - r_m)_{t \to t+3.5}$														
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
VRP_t	0.070									0.362***	0.104	0.356**		0.044	0.037
	(0.486)									(4.283)	(0.564)	(2.438)		(0.270)	(0.325)
IV_t		0.014													
		(0.146)													
RV_t			-0.024												
			(-0.114)												
$\log(P/E)_t$				-85.393**						-111.333***			-144.762***	-143.116***	-257.172***
				(-2.499)						(-3.671)			(-3.586)	(-3.350)	(-9.430)
$\log(P/D)_t$					-14.537										85.379**
					(-0.527)										(2.014)
$DFSP_t$						-27.513									-49.172***
						(-1.026)									(-4.354)
$TMSP_t$							-2.248								2.785
							(-0.576)								(0.662)
CAY_t								0.538			-0.591		5.591***	5.174*	
								(0.220)			(-0.211)		(2.773)	(1.662)	
$RREL_t$									5.699			11.062**	-4.315	-3.918	-15.787***
									(1.253)			(2.158)	(-0.932)	(-0.817)	(-4.229)
Constant	1.910	2.699	3.614	249.915**	-40.182	29.977	7.216*	3.250	2.715	318.050***	1.232	-4.454	422.141***	416.496***	1,044.656***
	(0.482)	(0.540)	(0.728)	(2.560)	(-0.468)	(1.270)	(1.706)	(0.724)	(0.631)	(3.703)	(0.221)	(-0.851)	(3.652)	(3.390)	(6.236)
Observations	1,440	1,440	1,440	1,440	1,440	1,440	1,440	1,440	1,440	1,440	1,440	1,440	1,440	1,440	1,440
R^2	0.004	0.001	0.0003	0.216	0.013	0.067	0.023	0.001	0.045	0.302	0.004	0.108	0.345	0.345	0.545
Adjusted R^2	0.003	-0.0002	-0.0004	0.215	0.012	0.067	0.022	0.001	0.044	0.301	0.003	0.106	0.343	0.343	0.543

Note: *Parentheses denote t-statistics* $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table Q.3: VRP 3.5 month return regressions, winsorized financial crisis sample (December 2007 to July 2009)

	Dependent variable:														
	$(r_{SPX} - r_m)_{t\to t+3.5}$														
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
VRP_t	0.599**									0.557**	0.684**	0.743**		0.550**	0.505***
	(2.196)									(2.001)	(2.372)	(2.537)		(2.205)	(3.166)
IV_t		0.103													
		(1.043)													
RV_t			0.034												
			(0.330)												
$\log(P/E)_t$				-62.511						-21.689			-203.881	-153.235**	-324.511***
				(-0.520)						(-0.481)			(-1.344)	(-1.967)	(-2.939)
$\log(P/D)_t$					1,218.831										877.376**
					(0.846)										(2.073)
$DFSP_t$						11.655									3.456
						(0.662)									(0.229)
$TMSP_t$							-11.285								-52.255***
							(-0.726)								(-6.208)
CAY_t								-12.803			-15.321*		-28.837*	-26.017**	
								(-0.716)			(-1.648)		(-1.870)	(-2.199)	
$RREL_t$									-16.698			-27.898	-12.933	-20.652	-60.103***
									(-0.412)			(-1.611)	(-0.558)	(-1.296)	(-7.827)
Constant	-48.89***	-47.492**	-40.140	127.519	4,013.344	-57.399*	-15.827	-32.423*	-60.351	9.127	-44.667***	-90.148***	493.517	337.615	3,735.243**
	(-3.512)	(-2.149)	(-1.429)	(0.395)	(0.839)	(-1.922)	(-0.964)	(-1.846)	(-0.745)	(0.079)	(-3.740)	(-2.776)	(1.139)	(1.502)	(2.491)
Observations	389	389	389	389	389	389	389	389	389	389	389	389	389	389	389
R^2	0.119	0.041	0.005	0.034	0.149	0.042	0.042	0.082	0.032	0.122	0.233	0.200	0.321	0.399	0.709
Adjusted R^2	0.116	0.038	0.002	0.032	0.147	0.039	0.040	0.079	0.029	0.118	0.229	0.196	0.316	0.392	0.705

Note: *p<0.1; **p<0.05; ***p<0.01

Table Q.4: VRP 3.5 month return regressions, winsorized post-financial crisis sample (July 2009 to September 2017)

	Dependent variable:														
	$(r_{SPX} - r_m)_{t\to t+3.5}$														
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
VRP_t	0.605***									0.389***	0.517***	0.551***		0.495***	0.623***
	(3.919)									(2.799)	(3.190)	(3.249)		(3.364)	(3.958)
IV_t		0.354***													
		(5.084)													
RV_t			0.364***												
			(3.127)												
$\log(P/E)_t$				-58.117***						-47.484**			-79.023**	-78.436**	-64.738
				(-2.823)						(-2.445)			(-2.033)	(-2.122)	(-1.633)
$\log(P/D)_t$					8.320										-17.852
					(0.573)										(-0.906)
$DFSP_t$						18.265									-0.792
						(1.546)									(-0.070)
$TMSP_t$							-3.186								-4.030
							(-0.592)								(-0.803)
CAY_t								3.186			1.777		-2.201	-2.996	
								(1.484)			(0.845)		(-0.606)	(-0.877)	
$RREL_t$									-31.621			-11.417	7.237	20.711	-8.702
									(-1.429)			(-0.560)	(0.293)	(0.887)	(-0.288)
Constant	4.774	1.912	6.386	172.614***	41.894	-5.860	20.463*	17.814***	13.162***	138.117**	8.658	5.563	226.674**	217.056**	130.626
	(1.472)	(0.476)	(1.591)	(3.055)	(0.804)	(-0.474)	(1.830)	(3.393)	(4.055)	(2.567)	(1.522)	(1.483)	(2.227)	(2.250)	(1.490)
Observations	2,022	2,022	2,022	2,022	2,022	2,022	2,022	2,022	2,022	2,022	2,022	2,022	2,022	2,022	2,022
R^2	0.094	0.175	0.127	0.145	0.013	0.065	0.013	0.048	0.033	0.179	0.107	0.098	0.156	0.206	0.252
Adjusted R^2	0.094	0.174	0.126	0.144	0.013	0.064	0.012	0.047	0.033	0.178	0.106	0.097	0.155	0.205	0.250
Note:	*Parentheses denote t-statistics*														*p<0.1; **p<0.05; ***p<0.01

Table Q.5: VRP 4 month return regressions, winsorized post-financial crisis sample (July 2009 to September 2017)

	Dependent variable:														
	$(r_{SPX} - r_m)_{t \to t+4}$														
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
VRP_t	0.638***									0.409***	0.541***	0.559***		0.510***	0.617***
	(4.365)									(3.178)	(3.546)	(3.615)		(3.790)	(4.393)
IV_t		0.354***													
		(6.595)													
RV_t			0.358***												
			(2.925)												
$\log(P/E)_t$				-61.203***						-49.421***			-79.068**	-79.144***	-67.749**
				(-3.390)						(-2.975)			(-2.568)	(-2.810)	(-2.051)
$\log(P/D)_t$					8.967										-20.106
					(0.674)										(-1.262)
$DFSP_t$						20.059**									0.725
						(2.202)									(0.089)
$TMSP_t$							-2.851								-2.942
							(-0.556)								(-0.604)
CAY_t								3.456*			1.908		-2.145	-3.021	
								(1.731)			(1.062)		(-0.736)	(-1.166)	
$RREL_t$									-36.119*			-15.154	1.623	16.303	-6.616
									(-1.758)			(-0.844)	(0.077)	(0.824)	(-0.261)
Constant	4.533	2.014	6.663*	181.251***	44.451	-7.667	20.033*	18.485***	13.321***	143.280***	8.713*	5.616*	227.072***	218.942***	127.081*
	(1.585)	(0.630)	(1.810)	(3.633)	(0.920)	(-0.758)	(1.931)	(3.690)	(4.568)	(3.091)	(1.715)	(1.702)	(2.809)	(2.974)	(1.873)
Observations	2,022	2,022	2,022	2,022	2,022	2,022	2,022	2,022	2,022	2,022	2,022	2,022	2,022	2,022	2,022
R^2	0.126	0.216	0.152	0.187	0.018	0.106	0.012	0.066	0.056	0.232	0.143	0.134	0.198	0.259	0.315
Adjusted R^2	0.126	0.216	0.151	0.186	0.017	0.106	0.011	0.065	0.056	0.231	0.142	0.133	0.197	0.258	0.313

Note: *Parentheses denote t-statistics* *p<0.1; **p<0.05; ***p<0.01

Table Q.6: Intraday regressions between S&P 500 returns and key variables, winsorized full sample from January 2002 till February 2018

	Dependent variable:											
	Hourly return			Return per 2 hours			Half day returns			Daily returns		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$VRP_{t-1hour}$	-0.437	-0.400	-0.336									
	(-1.468)	(-1.279)	(-0.810)									
$RV_{t-1hour}$		-0.070										
		(-0.413)										
$IV_{t-1hour}$			-0.062									
			(-0.372)									
$VRP_{t-2hours}$				-0.114	-0.053	0.049						
				(-0.340)	(-0.151)	(0.112)						
$RV_{t-2hours}$					-0.116							
					(-0.636)							
$IV_{t-2hours}$						-0.099						
						(-0.586)						
$VRP_{t-half\ day}$							0.006	0.099	0.249			
							(0.016)	(0.255)	(0.518)			
$RV_{t-half\ day}$								-0.176				
								(-0.862)				
$IV_{t-half\ day}$									-0.148			
									(-0.791)			
VRP_{t-1day}										0.215	0.294	0.417
										(0.429)	(0.581)	(0.678)
RV_{t-1day}											-0.150	
											(-0.545)	
$IV_{t-1\ day}$												-0.123
												(-0.508)
Constant	7.099*	8.171*	8.019*	5.842	7.626	7.328	5.180	7.875	7.392	3.615	5.910	5.449
	(1.748)	(1.937)	(1.952)	(1.291)	(1.565)	(1.531)	(1.026)	(1.457)	(1.401)	(0.534)	(0.809)	(0.747)
Observations	265,588	265,588	265,588	265,588	265,588	265,588	265,588	265,588	265,588	265,588	265,588	265,588
R^2	0.0002	0.0002	0.0002	0.00002	0.0001	0.0001	0.00000	0.0002	0.0002	0.0001	0.0004	0.0003
Adjusted R^2	0.0001	0.0002	0.0002	0.00001	0.0001	0.0001	-0.0000	0.0002	0.0002	0.0001	0.0004	0.0003

Note: *Parentheses denote t-statistics*
*p<0.1; **p<0.05; ***p<0.01

Table Q.7: Intraday regressions between S&P 500 returns and key variables, winsorized pre-financial crisis sample, January 2002 till December 2007

	Dependent variable:											
	Hourly return			Return per 2 hours			Half day returns			Daily returns		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$VRP_{t-1hour}$	-0.598	-0.927*	-1.481*									
	(-1.297)	(-1.723)	(-1.808)									
$RV_{t-1hour}$		0.385										
		(0.959)										
$IV_{t-1hour}$			0.414									
			(1.159)									
$VRP_{t-2hours}$				-0.358	-0.474	-0.609						
				(-0.66)	(-0.718)	(-0.623)						
$RV_{t-2hours}$					0.136							
					(0.292)							
$IV_{t-2hours}$						0.117						
						(0.286)						
$VRP_{t-half\ day}$							-0.471	-0.478	-0.512			
							(-0.72)	(-0.63)	(-0.452)			
$RV_{t-half\ day}$								0.008				
								(0.015)				
$IV_{t-half\ day}$									0.019			
									(0.040)			
VRP_{t-1day}										-0.472	-0.509	-0.513
										(-0.566)	(-0.521)	(-0.342)
RV_{t-1day}											0.043	
											(0.060)	
$IV_{t-1\ day}$												0.019
												(0.031)
Constant	5.570	3.319	4.123	5.136	4.344	4.727	8.293	8.246	8.227	9.410	9.159	9.343
	(0.862)	(0.487)	(0.627)	(0.672)	(0.530)	(0.601)	(0.914)	(0.858)	(0.882)	(0.835)	(0.793)	(0.822)
Observations	96,414	96,414	96,414	96,414	96,414	96,414	96,414	96,414	96,414	96,414	96,414	96,414
R^2	0.0003	0.001	0.001	0.0002	0.0002	0.0002	0.0004	0.0004	0.0004	0.001	0.001	0.001
Adjusted R^2	0.0003	0.001	0.001	0.0002	0.0002	0.0002	0.0004	0.0004	0.0004	0.001	0.001	0.001
Note:	*Parentheses denote t-statistics* *p<0.1; **p<0.05; ***p<0.01											

Table Q.8: Intraday regressions between S&P 500 returns and key variables, winsorized financial crisis sample, December 2007 till July 2009

	Dependent variable:											
	Hourly return			Return per 2 hours			Half day returns			Daily returns		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$VRP_{t-1hour}$	-0.023	-0.031	-0.032									
	(-0.027)	(-0.035)	(-0.033)									
$RV_{t-1hour}$		0.068										
		(0.142)										
$IV_{t-1hour}$			0.011									
			(0.030)									
$VRP_{t-2hours}$				0.193	0.172	0.122						
				(0.221)	(0.197)	(0.132)						
$RV_{t-2hours}$					0.177							
					(0.373)							
$IV_{t-2hours}$						0.095						
						(0.256)						
$VRP_{t-half\ day}$							0.364	0.337	0.272			
							(0.356)	(0.330)	(0.255)			
$RV_{t-half\ day}$								0.225				
								(0.394)				
$IV_{t-half\ day}$									0.123			
									(0.279)			
VRP_{t-1day}										0.740	0.699	0.547
										(0.694)	(0.660)	(0.502)
RV_{t-1day}											0.336	
											(0.545)	
$IV_{t-1\ day}$												0.256
												(0.545)
Constant	-17.349	-21.344	-18.127	-22.814	-33.166	-29.413	-29.831	-42.997	-38.359	-35.782	-55.486	-53.571
	(-0.960)	(-0.678)	(-0.620)	(-1.24)	(-1.054)	(-1.002)	(-1.37)	(-1.106)	(-1.052)	(-1.551)	(-1.283)	(-1.295)
Observations	26,076	26,076	26,076	26,076	26,076	26,076	26,076	26,076	26,076	26,076	26,076	26,076
R^2	0.00000	0.00001	0.00000	0.0000	0.0002	0.0001	0.0002	0.0005	0.0003	0.001	0.002	0.002
Adjusted R^2	-0.0004	-0.0001	-0.0001	0.0000	0.0001	0.00003	0.0002	0.0004	0.0003	0.001	0.002	0.002
Note:	*Parentheses denote t-statistics* *p<0.1; **p<0.05; ***p<0.01											

Table Q.9: Intraday regressions between S&P 500 returns and key variables, winsorized post-financial crisis sample, July 2009 till February 2018

	Dependent variable:											
	Hourly return			Return per 2 hours			Half day returns			Daily returns		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$VRP_{t-1hour}$	-0.238	-0.245	-0.339									
	(-0.556)	(-0.575)	(-0.647)									
$RV_{t-1hour}$		0.036										
		(0.150)										
$IV_{t-1hour}$			0.075									
			(0.303)									
$VRP_{t-2hours}$				0.282	0.256	-0.027						
				(0.565)	(0.515)	(-0.042)						
$RV_{t-2hours}$					0.124							
					(0.439)							
$IV_{t-2hours}$						0.230						
						(0.751)						
$VRP_{t-half\ day}$							0.663	0.628	0.256			
							(1.178)	(1.095)	(0.338)			
$RV_{t-half\ day}$								0.171				
								(0.506)				
$IV_{t-half\ day}$									0.304			
									(0.856)			
VRP_{t-1day}										1.038	0.982	0.487
										(1.438)	(1.346)	(0.485)
RV_{t-1day}											0.264	
											(0.581)	
$IV_{t-1\ day}$												0.410
												(0.858)
Constant	10.809**	10.262*	9.779*	8.660	6.746	5.511	5.793	3.170	1.637	2.943	-1.103	-2.653
	(2.163)	(1.790)	(1.722)	(1.472)	(1.018)	(0.834)	(0.857)	(0.414)	(0.218)	(0.335)	(-0.112)	(-0.275)
Observations	143,098	143,098	143,098	143,098	143,098	143,098	143,098	143,098	143,098	143,098	143,098	143,098
R^2	0.00004	0.00004	0.0001	0.0001	0.0001	0.0003	0.001	0.001	0.001	0.002	0.003	0.004
Adjusted R^2	0.00003	0.00003	0.00004	0.0001	0.0001	0.0003	0.001	0.001	0.001	0.002	0.003	0.004

Note: *Parentheses denote t-statistics* $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Appendix R: EVRP winsorized samples

Table R.1: EVRP 4 month return regressions, winsorized full sample from January 2002 to September 2017

	Dependent variable:														
	$(r_{SPX} - r_m)_{t \to t+4}$														
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
$EVRP_t$	0.249***									0.229**	0.453***	0.514***		0.586***	0.586***
	(2.629)									(2.388)	(4.210)	(5.160)		(5.502)	(5.271)
IV_t		0.049													
		(0.604)													
ERV_t			0.028												
			(0.188)												
$\log(P/E)_t$				-38.084						-36.402			-41.637*	-40.352***	-43.696***
				(-1.466)						(-1.637)			(-1.892)	(-3.335)	(-2.768)
$\log(P/D)_t$					-7.381										-10.115**
					(-0.819)										(-2.116)
$DFSP_t$						-4.312									-9.324
						(-0.286)									(-1.019)
$TMSP_t$							-0.674								1.914
							(-0.227)								(0.910)
CAY_t								-1.756			-4.289***		0.325	-2.349*	
								(-0.805)			(-2.581)		(0.171)	(-1.758)	
$RREL_t$									11.424**			16.507***	12.354***	15.435***	16.218***
									(2.570)			(5.457)	(2.740)	(5.328)	(5.147)
Constant	1.133	3.557	4.834	111.590	-18.733	9.961	6.829	4.064	6.548**	102.967	-5.692	-1.793	122.968**	107.543***	91.479
	(0.392)	(0.945)	(1.099)	(1.524)	(-0.599)	(0.690)	(1.258)	(0.884)	(2.248)	(1.628)	(-1.479)	(-0.765)	(1.998)	(3.130)	(1.639)
Observations	3,850	3,850	3,850	3,850	3,850	3,850	3,850	3,850	3,850	3,850	3,850	3,850	3,850	3,850	3,850
R^2	0.030	0.005	0.001	0.053	0.010	0.003	0.001	0.013	0.102	0.078	0.085	0.208	0.165	0.280	0.293
Adjusted R^2	0.030	0.005	0.0005	0.053	0.010	0.003	0.001	0.012	0.101	0.077	0.085	0.208	0.165	0.279	0.292

Note: *Parentheses denote t-statistics* $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table R.2: EVRP 4 month return regressions, winsorized pre-GFC sample from January 2002 to December 2007

	Dependent variable:														
	$(r_{SPX} - r_m)_{t \to t+4}$														
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
$EVRP_t$	0.054									0.293***	0.028	0.296**		-0.109	-0.144**
	(0.493)									(4.024)	(0.230)	(2.564)		(-1.028)	(-2.296)
IV_t		0.020													
		(0.216)													
ERV_t			-0.005												
			(-0.027)												
$\log(P/E)_t$				-81.760**						-102.610***			-141.469***	-146.739***	-268.424***
				(-2.139)						(-4.319)			(-3.444)	(-3.710)	(-11.110)
$\log(P/D)_t$					-12.343										107.358***
					(-0.397)										(2.620)
$DFSP_t$						-25.053									-45.540***
						(-0.952)									(-4.824)
$TMSP_t$							-1.961								1.943
							(-0.463)								(0.488)
CAY_t								0.801			0.479		5.689**	6.822***	
								(0.322)			(0.194)		(2.548)	(2.875)	
$RREL_t$									5.396			9.949**	-4.161	-5.200	-17.151***
									(0.859)			(2.343)	(-0.754)	(-0.986)	(-4.423)
Constant	2.416	2.718	3.516	239.799**	-33.372	27.778	6.949	3.472	3.016	294.568***	2.936	-2.912	412.991***	430.404***	1,144.398***
	(0.647)	(0.571)	(0.663)	(2.186)	(-0.346)	(1.195)	(1.499)	(0.691)	(0.596)	(4.315)	(0.549)	(-0.745)	(3.487)	(3.777)	(10.485)
Observations	1,440	1,440	1,440	1,440	1,440	1,440	1,440	1,440	1,440	1,440	1,440	1,440	1,440	1,440	1,440
R^2	0.003	0.001	0.00001	0.232	0.011	0.066	0.020	0.003	0.049	0.308	0.004	0.107	0.387	0.390	0.605
Adjusted R^2	0.002	0.0005	-0.001	0.231	0.010	0.065	0.019	0.003	0.048	0.307	0.002	0.106	0.385	0.389	0.604
Note:	*Parentheses denote t-statistics*														*p<0.1; **p<0.05; ***p<0.01

Table R.3: EVRP 4 month return regressions, winsorized GFC sample from December 2007 to July 2009

	Dependent variable:														
	$(r_{SPX} - r_m)_{t \to t+4}$														
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
$EVRP_t$	0.201***									0.202***	0.177*	0.219**		0.164**	0.115**
	(2.876)									(3.038)	(1.894)	(2.524)		(2.475)	(2.090)
IV_t		0.096													
		(0.807)													
ERV_t			0.050												
			(0.410)												
$\log(P/E)_t$				-43.715						-44.305			-165.205	-156.130	-320.052***
				(-0.490)						(-0.873)			(-1.296)	(-1.637)	(-3.374)
$\log(P/D)_t$					1,055.260										949.048***
					(1.217)										(3.389)
$DFSP_t$						10.625									9.475
						(0.676)									(0.722)
$TMSP_t$							-12.658								-50.273***
							(-1.004)								(-6.609)
CAY_t								-10.710			-9.582		-23.236	-21.414	
								(-0.661)			(-0.759)		(-1.315)	(-1.368)	
$RREL_t$									-18.784			-20.775	-15.225	-16.994	-56.921***
									(-0.746)			(-1.050)	(-0.816)	(-1.113)	(-9.248)
Constant	-39.223***	-47.159**	-42.070	77.682	3,467.963	-55.840*	-14.898	-34.649*	-63.834	78.114	-36.002***	-67.784*	386.069	358.107	3,960.422***
	(-3.070)	(-2.096)	(-1.501)	(0.321)	(1.209)	(-1.768)	(-1.157)	(-1.874)	(-1.201)	(0.597)	(-2.583)	(-1.764)	(1.042)	(1.303)	(4.110)
Observations	389	389	389	389	389	389	389	389	389	389	389	389	389	389	389
R^2	0.062	0.041	0.013	0.018	0.160	0.040	0.069	0.070	0.050	0.081	0.118	0.123	0.260	0.300	0.771
Adjusted R^2	0.060	0.039	0.010	0.015	0.158	0.037	0.067	0.068	0.047	0.076	0.113	0.118	0.254	0.293	0.767

Note: *Parentheses denote t-statistics* $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table R.4: EVRP 4 month return regressions, winsorized post-GFC sample July 2009 to September 2017

	Dependent variable:														
	$(r_{SPX} - r_m)_{t \to t+4}$														
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
$EVRP_t$	0.574***									0.318***	0.489***	0.506***		0.426***	0.524***
	(6.499)									(3.418)	(4.025)	(4.876)		(3.980)	(5.209)
IV_t		0.354***													
		(6.595)													
ERV_t			0.358***												
			(2.925)												
$\log(P/E)_t$				-61.203***						-48.153***			-79.068**	-76.740***	-67.419**
				(-3.390)						(-2.919)			(-2.568)	(-3.198)	(-2.420)
$\log(P/D)_t$					8.967										-21.092
					(0.674)										(-1.642)
$DFSP_t$						20.059**									-1.769
						(2.202)									(-0.250)
$TMSP_t$							-2.851								-2.298
							(-0.556)								(-0.523)
CAY_t								3.457*			1.436		-2.145	-3.266	
								(1.731)			(0.826)		(-0.736)	(-1.443)	
$RREL_t$									-36.119*			-13.615	1.623	13.368	-7.881
									(-1.758)			(-0.942)	(0.077)	(0.808)	(-0.371)
Constant	4.011*	2.014	6.663*	181.251***	44.451	-7.667	20.033*	18.485***	13.321***	140.279***	7.530	5.105*	227.072***	212.099***	123.854*
	(1.894)	(0.630)	(1.810)	(3.633)	(0.920)	(-0.758)	(1.931)	(3.690)	(4.568)	(3.051)	(1.568)	(1.894)	(2.809)	(3.365)	(1.908)
Observations	2,022	2,022	2,022	2,022	2,022	2,022	2,022	2,022	2,022	2,022	2,022	2,022	2,022	2,022	2,022
R^2	0.127	0.216	0.152	0.187	0.018	0.106	0.012	0.066	0.056	0.217	0.135	0.133	0.198	0.245	0.292
Adjusted R^2	0.126	0.216	0.151	0.186	0.017	0.106	0.011	0.065	0.056	0.216	0.135	0.132	0.197	0.244	0.290

Note: *Parentheses denote t-statistics* *p<0.1; **p<0.05; ***p<0.01

Table R.5: EVRP 3 month return regressions, winsorized GFC sample December 2007 to July 2009

	Dependent variable:														
	$(r_{SPX} - r_m)_{t\rightarrow t+3}$														
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
$EVRP_t$	0.223***									0.212***	0.187	0.245***		0.116*	0.169**
	(2.608)									(2.656)	(1.599)	(2.664)		(1.823)	(2.325)
IV_t		0.097													
		(1.018)													
ERV_t			0.036												
			(0.483)												
$\log(P/E)_t$				-89.855						-86.408			-249.696**	-241.827***	-535.031***
				(-1.105)						(-1.242)			(-2.426)	(-2.602)	(-3.946)
$\log(P/D)_t$					1,446.712										1,375.073***
					(0.782)										(2.833)
$DFSP_t$						13.140									-37.888
						(0.880)									(-1.540)
$TMSP_t$							-6.538								-36.311***
							(-0.622)								(-3.351)
CAY_t								-15.017			-13.735		-35.970***	-34.262***	
								(-0.937)			(-0.951		(-3.170)	(-3.368)	
$RREL_t$									-10.898			-14.665	-8.464	-10.574	-52.303***
									(-0.206)			(-0.359	(-0.282)	(-0.363)	(-4.499)
Constant	-37.863***	-45.900*	-39.099	199.873	4,772.606	-59.459*	-23.245	-29.390**	-50.996	189.102	-31.472***	-58.146	623.903**	598.653**	6,004.797***
	(-2.653)	(-1.949)	(-1.474)	(0.931)	(0.776)	(-1.922)	(-1.477)	(-2.397)	(-0.508)	(1.060)	(-3.093)	(-0.789)	(2.092)	(2.205)	(3.781)
Observations	389	389	389	389	389	389	389	389	389	389	389	389	389	389	389
R^2	0.052	0.032	0.005	0.067	0.157	0.047	0.012	0.092	0.012	0.115	0.128	0.073	0.418	0.431	0.577
Adjusted R^2	0.050	0.029	0.002	0.065	0.155	0.044	0.009	0.090	0.009	0.110	0.124	0.068	0.414	0.425	0.571

Note: *Parentheses denote t-statistics* $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table R.6: EVRP 3.5 month return regressions, winsorized full sample from January 2002 to September 2017

	Dependent variable:														
	$(r_{SPX} - r_m)_{t \to t+3.5}$														
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
$EVRP_t$	0.261**									0.239**	0.485***	0.537***		0.624***	0.617***
	(2.468)									(2.359)	(4.324)	(4.986)		(5.740)	(5.564)
IV_t		0.042													
		(0.495)													
ERV_t			0.022												
			(0.144)												
$\log(P/E)_t$				-37.596						-35.591			-42.692**	-41.445***	-45.420***
				(-1.447)						(-1.507)			(-2.124)	(-3.194)	(-2.605)
$\log(P/D)_t$					-7.197										-10.546**
					(-0.735)										(-2.000)
$DFSP_t$						-5.289									-10.296
						(-0.358)									(-1.046)
$TMSP_t$							-0.847								1.904
							(-0.282)								(0.881)
CAY_t								-1.963			-4.675***		0.115	-2.733**	
								(-0.869)			(-2.695)		(0.058)	(-1.983)	
$RREL_t$									11.847***			17.207***	12.780***	16.101***	16.966***
									(2.938)			(5.242)	(3.214)	(5.145)	(4.969)
Constant	0.964	3.862	4.986	110.240	-18.121	11.019	7.220	3.915	6.554**	100.553	-6.525*	-2.162	125.725**	109.632***	95.358
	(0.319)	(1.019)	(1.184)	(1.506)	(-0.542)	(0.787)	(1.310)	(0.870)	(2.129)	(1.502)	(-1.657)	(-0.851)	(2.234)	(2.989)	(1.526)
Observations	3,850	3,850	3,850	3,850	3,850	3,850	3,850	3,850	3,850	3,850	3,850	3,850	3,850	3,850	3,850
R^2	0.029	0.003	0.0004	0.046	0.009	0.004	0.001	0.014	0.096	0.070	0.088	0.200	0.155	0.270	0.279
Adjusted R^2	0.029	0.003	0.0001	0.045	0.009	0.004	0.001	0.014	0.096	0.069	0.087	0.199	0.154	0.269	0.278

Note: *Parentheses denote t-statistics* — *p<0.1; **p<0.05; ***p<0.01

Table R.7: EVRP 3.5 month return regressions, winsorized pre-GFC sample from January 2002 to December 2007

	Dependent variable:														
	$(r_{SPX} - r_m)_{t\to t+3.5}$														
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
$EVRP_t$	0.064									0.319^{***}	0.097	0.323^{***}		-0.029	-0.131^{*}
	(0.633)									(4.654)	(0.832)	(2.911)		(-0.307)	(-1.828)
IV_t		0.014													
		(0.146)													
ERV_t			-0.024												
			(-0.114)												
$\log(P/E)_t$				-85.393^{**}						-108.415^{***}			-144.762^{***}	-146.081^{***}	-270.682^{***}
				(-2.499)						(-4.258)			(-3.586)	(-3.601)	(-10.433)
$\log(P/D)_t$					-14.537										116.811^{***}
					(-0.527)										(3.242)
$DFSP_t$						-27.513									-51.214^{***}
						(-1.026)									(-4.425)
$TMSP_t$							-2.248								0.739
							(-0.576)								(0.192)
CAY_t								0.538			-0.597		5.590^{***}	5.889^{***}	
								(0.220)			(-0.243)		(2.773)	(2.701)	
$RREL_t$									5.699			10.760^{***}	-4.315	-4.585	-18.166^{***}
									(1.253)			(2.765)	(-0.932)	(-0.975)	(-5.248)
Constant	2.023	2.699	3.614	249.915^{**}	-40.182	29.977	7.216^{*}	3.250	2.715	310.472^{***}	1.371	-3.746	422.141^{***}	426.528^{***}	$1{,}186.498^{***}$
	(0.552)	(0.540)	(0.728)	(2.560)	(-0.468)	(1.270)	(1.706)	(0.724)	(0.631)	(4.264)	(0.272)	(-0.995)	(3.652)	(3.673)	(7.938)
Observations	1,440	1,440	1,440	1,440	1,440	1,440	1,440	1,440	1,440	1,440	1,440	1,440	1,440	1,440	1,440
R^2	0.004	0.001	0.0003	0.216	0.013	0.067	0.023	0.001	0.045	0.292	0.004	0.104	0.345	0.345	0.548
Adjusted R^2	0.003	-0.0002	-0.0004	0.215	0.012	0.067	0.022	0.001	0.044	0.291	0.003	0.103	0.343	0.343	0.546

Note: *Parentheses denote t-statistics* $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table R.8: EVRP 3.5 month return regressions, winsorized GFC sample from December 2007 to July 2009

	Dependent variable:														
	$(r_{SPX} - r_m)_{t \to t+3.5}$														
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
$EVRP_t$	0.175**									0.176***	0.143	0.195**		0.119**	0.099
	(2.244)									(2.581)	(1.290)	(1.975)		(2.003)	(1.329)
IV_t		0.103													
		(1.043)													
ERV_t			0.034												
			(0.330)												
$\log(P/E)_t$				-62.511						-62.960			-203.881	-197.834	-441.525***
				(-0.520)						(-0.833)			(-1.441)	(-1.599)	(-3.278)
$\log(P/D)_t$					1,218.831										942.425*
					(0.846)										(1.662)
$DFSP_t$						11.655									-9.534
						(0.662)									(-0.464)
$TMSP_t$							-11.285								-53.155***
							(-0.726)								(-4.344)
CAY_t								-12.803			-11.788		-28.837**	-27.348*	
								(-0.716)			(-0.825)		(-2.017)	(-1.912)	
$RREL_t$									-16.698			-19.021	-12.933	-14.682	-57.119***
									(-0.412)			(-0.643)	(-0.566)	(-0.693)	(-6.884)
Constant	-38.435**	-47.492**	-40.140	127.519	4,013.344	-57.399*	-15.827	-32.423*	-60.351	127.585	-33.718**	-64.794	493.517	473.831	4,297.322**
	(-2.465)	(-2.149)	(-1.429)	(0.395)	(0.839)	(-1.922)	(-0.964)	(-1.846)	(-0.745)	(0.636)	(-2.488)	(-1.141)	(1.215)	(1.345)	(2.036)
Observations	389	389	389	389	389	389	389	389	389	389	389	389	389	389	389
R^2	0.040	0.041	0.005	0.034	0.149	0.042	0.042	0.082	0.032	0.075	0.108	0.080	0.321	0.339	0.655
Adjusted R^2	0.037	0.038	0.002	0.032	0.147	0.039	0.040	0.079	0.029	0.070	0.103	0.075	0.316	0.332	0.650
Note:	*Parentheses denote t-statistics*														*p<0.1; **p<0.05; ***p<0.01

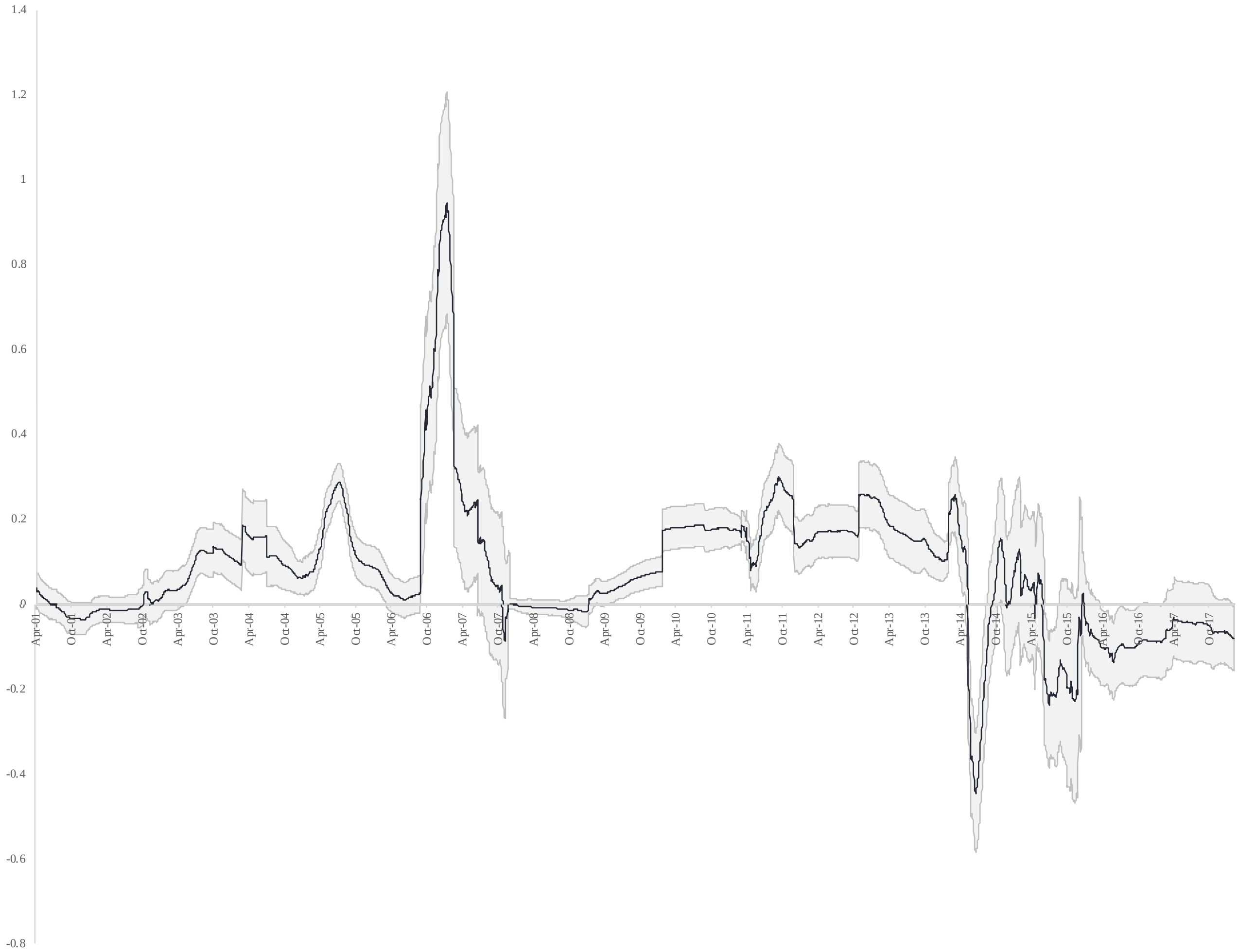
Table R.9: EVRP 3.5 month return regressions, winsorized post-GFC sample July 2009 to September 2017

	Dependent variable:														
	$(r_{SPX} - r_m)_{t\rightarrow t+3.5}$														
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
$EVRP_t$	0.615***									0.389***	0.567***	0.598***		0.531***	0.678***
	(8.247)									(4.299)	(5.324)	(6.723)		(5.019)	(6.910)
IV_t		0.354***													
		(5.084)													
ERV_t			0.364***												
			(3.127)												
$\log(P/E)_t$				-58.117***						-42.031**			-79.023**	-75.779***	-66.815**
				(-2.823)						(-2.324)			(-2.033)	(-2.581)	(-2.241)
$\log(P/D)_t$					8.320										-20.637
					(0.573)										(-1.473)
$DFSP_t$						18.265									-6.920
						(1.546)									(-0.665)
$TMSP_t$							-3.186								-3.136
							(-0.592)								(-0.749)
CAY_t								3.186			0.807		-2.201	-3.617	
								(1.484)			(0.449)		(-0.606)	(-1.288)	
$RREL_t$									-31.621			-3.538	7.237	22.382	-2.542
									(-1.429)			(-0.243	(0.293)	(1.092)	(-0.104)
Constant	3.057	1.912	6.386	172.614***	41.894	-5.860	20.463*	17.814***	13.162***	122.133**	5.055	3.344	226.674**	206.973***	128.373
	(1.228)	(0.476)	(1.591)	(3.055)	(0.804)	(-0.474)	(1.830)	(3.393)	(4.055)	(2.431)	(1.041)	(1.126)	(2.227)	(2.672)	(1.641)
Observations	2,022	2,022	2,022	2,022	2,022	2,022	2,022	2,022	2,022	2,022	2,022	2,022	2,022	2,022	2,022
R^2	0.125	0.175	0.127	0.145	0.013	0.065	0.013	0.048	0.033	0.184	0.127	0.125	0.156	0.219	0.262
Adjusted R^2	0.124	0.174	0.126	0.144	0.013	0.064	0.012	0.047	0.033	0.183	0.126	0.124	0.155	0.217	0.260

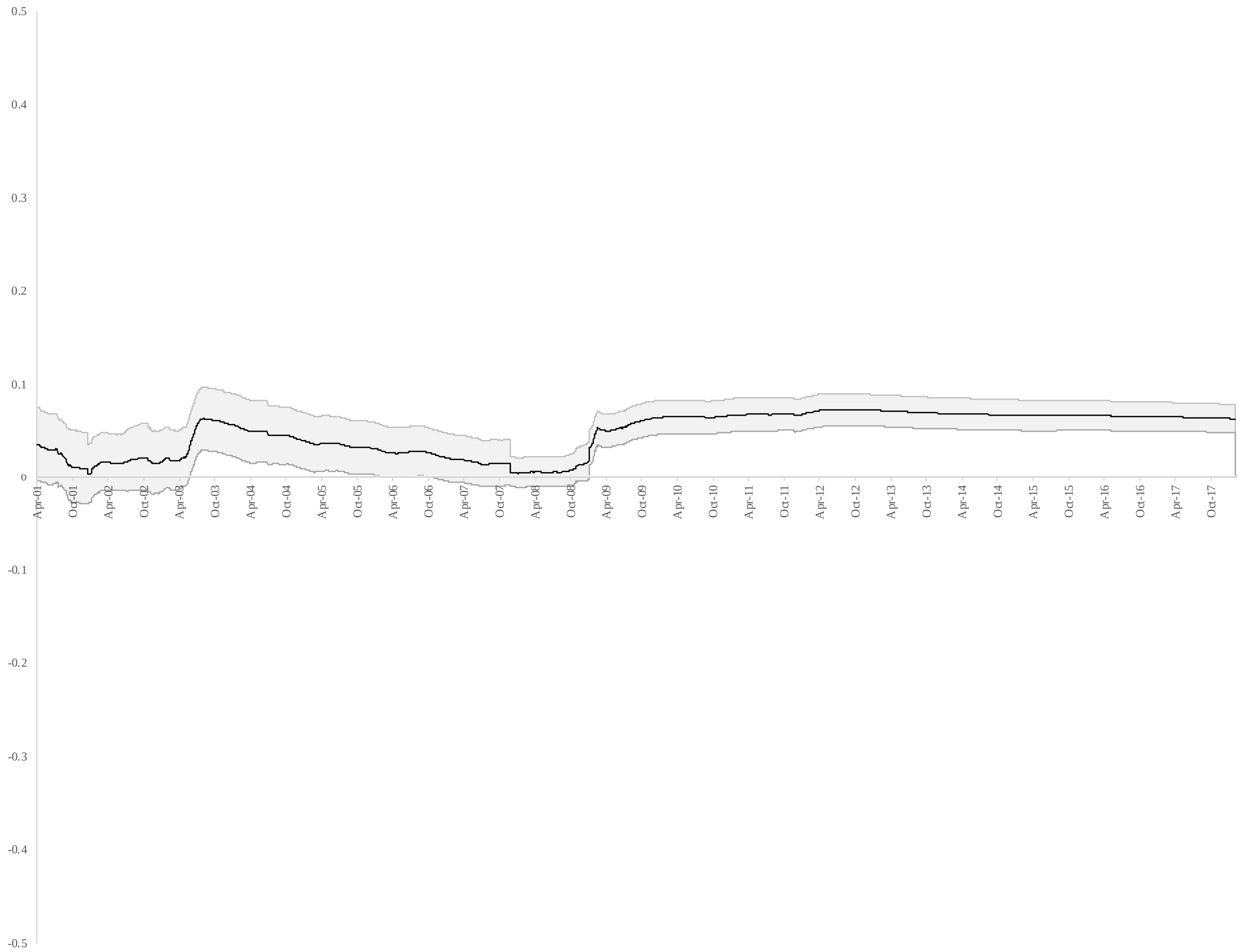
Note: *Parentheses denote t-statistics* *p<0.1; **p<0.05; ***p<0.01

Appendix S: EVRP 4-months rolling and recursive return regressions

Graph S.1: Rolling 4-month return regression for EVRP

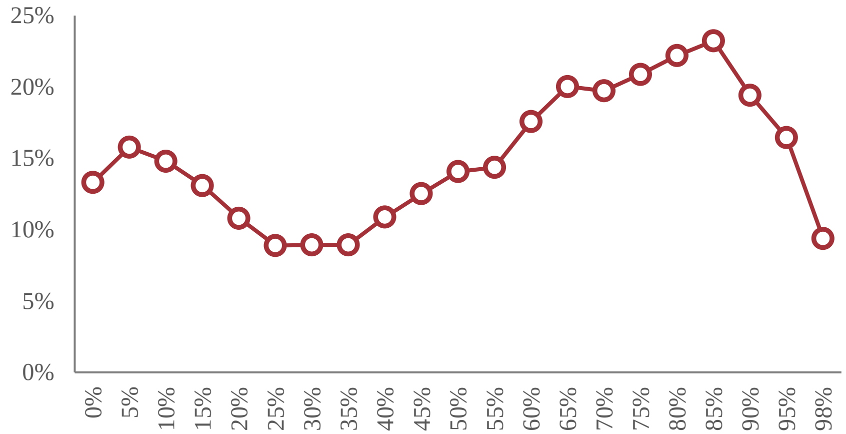


Graph S.2: Recursive 4-month return regression for EVRP:



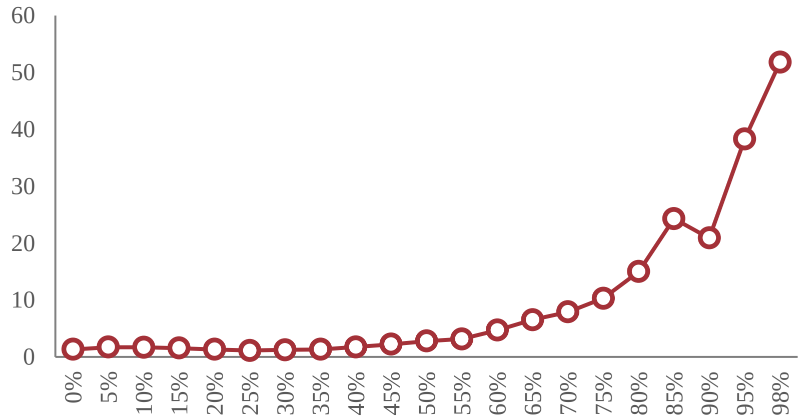
Appendix T: Sharpe and Sortino ratios and total return profiles for VRP trading strategy

Figure T.1: Sharpe ratio profile



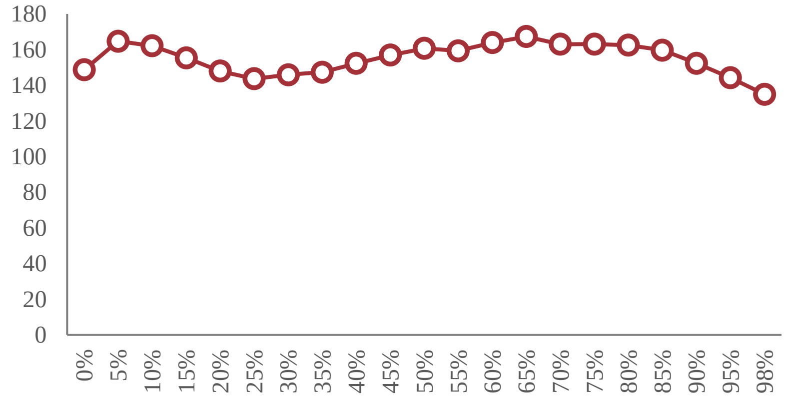
Value axis denotes the Sharpe Ratio. Horizontal axis denotes VRP-percentile utilized as threshold for market investment

Figure T.2: Sortino ratio profile



Value axis denotes the Sortino Ratio. Horizontal axis denotes VRP-percentile utilized as threshold for market investment

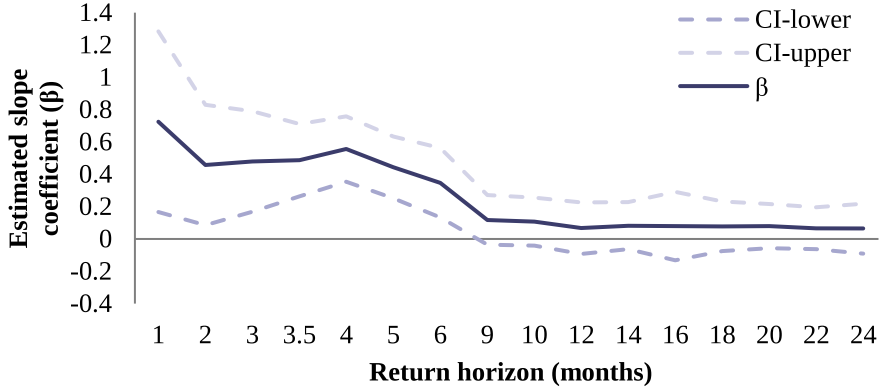
Figure T.3: Total return profile

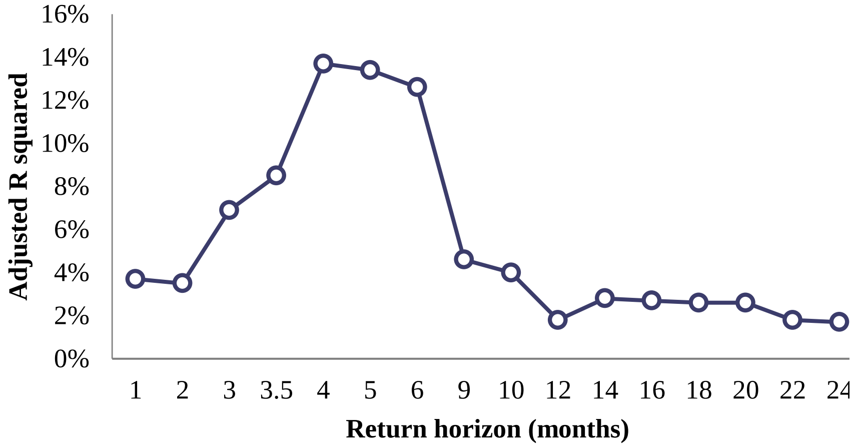


Value axis denotes the total return. Horizontal axis denotes VRP-percentile utilized as threshold for market investment

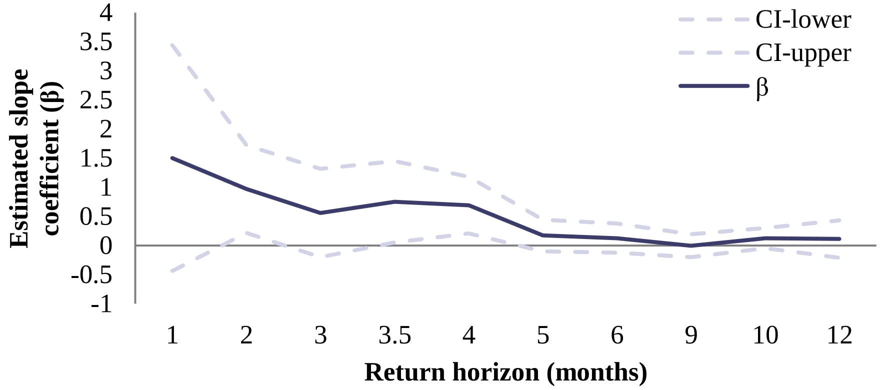
Appendix U: Overview of VRP slope coefficients (with 95% confidence intervals) and adj. R squared for studied time samples

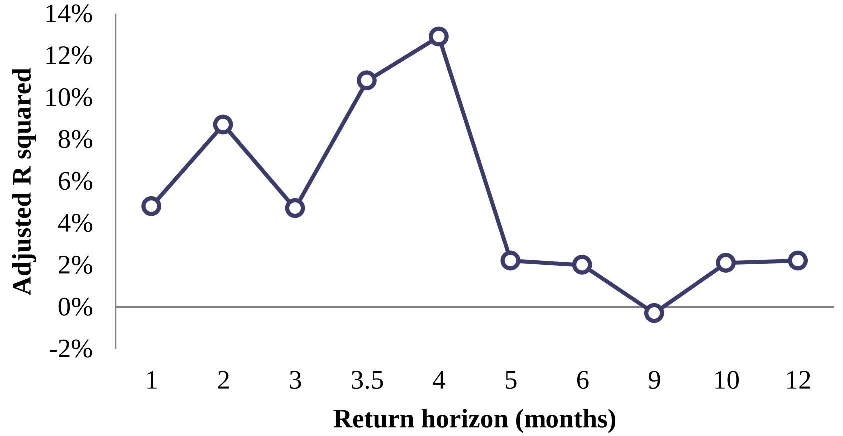
Figures U.1 VRP for the sample pre-election of Trump (July 2009 to 8. November 2016)



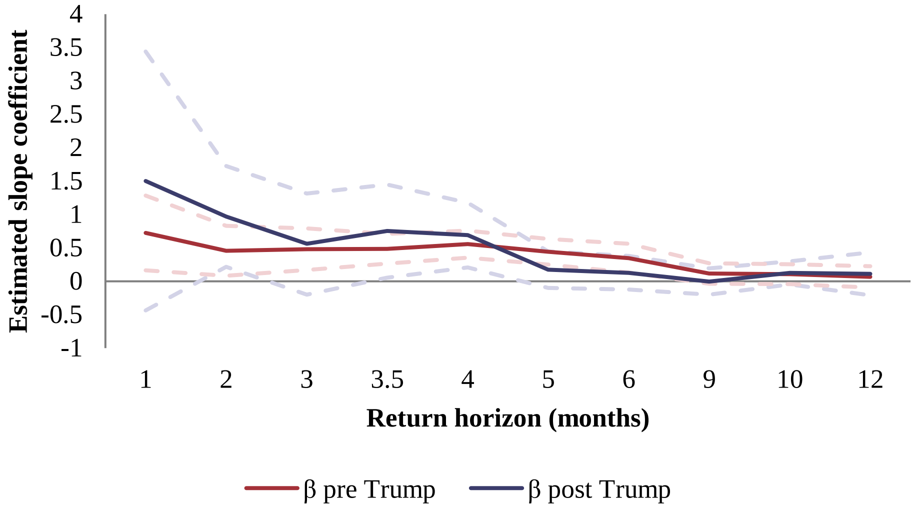


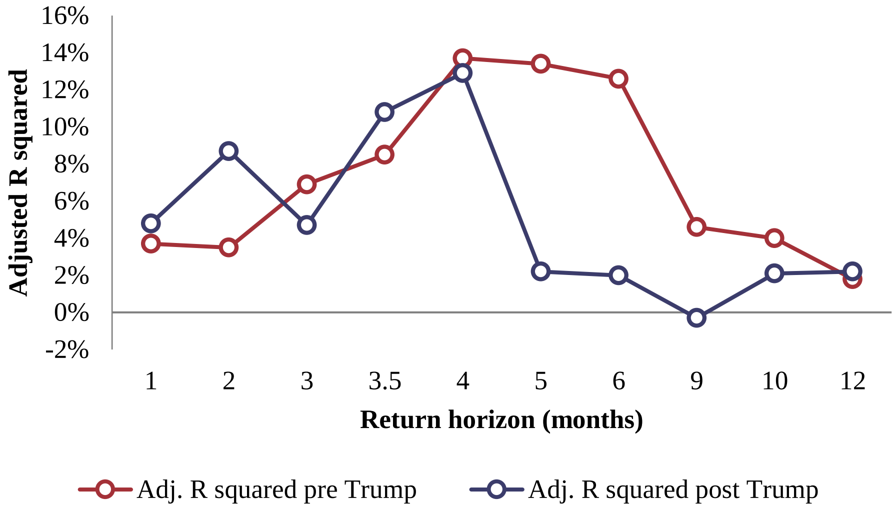
Figures U.2: VRP for the sample post-election of Trump (8. November 2016 to March 2018)



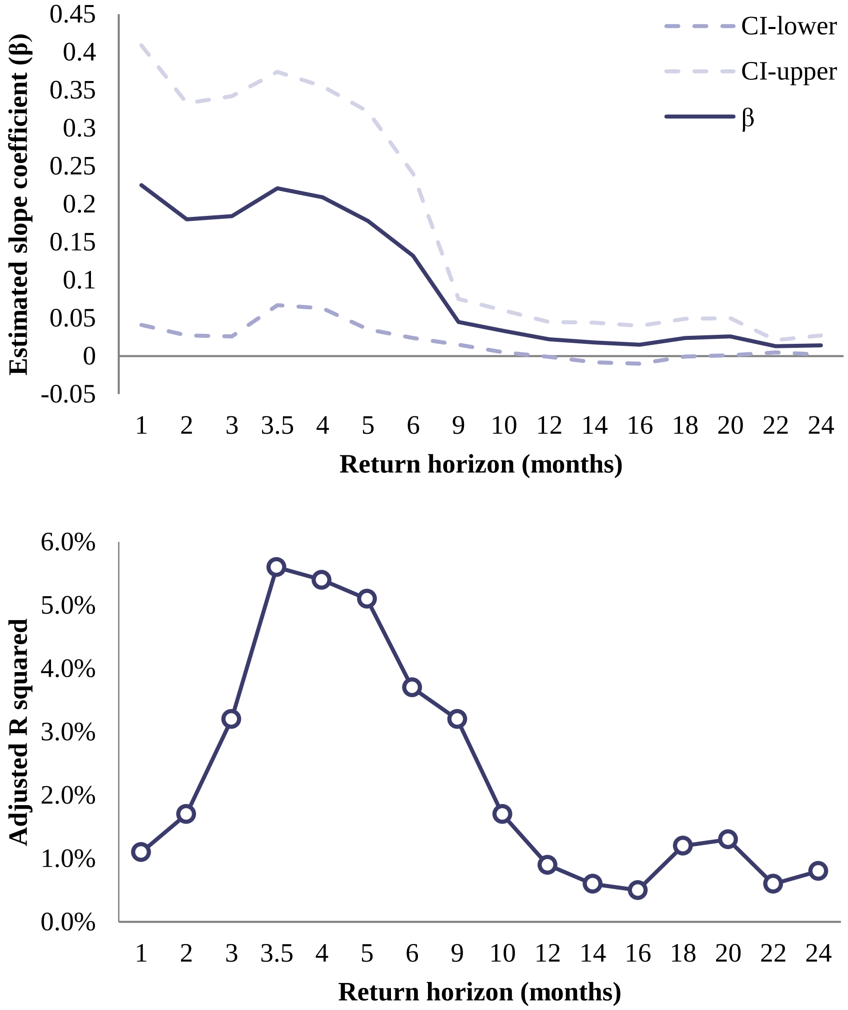


Figures U.3: Comparison of pre- and post-election of Trump samples
VRP

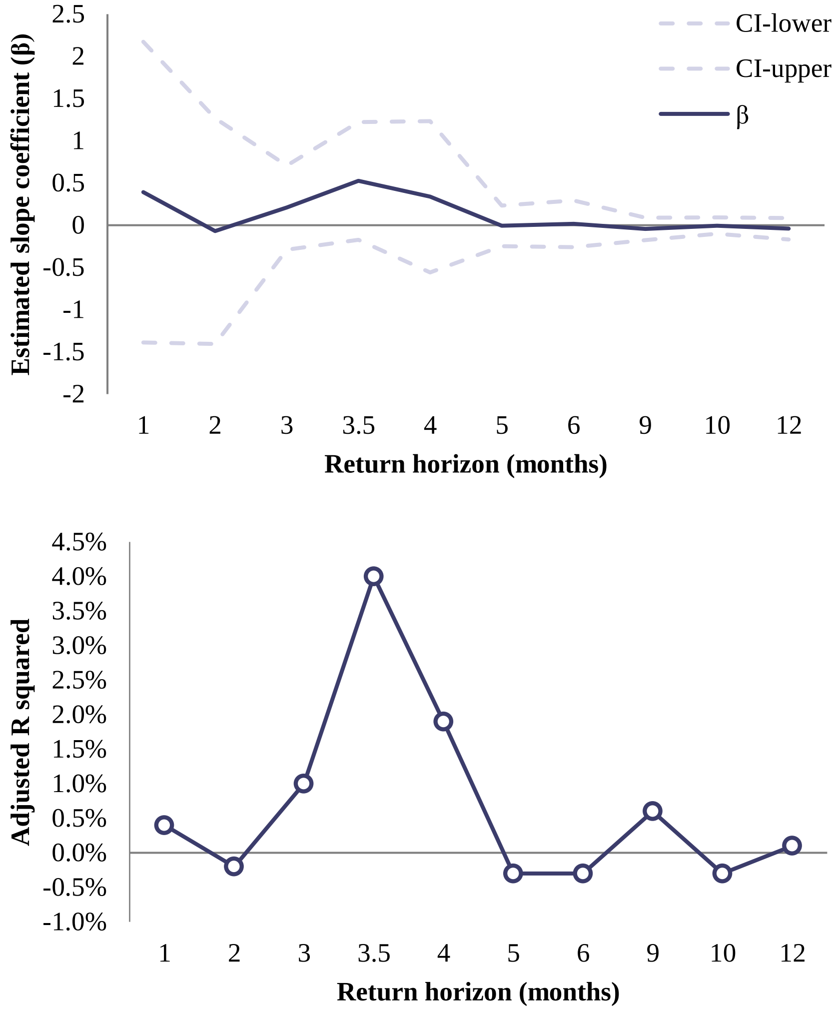




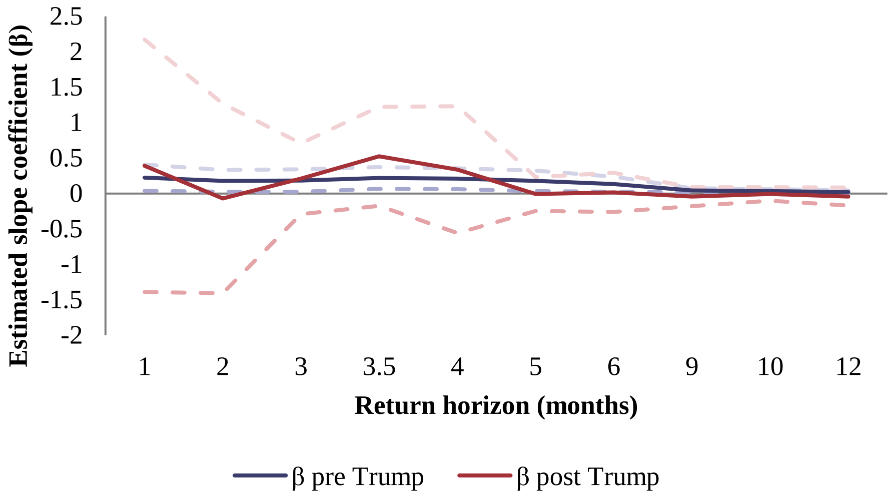
Figures U.4: EVRP for the sample pre-election of Trump (July 2009 to 8. November 2016)

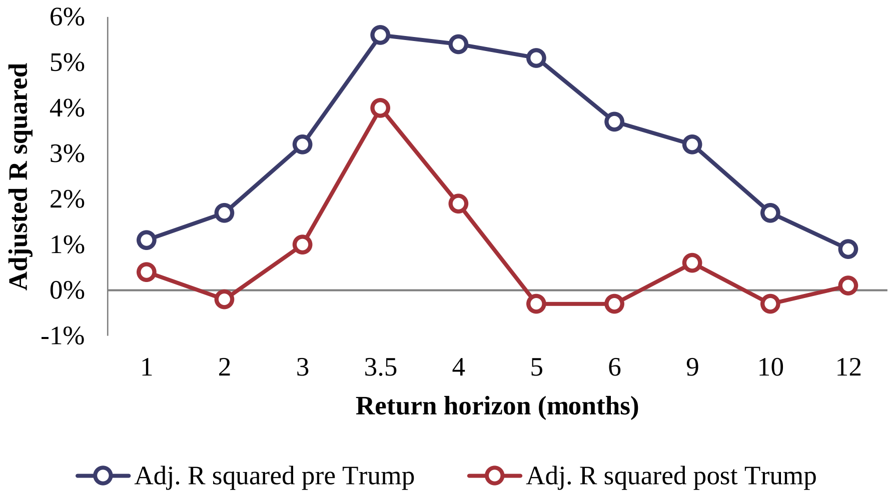


Figures U.5: EVRP for the sample post-election of Trump (8. November 2016 to March 2018)



Figures U.6: Comparison of pre- and post-election of Trump EVRP





Appendix V: VRP return regressions, pre-election sample from July 2009 to November 2016

Table V.1: VRP, 3.5-month return horizon, pre-election

	Dependent variable:												
	$(r_{SPX} - r_m)_{t \to t+3.5}$												
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
VRP_t	0.488^{***}								0.267^{***}	0.337^{***}		0.244^{**}	0.345^{***}
	(4.271)								(2.723)	(3.124)		(2.474)	(3.069)
IV_t		0.340^{***}											
		(5.319)											
RV_t			0.356^{***}										
			(3.150)										
$\log(P/E)_t$				-87.329^{***}					-78.376^{***}		-76.944^{***}	-72.302^{***}	-70.786
				(-5.184)					(-4.870)		(-3.085)	(-3.139)	(-1.549)
$\log(P/D)_t$					12.279								-13.593
					(0.682)								(-0.596)
$DFSP_t$						20.897^{***}							4.107
						(5.937)							(0.459)
$TMSP_t$							-3.795						-3.150
							(-0.609)						(-0.485)
$RREL_t$								-46.411^{***}		-36.834^{***}	-14.671	-9.646	-13.778
								(-4.787)		(-4.135)	(-1.043)	(-0.712)	(-0.574)
Constant	5.775^{*}	0.771	5.292	250.388^{***}	54.839	-10.390	21.966	11.304^{***}	222.217^{***}	6.790^{*}	221.673^{***}	205.709^{***}	156.518^{*}
	(1.808)	(0.176)	(1.144)	(5.433)	(0.860)	(-1.596)	(1.587)	(2.812)	(5.024)	(1.914)	(3.229	(3.250)	(1.872)
Observations	1,804	1,804	1,804	1,804	1,804	1,804	1,804	1,804	1,804	1,804	1,804	1,804	1,804
R^2	0.085	0.194	0.141	0.229	0.018	0.154	0.013	0.111	0.252	0.147	0.237	0.256	0.300
Adjusted R^2	0.085	0.193	0.140	0.229	0.018	0.154	0.013	0.111	0.252	0.146	0.236	0.254	0.298

Note: *Parentheses denote t-statistics* $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table V.2: VRP, 3.5-month return horizon, winsorized pre-election

	Dependent variable:												
	$(r_{SPX} - r_m)_{t\to t+3.5}$												
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
VRP_t	0.633^{***}								0.371^{***}	0.485^{***}		0.349^{**}	0.488^{***}
	(3.885)								(2.734)	(2.707)		(2.229)	(3.163)
IV_t		0.389^{***}											
		(5.090)											
RV_t			0.400^{***}										
			(3.118)										
$\log(P/E)_t$				-83.998^{***}					-73.648^{***}		-76.745^{***}	-71.374^{***}	-68.658^{*}
				(-4.218)					(-3.857)		(-3.318)	(-3.257)	(-1.726)
$\log(P/D)_t$					12.541								-13.782
					(0.716)								(-0.717)
$DFSP_t$						22.950^{**}							3.009
						(2.012)							(0.285)
$TMSP_t$							-3.558						-4.446
							(-0.586)						(-0.783)
$RREL_t$								-57.809^{***}		-37.810^{*}	-19.494	-7.797	-32.387
								(-2.650)		(-1.703)	(-0.848)	(-0.321)	(-1.070)
Constant	3.744	-0.353	4.811	241.565^{***}	55.738	-11.870	21.394	11.623^{***}	208.095^{***}	5.118	221.428^{***}	202.070^{***}	152.548^{*}
	(0.997)	(-0.076)	(1.024)	(4.433)	(0.901)	(-0.903)	(1.592)	(3.090)	(3.940)	(1.277)	(3.484)	(3.361)	(1.852)
Observations	1,804	1,804	1,804	1,804	1,804	1,804	1,804	1,804	1,804	1,804	1,804	1,804	1,804
R^2	0.099	0.198	0.144	0.222	0.023	0.103	0.013	0.078	0.252	0.127	0.229	0.253	0.306
Adjusted R^2	0.098	0.198	0.143	0.221	0.022	0.102	0.013	0.078	0.251	0.126	0.228	0.252	0.304

Note: *Parentheses denote t-statistics* $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table V.3: VRP, 4-month return horizon, pre-election

	Dependent variable:												
	$(r_{SPX} - r_m)_{t\to t+3.5}$												
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
VRP_t	0.556***								0.303***	0.368***		0.274***	0.352***
	(5.401)								(3.573)	(4.050)		(3.139)	(3.433)
IV_t		0.353***											
		(8.168)											
RV_t			0.390***										
			(3.247)										
$\log(P/E)_t$				-92.196***					-79.501***		-78.642***	-72.997***	-74.248**
				(-6.133)					(-6.050)		(-3.928)	(-4.230)	(-2.017)
$\log(P/D)_t$					12.063								-16.133
					(0.702)								(-0.917)
$DFSP_t$						22.760***							5.044
						(5.747)							(0.747)
$TMSP_t$							-4.004						-2.271
							(-0.641)						(-0.365)
$RREL_t$								-50.545***		-37.355***	-17.345	-9.886	-9.286
								(-5.044)		(-4.426)	(-1.419)	(-0.891)	(-0.465)
Constant	4.872*	0.276	4.683	263.687***	54.408	-12.371*	22.853*	11.240***	224.695***	6.290*	226.211***	207.087***	153.991**
	(1.686)	(0.075)	(1.070)	(6.356)	(0.881)	(-1.837)	(1.737)	(3.075)	(6.129)	(1.755)	(4.075)	(4.324)	(2.415)
Observations	1,804	1,804	1,804	1,804	1,804	1,804	1,804	1,804	1,804	1,804	1,804	1,804	1,804
R^2	0.138	0.267	0.199	0.288	0.019	0.216	0.015	0.160	0.323	0.209	0.300	0.327	0.380
Adjusted R^2	0.137	0.267	0.198	0.287	0.018	0.216	0.015	0.160	0.323	0.209	0.300	0.326	0.378

Note: *Parentheses denote t-statistics* $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table V.4: VRP, 4-month return horizon, winsorized pre-election

	Dependent variable:												
	$(r_{SPX} - r_m)_{t \to t+3.5}$												
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
VRP_t	0.675***								0.405***	0.501***		0.375***	0.513***
	(4.358)								(3.177)	(2.980)		(2.600)	(3.574)
IV_t		0.383***											
		(6.953)											
RV_t			0.383***										
			(2.806)										
$\log(P/E)_t$				-85.447***					-73.575***		-76.064***	-70.547***	-74.419**
				(-5.128)					(-4.675)		(-3.909)	(-3.896)	(-2.024)
$\log(P/D)_t$					12.913								-16.182
					(0.823)								(-0.929)
$DFSP_t$						23.554**							2.289
						(2.391)							(0.286)
$TMSP_t$							-3.279						-2.899
							(-0.561)						(-0.504)
$RREL_t$								-56.382***		-36.722**	-20.784	-8.650	-21.756
								(-3.349)		(-2.275	(-1.135	(-0.465	(-0.894)
Constant	3.343	-0.018	5.329	245.708***	57.368	-12.304	21.130*	11.679***	207.522***	4.920	219.632***	199.489***	156.858**
	(0.999)	(-0.005)	(1.243)	(5.333)	(1.022)	(-1.048)	(1.685)	(3.579)	(4.712)	(1.383)	(4.082)	(3.978)	(2.410)
Observations	1,804	1,804	1,804	1,804	1,804	1,804	1,804	1,804	1,804	1,804	1,804	1,804	1,804
R^2	0.134	0.243	0.169	0.269	0.027	0.135	0.013	0.113	0.312	0.173	0.281	0.313	0.369
Adjusted R^2	0.133	0.243	0.169	0.268	0.027	0.134	0.012	0.112	0.311	0.172	0.280	0.312	0.367
Note:	*Parentheses denote t-statistics*												*p<0.1; **p<0.05; ***p<0.01

Table V.5: VRP, 4-month return horizon, post-election

	Dependent variable:												
	$(r_{SPX} - r_m)_{t \to t+4}$												
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
VRP_t	0.692***								0.710***	0.745***		0.749***	0.691***
	(2.793)								(3.231)	(3.464)		(3.361)	(5.681)
IV_t		0.405											
		(1.054)											
RV_t			-0.511										
			(-0.778)										
$\log(P/E)_t$				-2.579					11.169		-2.688	-9.251	-476.134***
				(-0.037)					(0.209)		(-0.032)	(-0.142)	(-7.966)
$\log(P/D)_t$					-109.754								-680.170***
					(-0.770)								(-6.389)
$DFSP_t$						-11.944							-70.565**
						(-0.459)							(-2.521)
$TMSP_t$							-5.145						21.790***
							(-0.660)						(4.244)
$RREL_t$								-0.499		5.469	0.038	7.340	-7.133
								(-0.031)		(0.528)	(0.003)	(0.651)	(-0.550)
Constant	11.216***	11.368**	19.158***	24.118	-405.473	25.672	24.057*	16.684***	-21.701	9.330**	24.428	35.948	-1,182.801***
	(3.478)	(2.048)	(4.744)	(0.118)	(-0.740)	(1.236)	(1.788)	(2.632)	(-0.138)	(2.061)	(0.101)	(0.191)	(-3.008)
Observations	318	318	318	318	318	318	318	318	318	318	318	318	318
R^2	0.131	0.051	0.033	0.0002	0.090	0.020	0.033	0.0001	0.134	0.141	0.0002	0.141	0.698
Adjusted R^2	0.129	0.048	0.030	-0.003	0.087	0.017	0.030	-0.003	0.129	0.135	-0.006	0.133	0.692

Note: *Parentheses denote t-statistics* — *p<0.1; **p<0.05; ***p<0.01

Table V.6: VRP, 4-month return horizon, post-election

	Dependent variable:												
	$(r_{SPX} - r_m)_{t\rightarrow t+4}$												
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
VRP_t	0.695								0.732^{*}	0.791^{*}		0.790^{*}	0.731^{***}
	(1.527)								(1.710)	(1.835)		(1.830)	(2.837)
IV_t		0.372											
		(0.789)											
RV_t			-0.388										
			(-0.414)										
$\log(P/E)_t$				-7.088					9.854		-11.535	-10.359	-490.206^{***}
				(-0.091)					(0.164)		(-0.122)	(-0.138)	(-7.245)
$\log(P/D)_t$					-103.254								-710.567^{***}
					(-0.757)								(-6.916)
$DFSP_t$						-9.521							-65.494^{**}
						(-0.365)							(-2.546)
$TMSP_t$							-4.989						24.187^{***}
							(-0.721)						(5.056)
$RREL_t$								-0.822		5.399	1.552	7.522	-5.652
								(-0.049)		(0.444)	(0.103)	(0.564)	(-0.476)
Constant	11.196^{***}	11.847^{**}	18.465^{***}	37.316	-380.508	23.781	23.793^{**}	16.736^{***}	-18.007	9.000	49.947	38.837	$-1,266.334^{***}$
	(2.773)	(1.994)	(3.873)	(0.163)	(-0.725)	(1.149)	(1.998)	(2.645)	(-0.101)	(1.543)	(0.182)	(0.178)	(-3.341)
Observations	318	318	318	318	318	318	318	318	318	318	318	318	318
R^2	0.072	0.030	0.016	0.001	0.086	0.013	0.033	0.0002	0.075	0.081	0.002	0.082	0.687
Adjusted R^2	0.069	0.027	0.013	-0.002	0.083	0.010	0.030	-0.003	0.069	0.075	-0.005	0.073	0.681

Note: *Parentheses denote t-statistics* $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Appendix W: EVRP return regressions, pre-election sample from July 2009 to November 2016

Table W.1: EVRP, 4-month return horizon, pre-election

	Dependent variable:												
	$(r_{SPX} - r_m)_{t\to t+3.5}$												
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
$EVRP_t$	0.209***								0.091***	0.125***		0.078***	0.084**
	(2.809)								(2.840)	(2.647)		(2.605)	(2.553)
IV_t		0.353***											
		(8.168)											
RV_t			0.390***										
			(3.247)										
$\log(P/E)_t$				-92.196***					-87.695***		-78.642***	-76.175***	-71.236*
				(-6.133)					(-6.019)		(-3.928)	(-3.984)	(-1.735)
$\log(P/D)_t$					12.063								-10.148
					(0.702)								(-0.485)
$DFSP_t$						22.760***							6.199
						(5.747)							(0.708)
$TMSP_t$							-4.004						-2.704
							(-0.641)						(-0.369)
$RREL_t$								-50.545***		-46.017***	-17.345	-15.555	-15.932
								(-5.044)		(-4.466)	(-1.419)	(-1.287)	(-0.715)
Constant	9.678***	0.276	4.683	263.687***	54.408	-12.371*	22.853*	11.240***	249.966***	9.364***	226.211***	218.296***	169.665**
	(2.802)	(0.075)	(1.070)	(6.356)	(0.881)	(-1.837)	(1.737)	(3.075)	(6.184)	(2.714)	(4.075)	(4.112)	(2.141)
Observations	1,804	1,804	1,804	1,804	1,804	1,804	1,804	1,804	1,804	1,804	1,804	1,804	1,804
R^2	0.054	0.267	0.199	0.288	0.019	0.216	0.015	0.160	0.297	0.178	0.300	0.307	0.348
Adjusted R^2	0.054	0.267	0.198	0.287	0.018	0.216	0.015	0.160	0.297	0.177	0.300	0.306	0.346

Note: *Parentheses denote t-statistics* $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table W.2: EVRP, 4-month return horizon, winsorized pre-election

	Dependent variable:												
	$(r_{SPX} - r_m)_{t \to t+3.5}$												
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
$EVRP_t$	0.622***								0.311***	0.467***		0.275**	0.400***
	(6.945)								(3.332)	(4.168)		(2.561)	(3.546)
IV_t		0.383***											
		(6.953)											
RV_t			0.383***										
			(2.806)										
$\log(P/E)_t$				-85.447***					-72.057***		-76.064***	-68.293***	-73.468**
				(-5.128)					(-4.668)		(-3.909)	(-3.723)	(-2.175)
$\log(P/D)_t$					12.913								-16.252
					(0.823)								(-1.028)
$DFSP_t$						23.554**							0.843
						(2.391)							(0.111)
$TMSP_t$							-3.279						-2.377
							(-0.561)						(-0.418)
$RREL_t$								-56.382***		-34.944**	-20.784	-11.773	-23.787
								(-3.349)		(-2.539)	(-1.135)	(-0.693)	(-1.041)
Constant	2.454	-0.018	5.329	245.708***	57.368	-12.304	21.130*	11.679***	203.914***	4.216	219.632***	193.982***	154.831**
	(0.982)	(-0.005)	(1.243)	(5.333)	(1.022)	(-1.048)	(1.685)	(3.579)	(4.719	(1.404)	(4.082)	(3.807)	(2.304)
Observations	1,804	1,804	1,804	1,804	1,804	1,804	1,804	1,804	1,804	1,804	1,804	1,804	1,804
R^2	0.142	0.243	0.169	0.269	0.027	0.135	0.013	0.113	0.298	0.177	0.281	0.301	0.350
Adjusted R^2	0.142	0.243	0.169	0.268	0.027	0.134	0.012	0.112	0.297	0.176	0.280	0.300	0.347

Note: *Parentheses denote t-statistics* $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table W.3: EVRP, 3.5-month return horizon, pre-election

	Dependent variable:												
	$(r_{SPX} - r_m)_{t \to t+3.5}$												
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
$EVRP_t$	0.221***								0.109***	0.146***		0.098***	0.101***
	(2.820)								(2.907)	(2.712)		(2.833)	(2.948)
IV_t		0.340***											
		(5.319)											
RV_t			0.356***										
			(3.150)										
$\log(P/E)_t$				-87.329***					-81.595***		-76.944***	-73.728***	-67.192
				(-5.184)					(-5.404)		(-3.085)	(-3.256)	(-1.571)
$\log(P/D)_t$					12.279								-7.440
					(0.682)								(-0.352)
$DFSP_t$						20.897***							4.664
						(5.937)							(0.515)
$TMSP_t$							-3.795						-3.411
							(-0.609)						(-0.509)
$RREL_t$								-46.411***		-40.367***	-14.671	-11.955	-17.061
								(-4.787)		(-4.680)	(-1.043)	(-0.923)	(-0.752)
Constant	9.157***	0.771	5.292	250.388***	54.839	-10.390	21.966	11.304***	233.012***	9.115**	221.673***	211.416***	171.030*
	(2.727)	(0.176)	(1.144)	(5.433)	(0.860)	(-1.596)	(1.587)	(2.812)	(5.585)	(2.559)	(3.229)	(3.372)	(1.939)
Observations	1,804	1,804	1,804	1,804	1,804	1,804	1,804	1,804	1,804	1,804	1,804	1,804	1,804
R^2	0.056	0.194	0.141	0.229	0.018	0.154	0.013	0.111	0.242	0.134	0.237	0.247	0.278
Adjusted R^2	0.056	0.193	0.140	0.229	0.018	0.154	0.013	0.111	0.241	0.133	0.236	0.246	0.276
Note:	*Parentheses denote t-statistics*										*p<0.1; **p<0.05; ***p<0.01		

Table W.4: EVRP, 3.5-month return horizon, winsorized pre-election

	Dependent variable:												
	$(r_{SPX} - r_m)_{t\to t+3.5}$												
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
$EVRP_t$	0.668***								0.374***	0.555***		0.357***	0.504***
	(8.272)								(3.793)	(5.254)		(3.229)	(4.207)
IV_t		0.389***											
		(5.090)											
RV_t			0.400***										
			(3.118)										
$\log(P/E)_t$				-83.998***					-67.834***		-76.745***	-66.385***	-70.657**
				(-4.218)					(-3.938)		(-3.318)	(-3.254)	(-2.157)
$\log(P/D)_t$					12.541								-16.442
					(0.716)								(-1.074)
$DFSP_t$						22.950**							-0.907
						(2.012)							(-0.095)
$TMSP_t$							-3.558						-3.389
							(-0.586)						(-0.670)
$RREL_t$								-57.809***		-28.502*	-19.494	-5.840	-26.674
								(-2.650)		(-1.765)	(-0.848)	(-0.291)	(-1.025)
Constant	1.319	-0.353	4.811	241.565***	55.738	-11.870	21.394	11.623***	191.141***	2.688	221.428***	187.368***	148.926*
	(0.458)	(-0.076)	(1.024)	(4.433)	(0.901)	(-0.903)	(1.592)	(3.090)	(3.985)	(0.783)	(3.484)	(3.310)	(1.947)
Observations	1,804	1,804	1,804	1,804	1,804	1,804	1,804	1,804	1,804	1,804	1,804	1,804	1,804
R^2	0.140	0.198	0.144	0.222	0.023	0.103	0.013	0.078	0.257	0.155	0.229	0.258	0.307
Adjusted R^2	0.139	0.198	0.143	0.221	0.022	0.102	0.013	0.078	0.256	0.154	0.228	0.257	0.304

Note: *Parentheses denote t-statistics* *p<0.1; **p<0.05; ***p<0.01

Table W.5: EVRP, 3.5-month return horizon, post-election

	Dependent variable:												
	$(r_{SPX} - r_m)_{t \to t+3.5}$												
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
$EVRP_t$	0.527								0.586*	0.538		0.558	0.520
	(1.482)								(1.777)	(1.469)		(1.606)	(1.627)
IV_t		0.616											
		(1.251)											
ERV_t			0.070										
			(0.089)										
$\log(P/E)_t$				-4.691					15.673		20.485	27.752	-380.269***
				(-0.065)					(0.248)		(0.220)	(0.320)	(-3.405)
$\log(P/D)_t$					-104.433								-723.437***
					(-0.833)								(-4.158)
$DFSP_t$						-3.036							-19.486
						(-0.145)							(-0.439)
$TMSP_t$							-4.661						23.825***
							(-0.751)						(3.394)
$RREL_t$								-4.687		0.630	-8.590	-4.452	-8.810
								(-0.304)		(0.054)	(-0.537)	(-0.308)	(-0.514)
Constant	12.660***	9.269	16.685***	30.791	-384.824	19.299	23.823**	18.306***	-33.888	12.400**	-40.817	-67.922	-1,670.931*
	(3.932)	(1.229)	(3.187)	(0.146)	(-0.798)	(1.176)	(2.327)	(3.181)	(-0.183)	(2.508)	(-0.151)	(-0.271)	(-1.895)
Observations	318	318	318	318	318	318	318	318	318	318	318	318	318
R^2	0.043	0.093	0.0003	0.0004	0.070	0.001	0.022	0.006	0.047	0.043	0.009	0.049	0.465
Adjusted R^2	0.040	0.090	-0.003	-0.003	0.067	-0.002	0.018	0.003	0.041	0.037	0.003	0.040	0.455
Note:	*Parentheses denote t-statistics*												*p<0.1; **p<0.05; ***p<0.01

Table W.6: EVRP, 3.5-month return horizon, post-election

	Dependent variable:												
	$(r_{SPX} - r_m)_{t \to t+3.5}$												
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
$EVRP_t$	0.556								0.598	0.539		0.557	0.474
	(1.144)								(1.382)	(1.130)		(1.187)	(1.398)
IV_t		0.589											
		(0.948)											
ERV_t			0.850										
			(0.613)										
$\log(P/E)_t$				-10.976					6.216		9.250	14.341	-408.554***
				(-0.137)					(0.086)		(0.090)	(0.146)	(-3.376)
$\log(P/D)_t$					-97.380								-742.145***
					(-0.762)								(-4.614)
$DFSP_t$						-0.388							-19.548
						(-0.017)							(-0.429)
$TMSP_t$							-4.840						25.426***
							(-0.721)						(3.331)
$RREL_t$								-5.156		-0.546	-6.971	-3.206	-7.706
								(-0.323)		(-0.044)	(-0.414)	(-0.192)	(-0.388)
Constant	12.483***	9.794	13.204*	49.282	-357.654	17.317	24.104**	18.457***	-6.133	12.769**	-8.223	-28.787	-1,661.837*
	(2.992)	(1.121)	(1.899)	(0.209)	(-0.727)	(0.965)	(2.176)	(3.118)	(-0.029)	(2.334)	(-0.027)	(-0.101)	(-1.956)
Observations	318	318	318	318	318	318	318	318	318	318	318	318	318
R^2	0.024	0.059	0.028	0.002	0.068	0.00002	0.025	0.007	0.025	0.024	0.008	0.026	0.501
Adjusted R^2	0.021	0.056	0.025	-0.001	0.065	-0.003	0.022	0.004	0.018	0.018	0.002	0.016	0.492
Note:	*Parentheses denote t-statistics*												*p<0.1; **p<0.05; ***p<0.01

Appendix X: Daily regressions between key variables and the sum of daily categorized Trump-tweets, from November 2016 till February 2018

Table X.1: Daily regressions from November 2016 till February 2018

	Dependent variable:											
	$r_{SPX,t\rightarrow t+1day}$		IV_{t+1day}		RV_{t+1day}		VRP_{t+1day}		ERV_{t+1day}		$EVRP_{t+1day}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Economic	0.0002		-0.509**		-0.214		-0.295		-0.394		-0.115	
	(1.369)		(-2.061)		(-1.480)		(-1.593)		(-0.951)		(-0.429)	
Political	-0.003*		0.362*		0.241		0.120		0.657		-0.295	
	(-1.878)		(1.745)		(1.362)		(0.736)		(1.560)		(-1.150)	
Military	0.0003		-0.512		-0.781*		0.268		0.010		-0.523	
	(0.788)		(-1.047)		(-1.940)		(0.633)		(0.011)		(-0.879)	
Presidential duties	0.0003*		-0.218		-0.118		-0.100		-0.063		-0.154	
	(1.880)		(-1.505)		(-1.217)		(-1.030)		(-0.258)		(-0.744)	
Personal	-0.0001		-0.292		-0.035		-0.257*		-0.444		0.153	
	(-0.064)		(-1.398)		(-0.276)		(-1.710)		(-1.207)		(0.811)	
Other	-0.0001		-2.243**		-1.600**		-0.643		-3.365**		1.122	
	(-0.082)		(-2.440)		(-2.120)		(-0.982)		(-2.287)		(1.538)	
Featured Democrats	0.001		-0.411		0.039		-0.450		-0.927		0.516	
	(1.294)		(-0.829)		(0.097)		(-1.088)		(-1.030)		(0.970)	
Political * Featured Democrats	-0.0001		-0.036		-0.045		0.010		-0.040		0.004	
	(-0.210)		(-0.832)		(-0.976)		(0.292)		(-0.584)		(0.100)	
Fake.news		0.0001		-1.144**		-0.476*		-0.668**		-1.226		0.082
		(0.364)		(-2.517)		(-1.695)		(-1.998)		(-1.500)		(0.193)
Constant	0.001	0.001*	13.90***	13.26***	5.830***	5.747***	8.071***	7.516***	7.458***	7.439***	6.444***	5.825***
	(0.957)	(1.696)	(11.03)	(10.503)	(7.645)	(6.862)	(9.622)	(8.827)	(3.543)	(3.453)	(5.997)	(5.576)
Observations	319	319	319	319	319	319	319	319	319	319	319	319
R^2	0.026	0.0002	0.032	0.013	0.024	0.005	0.021	0.008	0.017	0.005	0.011	0.0001
Adjusted R^2	0.001	-0.003	0.007	0.010	-0.001	0.002	-0.004	0.005	-0.008	0.002	-0.014	-0.003
Note:	*Parentheses denote t-statistics*											*p<0.1; **p<0.05; ***p<0.01

Table X.2: Daily regressions winsorized sample from November 2016 till February 2018

	Dependent variable:											
	$r_{SPX,t\rightarrow t+1day}$		IV_{t+1day}		RV_{t+1day}		VRP_{t+1day}		ERV_{t+1day}		$EVRP_{t+1day}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Economic	0.003**		-0.376**		-0.122		-0.208*		-0.151		-0.202	
	(2.132)		(-2.414)		(-1.281)		(-1.880)		(-1.071)		(-1.450)	
Political	-0.003**		0.187*		0.053		0.061		0.199		-0.003	
	(-2.428)		(1.655)		(0.884)		(1.040)		(1.510)		(-0.043)	
Military	0.0003		-0.575**		-0.36***		-0.073		-0.421		-0.247	
	(1.031)		(-2.383)		(-2.851)		(-0.440)		(-1.491)		(-1.376)	
Presidential duties	0.003***		-0.25***		-0.120**		-0.112*		-0.141		-0.087	
	(2.907)		(-2.863)		(-2.365)		(-1.923)		(-1.050)		(-1.129)	
Personal	-0.0001		-0.116		-0.014		-0.102*		-0.068		-0.030	
	(-0.570)		(-1.342)		(-0.330)		(-1.873)		(-0.601)		(-0.506)	
Other	-0.0002		-1.46***		-0.649**		-0.530		-1.91***		0.283	
	(-0.359)		(-2.990)		(-2.200)		(-1.630)		(-3.344)		(0.914)	
Featured Democrats	0.0001		-0.230		-0.203		-0.060		-0.540		0.217	
	(0.509)		(-0.779)		(-1.203)		(-0.314)		(-1.635)		(0.964)	
Political * Featured Democrats	0.00001		-0.022		0.003		-0.010		-0.002		-0.015	
	(0.316)		(-0.752)		(0.178)		(-0.610)		(-0.082)		(-0.720)	
Fake.news		-0.0001		-0.78***		-0.37***		-0.37***		-0.472*		-0.228
		(-0.372)		(-3.694)		(-3.213)		(-2.760)		(-1.929)		(-1.617)
Constant	0.001**	0.001***	12.72***	12.05***	4.948***	4.615***	7.451***	7.062***	5.571***	5.115***	7.297***	7.062***
	(2.138)	(4.072)	(22.28)	(22.643)	(14.65)	(15.86)	(20.99)	(24.73)	(8.083)	(8.526)	(18.33)	(24.63)
Observations	319	319	319	319	319	319	319	319	319	319	319	319
R^2	0.047	0.0003	0.082	0.032	0.060	0.027	0.053	0.022	0.042	0.008	0.026	0.006
Adjusted R^2	0.022	-0.003	0.058	0.029	0.035	0.024	0.028	0.019	0.017	0.005	0.001	0.003
Note:	*Parentheses denote t-statistics*											*p<0.1; **p<0.05; ***p<0.01

Appendix Y: Intraday regressions between key variables and categorized Trump-tweets,

Table Y.1: Daily regressions from November 2016 till February 2018

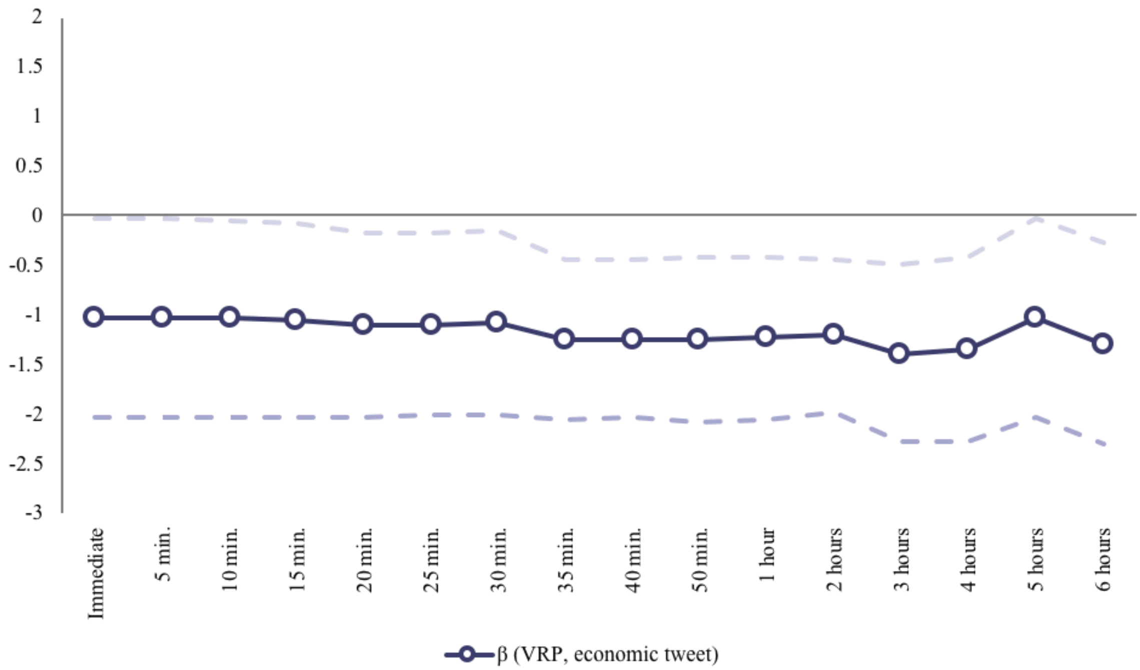
	Dependent variable:											
	$r_{SPX,t \to t+20min}$		$IV_{t+20min}$		$RV_{t+20min}$		$VRP_{t+20min}$		$ERV_{t+20min}$		$EVRP_{t+20min}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Economic	-32.899		-2.127***		-1.022		-1.105**		-2.87***		0.738	
	(-0.633)		(-3.226)		(-1.455)		(-2.328)		(-5.669)		(1.254)	
Political	84.291*		0.828		-0.096		0.924		2.401		-1.573	
	(1.663)		(0.640)		(-0.193)		(0.862)		(1.232)		(-1.434)	
Military	263.395***		-2.906***		-1.82***		-1.089**		-2.56***		-0.358	
	(3.817)		(-4.731)		(-6.529)		(-2.127)		(-2.904)		(-0.366)	
Presidential duties	32.356		0.055		0.618		-0.562		-0.609		0.664	
	(0.782)		(0.058)		(0.966)		(-0.797)		(-0.618)		(1.027)	
Personal	-5.633		-0.946		-0.079		-0.867*		0.167		-1.113	
	(-0.090)		(-1.162)		(-0.090)		(-1.808)		(0.153)		(-1.318)	
Other	-		-		-		-		-		-	
Featured Democrats	20.798		-1.945		1.044		-2.990**		-2.956		1.010	
			(-1.180)		(0.653)		(-2.293)		(-1.304)		(0.822)	
Political * Featured Democrats	-		-		-		-		-		-	
Fake.news		54.358		-1.592		-0.187		-1.406**		-1.632		0.040
		(0.636)		(-1.155)		(-0.105)		(-2.085)		(-1.549)		(0.063)
Constant	7.145	8.045	12.602***	12.596***	5.510***	5.511***	7.092***	7.085***	5.449***	5.451***	7.153***	7.145***
	(1.070)	(1.213)	(50.403)	(50.537)	(39.854)	(39.736)	(37.421)	(37.463)	(13.013)	(13.152)	(22.769)	(23.056)
Observations	21,317	21,317	21,317	21,317	21,317	21,317	21,317	21,317	21,317	21,317	21,317	21,317
R^2	0.0005	0.00001	0.0003	0.00002	0.0003	0.00000	0.0003	0.00003	0.0002	0.00001	0.0001	0.000
Adjusted R^2	0.0002	-0.0001	-0.0000	-0.0000	0.00000	-0.0001	0.0001	-0.0000	-0.0001	-0.0000	-0.0002	-0.0001

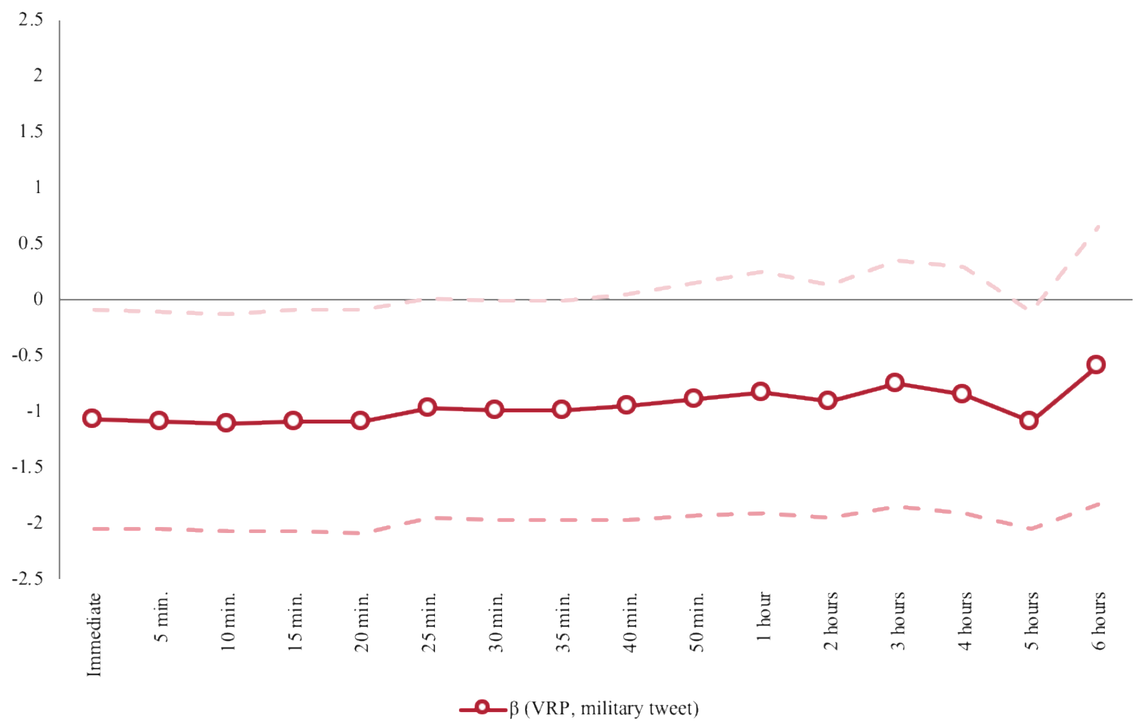
Note: *Parentheses denote t-statistics*
*p<0.1; **p<0.05; ***p<0.01

Table Y.2: Daily regressions winsorized sample from November 2016 till February 2018

	Dependent variable:											
	$r_{SPX,t\to t+20min}$		$IV_{t+20min}$		$RV_{t+20min}$		$VRP_{t+20min}$		$ERV_{t+20min}$		$EVRP_{t+20min}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Economic	-43.706		-1.083**		-0.69***		-0.468		-1.02***		-0.473	
	(-0.947)		(-2.426)		(-2.77)		(-1.287)		(-3.41)		(-1.430)	
Political	59.490		0.446		0.075		0.467*		1.179**		-0.841**	
	(1.567)		(1.178)		(0.307)		(1.660)		(2.420)		(-2.558)	
Military	229.0***		-1.580***		-1.00***		-0.499		-0.707		-0.768	
	(4.374)		(-2.855)		(-4.329)		(-1.038)		(-0.91)		(-1.207)	
Presidential duties	17.346		-0.395		-0.042		-0.505**		-0.043		-0.220	
	(0.638)		(-1.254)		(-0.220)		(-2.395)		(-0.106)		(-0.923)	
Personal	16.234		-0.330		-0.083		-0.323		1.108		-1.066**	
	(0.389)		(-0.787)		(-0.324)		(-1.001)		(1.453)		(-2.402)	
Other												
Featured Democrats	48.914		-1.035		-0.416		-1.172**		-0.475		-0.391	
			(-1.412)		(-0.891)		(-2.489)		(-0.537)		(-0.777)	
Political * Featured Democrats	-		-		-		-		-		-	
Fake.news		40.747		-0.987		-0.795*		-0.502		0.165		-0.923*
		(0.501)		(-1.327)		(-1.796)		(-1.083)		(0.173)		(-1.858)
Constant	11.88***	12.59***	11.33***	11.33***	4.733***	4.731***	6.502***	6.498***	3.614***	3.622***	8.048***	8.036***
	(2.841	(3.025)	(132.93)	(132.97)	(93.230)	(93.193)	(101.92)	(102.04)	(36.723)	(36.717)	(122.08)	(122.17)
Observations	21,317	21,317	21,317	21,317	21,317	21,317	21,317	21,317	21,317	21,317	21,317	21,317
R^2	0.001	0.00001	0.001	0.0001	0.001	0.0001	0.001	0.00003	0.001	0.00000	0.001	0.0001
Adjusted R^2	0.001	-0.0000	0.0004	0.00002	0.0002	0.0001	0.0004	-0.0000	0.001	-0.00005	0.001	0.00004
Note:	*Parentheses denote t-statistics*										*p<0.1; **p<0.05; ***p<0.01	

Appendix Z: Overview of Trump Tweet effects on VRP over time





APPENDIX AA: R-script for creating the MC-GARCH expected realized variance EVRP

```
## MC-GARCH script

## Setting timezones to align datasets
Sys.setenv(TZ = 'America/Chicago')

## Reading in necessary packages
library(quantmod)
library(rugarch)
library(xts)
library(aTSA)
library(stargazer)
library(lubridate)
library(AER)

## Reading data from csv files
SP <- read.csv('New SPX.csv')
VIX <- read.csv('New VIX.csv')
day.SP <- read.csv('Day-SP.csv')

## Convert to XTS files
SP = xts(SP[, 2], as.POSIXct(SP[, 1], format = c("%d-%m-%Y %H:%M")))
VIX = xts(VIX[, 2], as.POSIXct(VIX[, 1], format = c("%d-%m-%Y %H:%M")))
day.SP = xts(day.SP[, 2], as.Date(day.SP[, 1], format = c("%d-%m-%Y")))
colnames(SP) <- "SP"
colnames(VIX) <- "VIX"
colnames(day.SP) <- "SPX"

## Converting both time series to New York time - currently in Chicago time
indexTZ(VIX) <- "America/New_York"
indexTZ(SP) <- "America/New_York"

# Generate daily log returns
R_d <- log(day.SP$SPX/lag(day.SP$SPX, -1))
R_d <- na.omit(R_d)
plot(R_d)

## Create intraday log returns on the S&P 500
SP$R_i <- log(SP$SP/lag(SP$SP, -1))
SP <- na.omit(SP)

# cut sample to regular trading hours (9:30 to 16:00) less five minutes due to lacking data
SP <- window(SP, start = "1996-01-02", end = "2018-03-01")
SP <- SP["T09:30:00/T15:55:00"]

####### CHECKING DATA SERIES #######

## Checking acf for returns for full sample
par(cex.main = 0.85, col.main='black')
par(mfrow = c(1,1))
acf(abs(as.numeric(SP$R_i)), lag.max = 4000, main = '5-minute absolute returns on the S&P500 from 1996 to 2018',
cex.lab=0.8)

## Create window for 2018
data.2018 = window(SP, start = "2018-01-01")
head(data.2018)
tail(data.2018)

## checking acf for 2018 sub-sample
acf(abs(as.numeric(data.2018$R_i)), lag.max = 4000, main = '5-minute absolute returns on the S&P500 in 2018',
cex.lab=0.8)

###### Testing for heteroscedasticity in residuals (ARCH) ######

## ARCH test for full sample
mod <- estimate(SP$R_i, p = 1)
```

```
arch.test(mod, output = TRUE)

## both the Portmanteau-Q test and the Langrange multipler test reject the null that the residuals are homoscedastic.
## hence, it seems that the residuals are heteroscedastic, implying autocorrelation in the residuals.
## this supports the implementation of a GARCH model to estimate the intraday variance
# ARCH heteroscedasticity test for residuals
# alternative: heteroscedastic

#
# Portmanteau-Q test:
# order PQ p.value
# [1,] 4 54864 0
# [2,] 8 82085 0
# [3,] 12 90951 0
# [4,] 16 99244 0
# [5,] 20 106636 0
# [6,] 24 112052 0
# Lagrange-Multiplier test:
# order LM p.value
# [1,] 4 374516 0
# [2,] 8 160916 0
# [3,] 12 105121 0
# [4,] 16 77725 0
# [5,] 20 61491 0
# [6,] 24 50986 0

####### MC-GARCH ESTIMATION #######

## CREATING DAILY VARIANCE ESTIMATE
## Find the unique days in the intraday sample
n = length(unique(format(index(SP$R_i), '%Y-%m-%d')))
# n = 5547
## define daily specs

# GARCH MODEL
spec_garch = ugarchspec(mean.model = list(armaOrder = c(1,1)), variance.model = list(model = 'sGARCH', garchOrder =
c(1,1)), distribution = 'nig')

# EGARCH MODEL
spec_d = ugarchspec(mean.model = list(armaOrder = c(1,1)), variance.model = list(model='eGARCH', garchOrder=c(1,1)),
distribution='nig')

# estimate model to get coefficients and information criteria
fit_garch = ugarchfit(spec = spec_garch, data = R_d)
fit_d = ugarchfit(spec=spec_d, data = R_d)

# Checking information criteria

## EGARCH
infocriteria(fit_d)
# Akaike -6.567623
# Bayes -6.557292
# Shibata -6.567627
# Hannan-Quinn -6.564029

## GARCH
infocriteria(fit_garch)
# Akaike -6.535367
# Bayes -6.526184
# Shibata -6.535371
# Hannan-Quinn -6.532173
## the best model is the one with the highest absolute value
## as seen, both the AIC and BIC point to the EGARCH as the best model

# Use Ugarchroll method to create rolling forecast for the data
roll = ugarchroll(spec_d, data=R_d['/2018-03-12'], forecast.length = n, refit.every = 5, refit.window = 'moving',
moving.size = 30, calculate.VaR = FALSE, solver = 'hybrid')
```

```
# extract the sigma forecast for the daily model
df = as.data.frame(roll)
f_sigma = as.xts(df[, 'Sigma', drop = FALSE])
f_sigma <- window(f_sigma, start = "2018-01-01", end = "2018-02-28")

#drop timestamps in SP
daily <- apply.daily(SP$SP, mean)
head(daily)
str(index(daily))
strsplit(as.character(index(daily))," ")# split by space
lapply(strsplit(as.character(index(daily))," "), function(x) x[1]) #select the first vector element
unlist(lapply(strsplit(as.character(index(daily))," "), function(x) x[1])) #which is still a 'character' class
index(daily)<-unlist(lapply(strsplit(as.character(index(daily))," "), function(x) x[1]))
index(daily)<- as.Date(unlist(lapply(strsplit(as.character(index(daily))," "), function(x) x[1])))

#drop timestamps in f_sigma
str(index(f_sigma))
strsplit(as.character(index(f_sigma))," ")# split by space
lapply(strsplit(as.character(index(f_sigma))," "), function(x) x[1]) #select the first vector element
unlist(lapply(strsplit(as.character(index(f_sigma))," "), function(x) x[1])) #which is still a 'character' class
index(f_sigma)<-unlist(lapply(strsplit(as.character(index(f_sigma))," "), function(x) x[1]))
index(f_sigma)<- as.Date(unlist(lapply(strsplit(as.character(index(f_sigma))," "), function(x) x[1])))

dailyvar <- merge.xts(daily, f_sigma)
dailyvar <- na.omit(dailyvar)


## ESTIMATE INTRADAY MODEL
spec = ugarchspec(mean.model = list(armaOrder = c(1,1), include.mean = TRUE), variance.model =
list(model='mcsGARCH'), distribution = 'nig')
#DailyVar is the required xts object to forecast daily variance - this knits together the daily variance and intraday
pattern
fit = ugarchfit(data = SP['2018-01-01/2018-02-28']$R_i, spec = spec, DailyVar = dailyvar$Sigma^2)

######## Generating plots that show the components of the MC-GARCH model ########

# setting up the plots
ep <- axTicksByTime(fit@model$DiurnalVar)
par(mfrow = c(4,1), mar=c(2.5, 2.5, 2, 1))

## Diurnal component
plot(as.numeric(fit@model$DiurnalVar^0.5), type = 'l', main = 'Sigma[Diurnal]', col = 'tomato1', xaxt = 'n', ylab =
'sigma', xlab = ' ')
axis(1, at=ep, labels = names(ep), tick = TRUE)
grid()

## Daily forecast
plot(as.numeric(fit@model$DailyVar^0.5), type = 'l', main = 'Sigma[Daily-Forecast]', col = 'tomato2', xaxt = 'n',
ylab = 'sigma', xlab = ' ')
axis(1, at = ep, labels = names(ep), tick = TRUE)
grid()

## stochastic volatility component
plot(fit@fit$q, type = 'l', main = 'Sigma[Stochastic]', col = 'tomato3', xaxt = 'n', ylab = 'sigma', xlab = ' ')
axis(1, at = ep, labels = names(ep), tick = TRUE)
grid()

## Plot of total sigma
plot(as.numeric(sigma(fit)), type = 'l', main = 'sigma[Total]', col = 'tomato4', xaxt = 'n', ylab = 'sigma', xlab = '')
axis(1, at = ep, labels = names(ep), tick = TRUE)
grid()

######## Output of forecast ########

## Getting forecast in monthly variance terms
forecast.var <- (forecasted.sigma*100*sqrt(78)*sqrt(22))
```

```
forecast.var$var <- forecast.var$e1^2

## Create daily data
daily.forecast <- apply.daily(forecast.var$var, mean)

# dropping time stamps
str(index(daily.forecast))
strsplit(as.character(index(daily.forecast))," ")# split by space
lapply(strsplit(as.character(index(daily.forecast))," "), function(x) x[1]) #select the first vector element
unlist(lapply(strsplit(as.character(index(daily.forecast))," "), function(x) x[1])) #which is still a 'character'
class
index(daily.forecast)<-unlist(lapply(strsplit(as.character(index(daily.forecast))," "), function(x) x[1]))
index(daily.forecast)<- as.Date(unlist(lapply(strsplit(as.character(index(daily.forecast))," "), function(x) x[1])))
daily.forecast

## Generate CSV files
write.csv(daily.forecast, file = "daily-EGARCH.csv", row.names = index(daily.forecast))
write.csv(forecast.var$var, file = "EGARCH-forecast.csv", row.names = index(forecast.var))
```

APPENDIX AB: R-script - daily regressions on the full sample, as well as sub samples

```
## Script for primary regressions

## Setting timezones to align datasets
Sys.setenv(TZ = 'America/Chicago')

## Reading in necessary packages
library(quantmod)
library(rugarch)
library(xts)
library(aTSA)
library(stargazer)
library(lubridate)
library(AER)
library(DistributionUtils)
library(dynlm)
library(forecast)
library(strucchange)
library(zoo)
library(roll)
library(PerformanceAnalytics)
library(tidyquant)
library(cranlogs)
library(urca)
library(DescTools)

######## Reading in data and converting to correct formats ########
## Read in data from local csv files
SP <- read.csv('New SPX.csv')
VIX <- read.csv('New VIX.csv')

## Convert to xts files
SP = xts(SP[, 2], as.POSIXct(SP[, 1], format = c("%d-%m-%Y %H:%M")))
VIX = xts(VIX[, 2], as.POSIXct(VIX[, 1], format = c("%d-%m-%Y %H:%M")))

## Convert to New York time
indexTZ(VIX) <- "America/New_York"
indexTZ(SP) <- "America/New_York"

## Cut both samples to only cover trading hours (9:30 to 16:00)
SP <- SP["T09:30:00/T16:00:00"]
VIX <- VIX["T09:30:00/T16:00:00"]
colnames(SP) <- "SP"
colnames(VIX) <- "VIX"

######## Generate 5-minute returns ########
R_i <- log(SP$SP/lag(SP$SP))


## Squaring returns
R_i$sq.ret <- (R_i$SP*100)^2
R_i <- na.omit(R_i)

######## Create RV and returns: Sum rolling monthly squared and regular returns ########
## Create RV from squared intraday returns
R_i$var.day <- apply.daily(R_i$sq.ret, sum)

## Create returns from sum of intraday returns
R_i$ret.day <- apply.daily(R_i$SP, sum)
R_i <- na.omit(R_i)

## Create new files for RV and returns
RV <- R_i$var.day
ret <- R_i$ret.day

## Create the monthly RV
```

```
RV$var <- rollapply(RV$var.day, 22, sum)
RV <- na.omit(RV)

## Dropping time stamps
str(index(RV))
strsplit(as.character(index(RV))," ")# split by space
lapply(strsplit(as.character(index(RV))," "), function(x) x[1]) #select the first vector element
unlist(lapply(strsplit(as.character(index(RV))," "), function(x) x[1])) #which is still a 'character' class
index(RV)<-unlist(lapply(strsplit(as.character(index(RV))," "), function(x) x[1]))
index(RV)<- as.Date(unlist(lapply(strsplit(as.character(index(RV))," "), function(x) x[1])))

############## Reading in MC-GARCH RV #################

## Read in MC-GARCH results from csv
FORC <- read.csv("daily-EGARCH.csv")
FORC <- na.omit(FORC)

## Convert to xts
FORC = xts(FORC[,2], as.Date(FORC[,1], format = c("%Y-%m-%d")))
colnames(FORC) <- "var"

## Merge with the realized-var dataset
Real.var <- merge.xts(FORC, RV)
Real.var <- na.omit(Real.var)
colnames(Real.var)[3] <- "RV"
colnames(Real.var)[1] <- "EGARCH"

############## Generate monthly returns #################

## Generate monthly returns from sum of daily returns
##Example for the first month
ret$month1 <- rollapply(ret$ret.day, 22, sum)*12*100
#(...)
## similar line run for horizons up to the 24-month mark

ret <- na.omit(ret)

######## Creating excess returns ########

## Getting data on the 3-month T-bill
symbols <- c("DGS3MO")
getSymbols(symbols, from = "1990-01-01", src="FRED", auto.assign = TRUE)
#merge into SP.day
excess.ret <- merge.xts(DGS3MO, ret)
excess.ret <- na.omit(excess.ret)

## Example of excess return generation for the first month
excess.ret$ER1 <- excess.ret$month1 - excess.ret$DGS3MO
#(...)
## created for monthly return horizons up to the 24-month mark
############## Getting implied variances in the correct format #################

##Getting daily average of the VIX
IV.day <- apply.daily(VIX, mean)

## Convert VIX to monthly variance
IV.day$vix.month <- IV.day$VIX/sqrt(12)
IV.day$vix2 <- IV.day$vix.month^2

## Merging the two files together
VRP.data <- merge.xts(Real.var, IV.day)
VRP.data <- na.omit(VRP.data)

######## Generate the VRP and EVRP ########
VRP.data$VRP <- VRP.data$vix2 - VRP.data$RV
VRP.data$EVRP <- VRP.data$vix2 - VRP.data$EGARCH
```

```
######## Getting control variables ########
symbols <- c("DGS3MO", "DAAA", "DBAA", "DGS10", "TEDRATE")
getSymbols(symbols, from = "1996-01-01", src="FRED", auto.assign = TRUE)
controls <- merge.xts(DBAA, DGS10, DGS3MO, TEDRATE, DAAA)
controls <- na.omit(controls)

## Create rolling average of the risk-free to detrend the timeseries
controls$rolling <- rollmean(controls$DGS3MO, 252, align = "right")

## Create relevant spreads
controls$riskfree <- controls$DGS3MO - controls$rolling
controls$default <- controls$DBAA - controls$DAAA
controls$term <- controls$DGS10 - controls$DGS3MO

## Define window and merge with (E)VRP data
controls <-window(controls, start = '1996-01-01', end = '2018-02-28')
VRP.data <- merge.xts(controls, VRP.data)
VRP.data <- na.omit(VRP.data)

####### Creating lags for regressions #######
## To run regression, we create lags for implied and realized variance, the (E)VRP and relevant control variables for
months 1-24

## An example is the first month for the VRP
VRP.data$VRP.1 <- lag(VRP.data$VRP, 22)
#(...)

## Merge the two datasest to make sure the data lines up
merged.data <- merge(VRP.data, excess.ret)

## Read in CAY and Price-dividend and price-earnings ratios
CAY <- read.csv("CAY.csv")
CAY <- na.omit(CAY)
CAY = xts(CAY[, 2], as.Date(CAY[, 1], format = c("%d-%m-%Y")))
CAY$CAY <- CAY$CAY*100
price <- read.csv("price-div-earn.csv")
price <- na.omit(price)
price = xts(price[, 2:3], as.Date(price[, 1], format = c("%d-%m-%Y")))
controlv2 <- merge.xts(CAY)
controlv2 <- na.omit(controlv2)
mergedv2 <- merge.xts(merged.data, controlv2)
mergedv2 <- na.omit(mergedv2)

# We then create lags akin to the VRP data for the CAY and price ratios, example:
mergedv2$CAY.1 <- lag(mergedv2$CAY, 22)
#(...)
mergedv2 <- na.omit(mergedv2)


####### Cutting sample into desired subsamples #######
mergedv2 <- window(mergedv2, start = "2002-01-10", end = "2017-09-29")

post.GFC <- window(mergedv2, start = "2009-07-01", end = "2017-09-29")

pre.GFC <- window(mergedv2, start ="2002-01-01", end = "2007-12-01")

GFC <- window(mergedv2, start = "2007-12-01", end = "2009-07-01")

pre.elect <- window(merged.data, start = "2009-07-01", end = "2016-11-08")

post.elect <- window(merged.data, start = "2016-11-08", end = "2018-02-27")


####### Example of regressions run #######

# This represents the example fo the VRP on the 3.5 month for the full sample, regressions have been run across
```

horizons

```
output.formulas <- list(ER3.5 ~ VRP.3.5,
        ER3.5 ~ IV.3.5,
        ER3.5 ~ RV.3.5,
        ER3.5 ~ log(PE.3.5),
        ER3.5 ~ log(PD.3.5),
        ER3.5 ~ default.3.5,
        ER3.5 ~ term.3.5,
        ER3.5 ~ CAY.3.5,
        ER3.5 ~ riskfree.3.5,
        ER3.5 ~ VRP.3.5 + log(PE.3.5),
        ER3.5 ~ VRP.3.5 + CAY.3.5,
        ER3.5 ~ VRP.3.5 + riskfree.3.5,
        ER3.5 ~ log(PE.3.5) + CAY.3.5 + riskfree.3.5,
        ER3.5 ~ VRP.3.5 + log(PE.3.5) + CAY.3.5 + riskfree.3.5,
        ER3.5 ~ VRP.3.5 + log(PE.3.5) + log(PD.3.5) + default.3.5 + term.3.5 + riskfree.3.5)

output.models <- lapply(output.formulas, function(formula) lm(formula, data = mergedv2))
Newey.west.3.5 <- lapply(output.models, coeftest, vcov = NeweyWest)
stargazer(output.models, type = "html", out = "output.VRP.full.html" ,se = lapply(Newey.west.3.5, function(x) x[,2]), keep.stat = c("n", "rsq", "adj.rsq"),
report = ('vc*t'))

####### Winsorized example #######

## Example of winsorization (3.5 month VRP for the full sample)

full.sample.winsorized <- Winsorize(mergedv2$VRP.3.5, minval = NULL, maxval = NULL, probs = c(0.05,0.95), na.rm =FALSE)
full.winsorized.model <- lapply(output.formulas, function(formula) lm(formula, data = full.sample.winsorized))

Newey.west.3.5.wins <- lapply(full.winsorized.model, coeftest, vcov = NeweyWest)
stargazer(full.winsorized.model, type = "html", out = "winsorized.VRP.full.html" ,se = lapply(Newey.west.3.5.wins, function(x) x[, 2]), keep.stat = c("n",
"rsq", "adj.rsq"), report = ('vc*t'))

########## Rolling regression ##########

# Get rolling coefficients for 3.5 months on RV-VRP
rr3.5.coef <- rollapply(merged.data, width = 528, FUN = function(z) coef(lm(ER3.5 ~ VRP.3.5, data =
as.data.frame(z))), by.column = FALSE, align = "right")

# Get rolling confidence intervals for 3.5 months on RV-VRP
rr3.5.confint <- rollapply(merged.data, width = 528, FUN = function(z) confint(lm(ER3.5 ~ VRP.3.5, data =
as.data.frame(z))), by.column = FALSE, align = "right")

## merge estimates together
rr.3.5m <- merge.xts(rr3.5.coef, rr3.5.confint)

colnames(rr.3.5m)[3] <- "intercept.lower"
colnames(rr.3.5m)[4] <- "VRP3.5.lower"
colnames(rr.3.5m)[5] <- "intercept.upper"
colnames(rr.3.5m)[6] <- "VRP3.5.upper"
rr.3.5m <- na.omit(rr.3.5m)

########## Expanding regression ##########
# create for expanding regression for 3.5 month horizon RV-HORIZON
snip <- merged.data$ER3.5
snip$VRP.3.5 <- merged.data$VRP.3.5
exp.3.5 <- lapply( seq(528, nrow(snip) ), function(x) lm(ER3.5 ~ VRP.3.5, data = snip[1:x, ]) )

# Extract estimated coefficient
coefs.3.5 <- lapply(exp.3.5[1:4121], function(x)coef(x)[2])
coefs.3.5 <- as.data.frame(unlist(coefs.3.5, recursive = FALSE, use.names = FALSE))
colnames(coefs.3.5) <- "ER.3.5"

# Extract confidence lower confidence interval
confints.3.5 <- lapply(exp.3.5[1:4121], function(x)confint(x)[2])
confints.3.5 <- as.data.frame(unlist(confints.3.5, recursive = FALSE, use.names = FALSE))
```

```
colnames(confints.3.5) <- "CI.lower"

write.csv(coefs.3.5, file = "coefs35.csv")
write.csv(confints.3.5, file = "confints35.csv")
```

APPENDIX AC: R-script for intraday regressions

```
## Script for intraday regressions

## Setting timezones to align datasets
Sys.setenv(TZ = 'America/Chicago')

## Reading in necessary packages
library(quantmod)
library(rugarch)
library(xts)
library(aTSA)
library(stargazer)
library(lubridate)
library(AER)
library(DistributionUtils)
library(dynlm)
library(forecast)
library(strucchange)
library(zoo)
library(dplyr)
library(data.table)
library(Rfast)
library(DescTools)

## Read in data from local csv files
SP <- read.csv('New SPX.csv')
VIX <- read.csv('New VIX.csv')

## Convert to xts files
SP = xts(SP[, 2], as.POSIXct(SP[, 1], format = c("%d-%m-%Y %H:%M")))
VIX = xts(VIX[, 2], as.POSIXct(VIX[, 1], format = c("%d-%m-%Y %H:%M")))

## Convert to New York time
indexTZ(VIX) <- "America/New_York"
indexTZ(SP) <- "America/New_York"

## Cut both samples to only cover trading hours (9:30 to 16:00)
SP <- SP["T09:30:00/T16:00:00"]
VIX <- VIX["T09:30:00/T16:00:00"]
colnames(SP) <- "SP"
colnames(VIX) <- "VIX"

######## Create RV and returns: Sum rolling monthly squared and regular returns ########
R_i <- log(SP$SP/lag(SP$SP))

## Squaring returns
R_i$sq.ret <- (R_i$SP*100)^2
R_i <- na.omit(R_i)

## Create new datasets for RV and returns
RV <- R_i$sq.ret
ret <- R_i$SP

## CREATE A MONTHLY RV
RV$var <- rollapply(RV$sq.ret, 78*22, sum)
RV <- na.omit(RV)

## Example of creating annualized returns from rolling sums - example of one hour
ret$hour <- rollapply(ret$SP, 12, sum)*(12/((12/78)/22))*100
#(...)
##run up 24 months

############## MC-GARCH ##################
## Read in MC-GARCH results from csv
FORC <- read.csv("EGARCH-forecast.csv")
FORC <- na.omit(FORC)
```

```
## Convert to xts
FORC = xts(FORC[,2], as.POSIXct(FORC[,1], format = c("%Y-%m-%d %H:%M")))
colnames(FORC) <- "var"
FORC <- FORC["T09:35:00/T16:00:00"]

## Merge with the realized-var dataset
Real.var <- merge.xts(FORC, RV)
Real.var <- na.omit(Real.var)
colnames(Real.var)[3] <- "RV"
colnames(Real.var)[1] <- "EGARCH"

######## Treating intraday variance data ######
## Generate monthly data
VIX$VIX.month <- VIX$VIX/sqrt(12)
VIX$IV <- VIX$VIX.month^2

## Merging the two data series together
VRP.data <- merge.xts(Real.var, VIX)
VRP.data <- na.omit(VRP.data)

######## Generating the VRP ########
VRP.data$VRP <- VRP.data$IV - VRP.data$RV
VRP.data$EVRP <- VRP.data$IV - VRP.data$EGARCH

######## Generating lags for regressions ########
## Example with 1 hour VRP lag
VRP.data$IV.hour <- lag(VRP.data$IV, 12)

## Run for implied and realized variance, VRP and EVRP
VRP.data <- na.omit(VRP.data)

########## Generate leads for dummy regressions ##########
# Example with implied variance for a 5-minute lead
VRP.data$IV.lead.5 <- shift(VRP.data$IV, n = 1, type = "lead")
#(...)
#Run up to 6 hours. For VRP, EVRP, returns and realized and implied variances
#merge leads together
leads <- merge.xts(ret.leads, IV.leads, RV.leads, VRP.leads, ERV.leads, EVRP.leads)
leads <- na.omit(leads)

########## Generate leads for dummy regressions ##########
Trump <- read.csv('Intraday Trump.csv')
Trump$Within.NYSE.trading. <- NULL
Trump$Comments <- NULL
Trump = xts(Trump[, 2:9], as.POSIXct(Trump[, 1], format = c("%d-%m-%Y %H:%M")))

## Create a blank timeseries to merge with Trump
blank <- VRP.data$VRP
blank$newcol <- rep(0,nrow(blank))
blank$VRP <- NULL

## Merge blank timeseries with Trump
Trump.v2 <- merge.xts(Trump, blank)

## Create a window on the first and last observations in the Trump dataset
Trump.v2 <- window(Trump.v2, start = "2016-11-08 09:35", end = "2018-02-28 16:00")

## Create zero variables for NA variables
Trump.v2[is.na(Trump.v2)] <- 0

## Drop the blank column
Trump.v2$newcol <- NULL

## Merge data set with VRP data
merged <- merge.xts(Trump.v2, leads)
merged <- na.omit(merged)
```

```
## Merge datasets for intraday VRP regressions
intraday.reg <- merge.xts(ret, VRP.data)
intraday.reg <- na.omit(intraday.reg)
intraday.reg <- window(intraday.reg, start = "2002-01-01", end = "2018-02-27")

######### Dummy regressions, example for 5-minute reactions #########
formulas.5min <- list(ret.lead.5 ~ Economic + Political + Military + Presidential.duties + Personal + Other +
        Featured..Democrats. + Featured..Democrats.*Political,
        ret.lead.5 ~ Fake.news,
        IV.lead.5 ~ Economic + Political + Military + Presidential.duties + Personal + Other +
        Featured..Democrats. + Featured..Democrats.*Political,
        IV.lead.5 ~ Fake.news,
        RV.lead.5 ~ Economic + Political + Military + Presidential.duties + Personal + Other +
        Featured..Democrats. + Featured..Democrats.*Political,
        RV.lead.5 ~ Fake.news,
        VRP.lead.5 ~ Economic + Political + Military + Presidential.duties + Personal + Other +
        Featured..Democrats. + Featured..Democrats.*Political,
        VRP.lead.5 ~ Fake.news,
        ERV.lead.5 ~ Economic + Political + Military + Presidential.duties + Personal + Other +
        Featured..Democrats. + Featured..Democrats.*Political,
        ERV.lead.5 ~ Fake.news,
        EVRP.lead.5 ~ Economic + Political + Military + Presidential.duties + Personal + Other +
        Featured..Democrats. + Featured..Democrats.*Political,
        EVRP.lead.5 ~ Fake.news)

models.v2 <- lapply(formulas.5min, function(formula) lm(formula, data = merged))
se.PL.imm.v2 <- lapply(models.v2, coeftest, vcov = vcovPL)
stargazer(models.v2, type = "html", out = "intra 5min.html", se = lapply(se.PL.imm.v2, function(x) x[, 2]), report =('vc*t'), keep.stat = c("n", "rsq",
"adj.rsq"))

## Run from immediate reactions up until 6 hours

######### Intraday return regression #########
intraday.RV <- list(hour ~ VRP.hour,
        hour ~ VRP.hour + RV.hour,
        hour ~ VRP.hour + IV.hour,
        hour2 ~ VRP.2hour,
        hour2 ~ VRP.2hour + RV.2hour,
        hour2 ~ VRP.2hour + IV.2hour,
        halfday ~ VRP.halfday,
        halfday ~ VRP.halfday + RV.halfday,
        halfday ~ VRP.halfday + IV.halfday,
        day ~ VRP.day,
        day ~ VRP.day + RV.day,
        day ~ VRP.day + IV.day)
models.intra <- lapply(intraday.RV, function(formula) lm(formula, data = intraday.reg))
NeweyWest.intra <- lapply(models.intra, coeftest, vcov = NeweyWest)
stargazer(models.intra, type = "html", out = "intraday_reg.html", se = lapply(NeweyWest.intra, function(x) x[, 2]),
report = ('vc*t'), keep.stat = c("n", "rsq", "adj.rsq"))

## Run for subsamples of pre-GFC, post-GFC, GFC and pre- and post-election

######### Winsorized sample regressions #########

## For 20-minute reactions, example for full sample of returns
Winsorized.20.min <- Winsorize(merged$ret.lead.20, minval = NULL, maxval = NULL, probs = c(0.05,0.95), na.rm = FALSE)
# (...)

## Run for VRP, EVRP, Returns, Realized and Implied variances
formulas.20min <- list(ret.lead.20 ~ Economic + Political + Military + Presidential.duties + Personal + Other +
        Featured..Democrats. + Featured..Democrats.*Political,
        ret.lead.20 ~ Fake.news,
        IV.lead.20 ~ Economic + Political + Military + Presidential.duties + Personal + Other +
        Featured..Democrats. + Featured..Democrats.*Political,
        IV.lead.20 ~ Fake.news,
        RV.lead.20 ~ Economic + Political + Military + Presidential.duties + Personal + Other +
        Featured..Democrats. + Featured..Democrats.*Political,
```

```
            RV.lead.20 ~ Fake.news,
            VRP.lead.20 ~ Economic + Political + Military + Presidential.duties + Personal + Other +
            Featured..Democrats. + Featured..Democrats.*Political,
            VRP.lead.20 ~ Fake.news,
            ERV.lead.20 ~ Economic + Political + Military + Presidential.duties + Personal + Other +
            Featured..Democrats. + Featured..Democrats.*Political,
            ERV.lead.20 ~ Fake.news,
            EVRP.lead.20 ~ Economic + Political + Military + Presidential.duties + Personal + Other +
            Featured..Democrats. + Featured..Democrats.*Political,
            EVRP.lead.20 ~ Fake.news)

Winsorized.20min.model <- lapply(formulas.20min, function(formula) lm(formula, data = Winsorized.20.min))
se.PL.winsorized.20min <- lapply(Winsorized.20min.model, coeftest, vcov = vcovPL)
stargazer(Winsorized.20min.model, type = "html", out = "Winsorized intra 20min.html", se =
lapply(se.PL.winsorized.20min, function(x) x[, 2]), report = ('vc*t'), keep.stat = c("n", "rsq", "adj.rsq"))

## For intraday return regressions
## Example for 1-hour return
Winsorized.intraday <- Winsorize(intraday.reg$hour, minval = NULL, maxval = NULL, probs = c(0.05,0.95), na.rm =FALSE)
# (...)
## Run for periods from 1 hour to one day, for VRP, EVRP, RV and IV

## Subsampling
Winsorized.intraday.reg.pre.gfc <- window(Winsorized.intraday, start = "2002-01-01", end = "2007-12-01")
Winsorized.intraday.reg.post.gfc <- window(Winsorized.intraday, start = "2009-07-01", end = "2018-02-27")
Winsorized.intraday.reg.gfc <- window(Winsorized.intraday, start = "2007-12-01", end = "2009-07-01")
Winsorized.intraday.reg.trump <- window(Winsorized.intraday, start = "2016-11-08", end = "2018-02-27")

## Example for full-sample VRP
intraday.RV.winsorized <- list(hour ~ VRP.hour,
            hour ~ VRP.hour + RV.hour,
            hour ~ VRP.hour + IV.hour,
            hour2 ~ VRP.2hour,
            hour2 ~ VRP.2hour + RV.2hour,
            hour2 ~ VRP.2hour + IV.2hour,
            halfday ~ VRP.halfday,
            halfday ~ VRP.halfday + RV.halfday,
            halfday ~ VRP.halfday + IV.halfday,
            day ~ VRP.day,
            day ~ VRP.day + RV.day,
            day ~ VRP.day + IV.day)

models.intra.winsorized <- lapply(intraday.RV.winsorized, function(formula) lm(formula, data = Winsorized.intraday))
NeweyWest.intra.winsorized <- lapply(models.intra.winsorized, coeftest, vcov = NeweyWest)

stargazer(models.intra.winsorized, type = "html", out = "winsorized_intraday_reg.html", se =
lapply(NeweyWest.intra.winsorized, function(x) x[, 2]), report = ('vc*t'), keep.stat = c("n", "rsq", "adj.rsq"))
```

APPENDIX AD: R-script for daily Trump Tweet regressions

```
## Script for intraday regressions

## Setting timezones to align datasets
Sys.setenv(TZ = 'America/Chicago')

## Reading in necessary packages
library(quantmod)
library(rugarch)
library(xts)
library(aTSA)
library(stargazer)
library(lubridate)
library(AER)
library(DistributionUtils)
library(dynlm)
library(forecast)
library(strucchange)
library(zoo)
library(dplyr)
library(data.table)
library(Rfast)
library(DescTools)

## Read in data from local csv files
SP <- read.csv('New SPX.csv')
VIX <- read.csv('New VIX.csv')

## Convert to xts files
SP = xts(SP[, 2], as.POSIXct(SP[, 1], format = c("%d-%m-%Y %H:%M")))
VIX = xts(VIX[, 2], as.POSIXct(VIX[, 1], format = c("%d-%m-%Y %H:%M")))

## Convert to New York time
indexTZ(VIX) <- "America/New_York"
indexTZ(SP) <- "America/New_York"

## Cut both samples to only cover trading hours (9:30 to 16:00)
SP <- SP["T09:30:00/T16:00:00"]
VIX <- VIX["T09:30:00/T16:00:00"]
colnames(SP) <- "SP"
colnames(VIX) <- "VIX"

######## Create RV and returns: Sum rolling monthly squared and regular returns ########
R_i <- log(SP$SP/lag(SP$SP))

## Squaring returns
R_i$sq.ret <- (R_i$SP*100)^2
R_i <- na.omit(R_i)

## Create RV and returns from rolling sums
R_i$var.day <- apply.daily(R_i$sq.ret, sum)
```

```
R_i$ret.day <- apply.daily(R_i$SP, sum)
R_i <- na.omit(R_i)

## Create new datasets for RV and returns
RV <- R_i$var.day
ret <- R_i$ret.day

## Create monthly RV
RV$var <- rollapply(RV$var.day, 22, sum)
RV <- na.omit(RV)

## DROPPING THE TIME STAMPS
str(index(RV))
strsplit(as.character(index(RV))," ")# split by space
lapply(strsplit(as.character(index(RV))," "), function(x) x[1]) #select the first vector element
unlist(lapply(strsplit(as.character(index(RV))," "), function(x) x[1])) #which is still a 'character' class
index(RV)<-unlist(lapply(strsplit(as.character(index(RV))," "), function(x) x[1]))
index(RV)<- as.Date(unlist(lapply(strsplit(as.character(index(RV))," "), function(x) x[1])))

############## MC-GARCH ##################

## Read in MC-GARCH results from csv
FORC <- read.csv("daily-EGARCH.csv")
FORC <- na.omit(FORC)

## Convert to xts
FORC = xts(FORC[,2], as.Date(FORC[,1], format = c("%Y-%m-%d")))
colnames(FORC) <- "var"

## merge with the realized-var dataset
Real.var <- merge.xts(FORC, RV)
Real.var <- na.omit(Real.var)
colnames(Real.var)[3] <- "RV"
colnames(Real.var)[1] <- "EGARCH"

######## Generate monthly returns from rolling sums ########

## Example for 1-month
ret$month1 <- rollapply(ret$ret.day, 22, sum)*12*100
##(...)
## Run from 1 to 24 months

ret <- na.omit(ret)

######## Getting implied variance in the correct format ########
IV.day <- apply.daily(VIX, mean)
IV.day$vix.month <- IV.day$VIX/sqrt(12)
IV.day$vix2 <- IV.day$vix.month^2

## Merging the two files together
VRP.data <- merge.xts(Real.var, IV.day)
```

```
######## Generating the VRP ########
VRP.data$VRP <- VRP.data$vix2 - VRP.data$RV
VRP.data$EVRP <- VRP.data$vix2 - VRP.data$EGARCH

###### Generate excess returns ######
symbols <- c("DGS3MO")
getSymbols(symbols, from = "1990-01-01", src="FRED", auto.assign = TRUE)

## Merge into SP.day
excess.ret <- merge.xts(DGS3MO, ret)
excess.ret <- na.omit(excess.ret)

## Generate excess returns, example for 1-month
excess.ret$ER1 <- excess.ret$month1 - excess.ret$DGS3MO
## (...)
## Run for up to 24-months

###### Control variables ######
symbols <- c("DGS3MO", "DAAA", "DBAA", "DGS10", "TEDRATE")
getSymbols(symbols, from = "1996-01-01", src="FRED", auto.assign = TRUE)
controls <- merge.xts(DBAA, DGS10, DGS3MO, TEDRATE, DAAA)
controls <- na.omit(controls)

## Create rolling average of the risk-free to detrend the timeseries
controls$rolling <- rollmean(controls$DGS3MO, 252, align = "right")

## Create relevant spreads
controls$riskfree <- controls$DGS3MO - controls$rolling
controls$default <- controls$DBAA - controls$DAAA
controls$term <- controls$DGS10 - controls$DGS3MO

## Define window and merge with (E)VRP data
controls <-window(controls, start = '1996-01-01', end = '2018-02-28')
VRP.data <- merge.xts(controls, VRP.data)
VRP.data <- na.omit(VRP.data)

####### Creating lags for regressions #######

## To run regression, we create lags for implied and realized variance, the (E)VRP and relevant control variables for
months 1-24
## An example is the first month for the VRP
VRP.data$VRP.1 <- lag(VRP.data$VRP, 22)
#(...)

## Merge the two datasest to make sure the data lines up
merged.data <- merge(VRP.data, excess.ret)
merged.data <- na.omit(merged.data)

####### Dummy variable construction #######
## Read in Trump data
Trump.daily1 <- read.csv("Daily-data-trump1.csv",sep=";")
```

```
## convert to xts
Trump.daily1 = xts(Trump.daily1[, 2:9], as.POSIXct(Trump.daily1[, 1], format = c("%d-%m-%Y %H:%M")))

## Getting the daily sum of the Indicator variables
econ.sum <- apply.daily(Trump.daily1$Economic, sum)
pol.sum <- apply.daily(Trump.daily1$Political, sum)
dem.sum <- apply.daily(Trump.daily1$Featured..Democrats., sum)
mil.sum <- apply.daily(Trump.daily1$Military, sum)
pres.sum <- apply.daily(Trump.daily1$Presidential.duties, sum)
per.sum<- apply.daily(Trump.daily1$Personal, sum)
other.sum <- apply.daily(Trump.daily1$Other, sum)
fake.sum<-apply.daily(Trump.daily1$Fake.news,sum)
Trump.sum<-merge.xts(econ.sum,pol.sum, dem.sum, mil.sum, pres.sum, per.sum, other.sum, fake.sum)

##Merging sum and avg to one file
Trump_all<-Trump.sum

## Removing time stamps
str(index(Trump_all))
strsplit(as.character(index(Trump_all))," ")# split by space
lapply(strsplit(as.character(index(Trump_all))," "), function(x) x[1]) #select the first vector element
unlist(lapply(strsplit(as.character(index(Trump_all))," "), function(x) x[1])) #which is still a 'character' class
index(Trump_all)<-unlist(lapply(strsplit(as.character(index(Trump_all))," "), function(x) x[1]))
index(Trump_all)<- as.Date(unlist(lapply(strsplit(as.character(index(Trump_all))," "), function(x) x[1])))

## create a blank timeseries to merge with Trump, just to be sure all days are present for VRP
blank <- merged.data$VRP
blank$newcol <- rep(0,nrow(blank))

## drop the VRP column
blank$VRP <- NULL

# merge blank timeseries with Trump
Trump_all2 <- merge.xts(Trump_all, blank)

# create a window on the first and last observations in the Trump dataset
Trump_all2 <- window(Trump_all2, start = "2016-11-08", end = "2018-02-28")

# create zero variables for NA variables
Trump_all2[is.na(Trump_all2)] <- 0

## drop the blank column
Trump_all2$newcol <- NULL

# Merge Trump data set with VRP data
merged <- merge.xts(Trump_all2, merged.data)
merged <- na.omit(merged)

############### REGRESSIONS #######################

##General reactions - no controls, on SUMMED Trump tweets
formulas.sum <- list(ret.day ~ Economic + Political + Military + Presidential.duties + Personal + Other +
```

```
        Featured..Democrats. + Featured..Democrats.*Political,
        ret.day ~ Fake.news,
        vix2 ~ Economic + Political + Military + Presidential.duties + Personal + Other +
        Featured..Democrats. + Featured..Democrats.*Political,
        vix2 ~ Fake.news,
        RV ~ Economic + Political + Military + Presidential.duties + Personal + Other +
        Featured..Democrats. + Featured..Democrats.*Political,
        RV ~ Fake.news,
        VRP ~ Economic + Political + Military + Presidential.duties + Personal + Other +
        Featured..Democrats. + Featured..Democrats.*Political,
        VRP ~ Fake.news,
        EVRP ~ Economic + Political + Military + Presidential.duties + Personal + Other +
        Featured..Democrats. + Featured..Democrats.*Political,
        EVRP ~ Fake.news)
        models.v1 <- lapply(formulas.sum, function(formula) lm(formula, data = merged))
        se.PL.sum <- lapply(models.v1, coeftest, vcov = vcovPL)
        stargazer(models.v1, type = "html", out = "Daily_sum.html", se = lapply(se.PL.sum, function(x) x[, 2]), report =
        ('vc*t'), keep.stat = c("n", "rsq", "adj.rsq"))

#WINSORIZED

merged$ret.day.wins <- Winsorize(merged$ret.day, minval = NULL, maxval = NULL, probs = c(0.05,0.95), na.rm = FALSE)
merged$vix2.wins <- Winsorize(merged$vix2, minval = NULL, maxval = NULL, probs = c(0.05,0.95), na.rm = FALSE)
merged$RV.wins <- Winsorize(merged$RV, minval = NULL, maxval = NULL, probs = c(0.05,0.95), na.rm = FALSE)
merged$VRP.wins <- Winsorize(merged$VRP, minval = NULL, maxval = NULL, probs = c(0.05,0.95), na.rm = FALSE)
merged$EVRP.wins <- Winsorize(merged$EVRP, minval = NULL, maxval = NULL, probs = c(0.05,0.95), na.rm = FALSE)

formulas.sum.wins <- list(ret.day.wins ~ Economic + Political + Military + Presidential.duties + Personal + Other +
        Featured..Democrats. + Featured..Democrats.*Political,
        ret.day.wins ~ Fake.news,
        vix2.wins ~ Economic + Political + Military + Presidential.duties + Personal + Other +
        Featured..Democrats. + Featured..Democrats.*Political,
        vix2.wins ~ Fake.news,
        RV.wins ~ Economic + Political + Military + Presidential.duties + Personal + Other +
        Featured..Democrats. + Featured..Democrats.*Political,
        RV.wins ~ Fake.news,
        VRP.wins ~ Economic + Political + Military + Presidential.duties + Personal + Other +
        Featured..Democrats. + Featured..Democrats.*Political,
        VRP.wins ~ Fake.news,
        EVRP.wins ~ Economic + Political + Military + Presidential.duties + Personal + Other +
        Featured..Democrats. + Featured..Democrats.*Political,
        EVRP.wins ~ Fake.news)

models.v1.2 <- lapply(formulas.sum.wins, function(formula) lm(formula, data = merged))
se.PL.sum.wins <- lapply(models.v1.2, coeftest, vcov = vcovPL)

stargazer(models.v1.2, type = "html", out = "Daily_sum_wins.html", se = lapply(se.PL.sum.wins, function(x) x[, 2]),
report = ('vc*t'), keep.stat = c("n", "rsq", "adj.rsq"))
```