Essays on Volatility and Variance Risk Premium

Thesis submitted in partial fulfilment of the requirements

for the degree of Doctor of Philosophy

HENLEY BUSINESS SCHOOL

THE UNIVERSITY OF READING

ICMA Centre

Xiaoman Su

December 2020

Declaration

I confirm that this is my own work and the use of all material from other sources has been properly and fully acknowledged.

Xiaoman Su

Acknowledgements

I am deeply grateful to my supervisor Dr. Chardin Wese Simen for his patient guidance and immense support. I feel truly blessed that Chardin agrees to be my supervisor and encourages me throughout all the stages of my work. He teaches me how to conduct research and how to think as a researcher. He is always willing to provide insightful comments and encourage me to further my work. I am forever indebted to him for his in-depth knowledge and trustful advice and he is my most trusted advisor. I also would like to sincerely thank Professor Michael Clements for his continuous support and never lost faith in me. He suggested that I could be supervised by Chardin and helped me a lot throughout my PhD study. Without them, this PhD would not have been possible.

I would like to thank Dr. Andrew Urquhart and Dr. Feargle Kearney for being my examiners and sharing their valuable comments on my thesis. I also thank the ICMA Centre for giving me the chance to pursue a PhD and thank all the faculty for help and support. I am also very grateful to my family and friends for their endless care and form support.

Abstract

The thesis consists of three chapters on volatility and variance risk premium. In second chapter, we analyze volatility-managed strategies in commodity futures markets. We focus on two kinds of strategy: scaling original portfolio before and after its formation by volatility information, and three kinds of portfolio: momentum, basis momentum and carry trade. We find that both two strategies do not significantly improve the performance of the original portfolio. Exploring potential reasons behind this result, we find that the accuracy of the forecasting model, the economic conditions, the choice of the evaluation criteria, as well as as the method used to construct the portfolio cannot explain our main results.

In third chapter, we investigate the time-series models for volatility risk premium (VRP) forecasts and their implications for volatility forecasting. We employ the role of VRP to reduce the bias in the model-free implied volatility (MFIV) and get an efficient and unbiased forecast of volatility. We study on commodity-related ETFs and compare the time-series model for volatility forecasting, EWMA and MFIV-related forecasts. Using Mincer-Zarnowitz regres-

sion and two kinds of loss function, we confirm that MFIV performs better than EWMA and MFIV is biased. Furthermore, our adjustment for MFIV outperforms than pure MFIV and MFIV adjusted by historical averages of VRP. Our findings are robust to alternative proxies of the realized volatility, different VRP format and different rolling window of forecast.

In fourth chapter, we study the effects of federal fund rate announcements on the market price of variance risk. We find that there is a positive relationship between the change in the variance risk premium and the interest rate shocks and the response to FOMC surprise declines with increases of maturity. Additionally, we document that the response is mainly driven by the reactions of implied variance and variance risk premium with short maturity respond more to timing surprise. Furthermore, we show that investors matter the downside risk and need more compensation since most of the FOMC announcement effect is from the expansionary policy, negative surprise and bad variance risk premium.

Contents

List of Figures

List of Tables

Chapter 1

Introduction

1.1 Motivation

This thesis explores various issues related to the accurate modelling of volatility as well as the impact of important news events on the variance risk premium. Volatility, which reflects risk, is a kernel aspect of financial economic theory and practice. It is well-known that volatility forecasting is more manageable than return forecasting. Many investors select portfolios that seek to gain excess return and reduce risk. A growing number of studies, e.g. Moreira and Muir (2017) and Han et al. (2021), make the case for volatility-managed strategies. The volatility-managed strategies are widely used to boost portfolio return and adjust risk exposure by volatility information. The strategies exploit the information of volatility to adjust the leverage of the strategy. Fleming et al. (2001, 2003) show that volatility management can boost the performance of the original portfolio.

More recently, Barroso and Santa-Clara (2015), Moreira and Muir (2017) and Han et al. (2021) all provide evidence that volatility managed portfolios outperform the original portfolio by larger Sharpe ratio and less downside risk.

However, Liu et al. (2019) point that the methodology of Moreira and Muir (2017) has a look-ahead bias and is impractical. They also analyze another three volatility-managed strategies and find that they all fail to beat the market. Bongaerts et al. (2020) correct the look-ahead bias of the strategy and also find that the conventional volatility-timing strategy does not consistently increase the Sharpe ratio and may even incur dramatic drawdowns. A volatility-managed strategy is usually implemented by using the inverse of portfolio volatility to adjust portfolio weights. The strategy is based on the assumption of a negative relationship between volatility and return. Although there exists a broad literature on volatility-managed strategies in equity markets, there is little understanding in commodity futures markets, especially for portfolios exploiting the characteristics of commodity futures markets. In Chapter 2, we aim to enrich the literature on commodity futures markets and investigate whether volatility-management performs well in this asset class.

There exist several different kinds of volatility-managed strategies, e.g. Clements and Silvennoinen (2013), Moreira and Muir (2017) and Bongaerts et al. (2020). We focus on the following two strategies. Moskowitz et al. (2012) use the volatility of each asset to adjust its weight before the formation of a time-series momentum portfolio. Barroso and Santa-Clara (2015) use the volatility of cross-sectional momentum portfolio to adjust its risk exposure and find that the volatility management approach almost doubles the Sharpe ratio of the original portfolio and significantly reduce the tail risk. Kim et al. (2016) find that the unscaled time-series momentum portfolio is inferior to cross-sectional momentum. The outstanding performance of a scaled time-series momentum portfolio is due to volatility-managed strategy. To the best of our knowledge, there is little understanding in comparison to these strategies. It inspires us to investigate when is the best timing for volatility-managed strategy. In Chapter 2, we focus on whether there exists any significant difference between the timing of volatility-managed strategy before or after portfolio formation.

Volatility forecasting is vital for risk management. There exists extensive research on volatility forecasting, and most of it belongs to two streams. The first one is using historical information of volatility, and the second one is deriving the estimates of future volatility from implied volatility. In the second forecasting category, the implied volatility is extracted from traded options prices and is used to predict the realized volatility. The implicit assumption is that the difference between implied volatility and realized volatility is zero. However, a broad literature shows that there exists a significant and time-varying difference between implied and realized volatility, e.g. Carr and Wu (2009), Trolle and Schwartz (2010) and Prokopczuk et al. (2017). This difference between volatility under risk-neutral measure and volatility under physical measure is defined as volatility risk premium.

Poteshman (2000) state that embedding volatility risk premium in the Heston model can reduce the bias of implied volatility forecasting. Chernov (2007) points that the volatility risk premium introduces a bias in volatility forecasting. Thus, several studies on exploiting the volatility risk premium exist around volatility forecasting, e.g. DeMiguel et al. (2013), Prokopczuk and Wese Simen (2014) and Kourtis et al. (2016). These researches focus on equity market or commodity markets while the rapidly growing financial investment, Exchange Traded Funds (ETFs) have received very little attention. Chapter 3 investigates the role of volatility risk premium in volatility forecasting in commodity-related ETFs.

Bollerslev et al. (2011) show that volatility risk premium is time-varying and use an augment AR(1) model to forecast it. DeMiguel et al. (2013), Prokopczuk and Wese Simen (2014) and Kourtis et al. (2016) use the historical average of volatility risk premium to predict its future value. To the best of our knowledge, there is a lack of studies on comparisons of time-series forecasting models for volatility risk premium. In Chapter 3, we present and estimate several time-series models to capture the dynamics of volatility risk premium and explore their implications for volatility forecasting.

The variance risk premium is very close to volatility risk premium and is defined as the difference between the variance under the risk-neutral measure and the variance under the physical measure. An extensive literature, e.g. Carr and Wu (2009) and Trolle and Schwartz (2010), shows that there exists a significant and time-varying variance risk premium. Naturally, one may wonder what drives the variance risk premium. In recent years, a growing body of literature investigates the impact of scheduled macroeconomic news announcements, especially monetary policy news, on risk premium. Bernanke and Kuttner (2005) find that an unexpected change of federal fund rate significantly affects the S&P 500 index. Lucca and Moench (2015) point that the mean excess return of the S&P 500 stock index on interest rate announcement days is much larger than on other days. Avino et al. (2019) study the announcement effect on the term-structure of the dividend risk premium. They find that the announcement effect is strongest at the short-end of the term-structure of the dividend risk premium and declines with the maturity of the dividend asset. However, there is a lack of literature on the relation between interest rate news and the market price of variance risk. In Chapter 4, we set out to fill the research gap on whether monetary policy news significantly affects the term-structure of the variance risk premium.

Bekaert et al. (2013) start with the VIX index and analyze the relation between monetary policy and the components of the VIX, i.e. proxies for risk aversion and uncertainty.[1] They document that lowering interest rate decreases risk aversion and uncertainty. Feunou et al. (2018) and Kilic and Shaliastovich (2019) compute

[1] VIX is the volatility index of the S&P 500 Index.

the good and bad variance risk premium and analyze their relationship with the equity risk premium. Their study inspires us to dissect the variance risk premium and analyze different monetary policy stances. In Chapter 4, we investigate 1) the reaction of the term-structure of the variance risk premium to unexpected changes of interest rates and 2) the main channel of announcement effect.

1.2 Overview and Contribution

This thesis sets out to answer the questions in Section 1.1. Overall it investigates volatility and variance risk premium and offers several empirical findings.

Chapter 2 analyzes volatility-managed strategies in the commodity futures market. We focus on 22 liquid and actively traded commodity futures data, two kinds of volatility-managed strategies: scaling original portfolio before and after its formation by volatility information, and three kinds of portfolios: momentum, basis momentum, and carry trade. We enrich the literature on the implementation and investigation of volatility-managed strategies in commodity markets. The conventional volatility-managed strategies scale the portfolio by its volatility after its formation. We choose the target level of volatility, 18%, which is close to our portfolio annual standard deviation. Analyzing the Sharpe ratio, maximum drawdown and some statistics, we find that the conventional strategy cannot improve the original portfolio performance. Volatility-managed strategies essentially leverage up the risk exposure when the volatility is low and leverage down the risk exposure when the volatility is high. There is a gap in research on the efficient timing of volatility-managed strategies, and we contribute to fill it. We use the original portfolio as a benchmark and find that volatility-managed strategies, either scaling portfolio before or after its formation, do not significantly boost the Sharpe ratio and reduce downside risk. It suggests that there is no significant difference between the two strategies.

One aim of the volatility-managed strategy is to reduce the downside risk, especially in economic downturns. We analyze volatility-managed strategies under different economic conditions. To address the concerns of biases due to the performance of the volatility forecasting model, We consider several models, including the GJR-GARCH model, the HAR model and the historical average. Even the best estimator, which is calculated by the GJR-GARCH model, cannot help the strategy work. Additionally, we consider alternative benchmark and alternative performance evaluation. Overall, volatility management does not significantly improve the original portfolio performance.

In Chapter 3, we investigate various time-series models for the volatility risk premium (VRP) and their implications for volatility forecasting. We enrich the literature on correcting the implied volatility for the VRP. We show that doing so can significantly reduce the biasedness of volatility forecasts in commodity-related ETFs. We employ VIX and the other 5 commodity volatility indexes to investigate the role of VRP in volatility forecasting. We employ the model-free implied volatility (MFIV) and the EWMA model as benchmarks. Comparing the adjusted-MFIV with these two benchmarks, we can generally conclude that MFIV beats EWMA and adjusted-MFIV beats MFIV. Before our study, there is little research on the best VRP forecasts. We contribute to compare several time-series models to capture the time-varying of VRP and aiming for the best volatility estimators. Thus, we compare the VRP estimator from 1) the historical average, 2) the AR(1), 3) the EWMA, and 4) the combination of realized volatility and MFIV, and we find that this latter specification performs best.

To evaluate the accuracy of volatility forecasts, we employ Mincer-Zarnowitz regressions as well as the Wald test to test the efficiency of estimators. Furthermore, we employ two kinds of loss functions: MSE and QLIKE to assess forecasting accuracy, and use the Diebold-Mariano (DM) test and non-parametric Wilcoxon signed-rank test to assess the significance of the mean and median differences respectively. We conclude that VRP estimators for volatility forecasting from 1) the historical average, 2) the AR(1), and 4) the combination of realized volatility and MFIV, are not significantly different from one another, and VRP estimators from 4) performs better. Additionally, we consider alternative proxies of the realized volatility, different VRP format, different rolling window of forecasts and different benchmark to confirm our results are robust.

In Chapter 4, we analyze the effects of federal fund rate announcements on the market price of the variance risk. We employ a large dataset of S&P 500 index options and spot data to compute the term-structure of the variance risk premium. To the best of our knowledge, our study is the first to investigate the effect of monetary policy on the term-structure of the variance risk premium. We document that there is a positive relationship between the change in the variance risk premium and the interest rate shocks and the response of the variance risk premium to FOMC surprise declines with increases of maturity. Furthermore, we decompose the variance risk premium find that, for short maturity, the implied variance reacts more to interest rate shocks than the realized variance. We then decompose variance risk premium into its good and bad components and note that most responses are from the bad variance risk premium.

Savor and Wilson (2013) point that components of VIX react more strongly to expansionary monetary policy by the VAR model. We consider the monetary policy stance, and our finding supports their conclusion. We also analyze the positive and negative changes of interest rate and find that most of the announcement effect can be traced back to the negative interest rate shocks. Moreover, we conduct several robustness checks and confirm the consistency of our findings.

The rest of this thesis is organized as follows. Chapter 2 focuses on volatility-managed strategies in commodity markets. Chapter 3 studies the time-series models for the volatility risk premium in commodity-related ETFs. Chapter 4 analyzes the reaction of the term structures of the variance risk premium to monetary policy. Chapter 5 summarizes the thesis and discusses several suggestions for further research.

We make each chapter self-contained. As such, we (re)introduce variables and abbreviations in each chapter. We endeavour to use consistent notations throughout this thesis for a better reading experience.

Chapter 2

Volatility-managed Strategy in the Commodity Markets

2.1 Introduction

It is widely acknowledged that return forecasting is much more difficult than volatility forecasting. However, the relationship between volatility and return helps us improve the performance of the portfolio by the information of volatility. Early studies, e.g. Fleming et al. (2003), employ daily volatility information to estimate volatility and find that volatility-managed portfolios outperform the original optimal portfolio. They support that volatility management can increase the economic value of the portfolio. Recently, a growing stream of the literature, e.g. Barroso and Santa-Clara (2015) and Moreira and Muir (2017), uses the predicted portfolio volatility to scale the original portfolio and improve the performance of the portfolio. These studies confirms the success and importance of volatility-managed strategy.

Most studies focus on equity markets and employ the volatility scaling after the formation of the original portfolio. We are interested in the following questions. Whether the conventional volatility-managed strategy really improves the performance of the original portfolio in commodity markets? Is there an alternative volatility-managed strategy that can improve the performance? How about scaling the portfolio before its formation? Whether the volatility-managed strategies can have better performance by improving the accuracy of the volatility estimate?

In this paper, we use daily settlement prices for 22 commodity futures to investigate the performance of volatility-managed strategies and focus on the timing of risk-managed. We analyze several prominent commodity trading strategies: momentum, basis momentum, and carry trading strategies. We study two kinds of volatility-managed strategies: scaling the portfolio after its formation and scaling the portfolio before its formation. The scaling weight is proportional to the volatility estimate. We set the target volatility of the scaled portfolio as 18% per year, which is close to the volatility of the original portfolio.

We document several findings. First, analyzing the Sharpe ratio, we find that the conventional volatility-managed strategy does not significantly improve the performance of the original portfolio. Liu et al. (2019) and Bongaerts et al. (2020) show that volatility-scaling after portfolio formation cannot consistently outperform the original portfolio, and our conclusion is consistent with them. Liu et al. (2019) study the equity market and show that volatility-managed strategies cannot reduce the downside risk. We employ maximum drawdown to support their findings.

Second, volatility-managed strategy scaled after portfolio formation has no significant improvements of the original portfolio. Furthermore, there is no statistical difference between the strategy scaled before and after the portfolio formation. Our results contribute to the problem that volatility-scaling timing is not the critical point of improving the scaled portfolio. It suggests that only taking the information of volatility estimate cannot certainly improve original performance.

Third, we classify months into recession and expansion periods and investigate the performance of scaled and unscaled portfolios. Grundy and Martin (2001) document that in equity market momentum has time-varying factor exposures and it has a significant negative beta following a bear market. It suggests that momentum strategy can be managed by market states. Daniel and Moskowitz (2016) confirm that momentum has a time-varying beta and show that it easily occurs momentum crashes when the bear market with high volatility rebounds. Not surprisingly, we find that all the portfolios perform badly under recession to expansion condition and all the portfolios outperform under expansion to recession condition. Moreover, our results present that there are no statistically significant improvements of scaled portfolios under different economic condition.

Fourth, we notice that the failure of volatility-managed strategies in our sample is not due to biased volatility estimates. We use more sophisticated volatility forecasting models to get more accurate volatility estimates and then employ them to construct the volatility-managed portfolio. Although the GJR-GARCH model provides the least biased estimate, the improvements of scaled portfolios are still not statistically significant. Again, results suggest that volatility-managed strategies fail in our study and volatility information is not enough to ensure better performance.

We conduct several additional tests. We choose the different weight of assets by their ranking rather than equal weights. Unscaled portfolio of momentum and basis momentum both have a larger mean of excess return than the equal-weighted unscaled portfolio. For scaled portfolio, the Sharpe ratios of basis momentum increase while those of momentum and carry decrease. Collectively, our main finding, the difference of performance between scaled and unscaled portfolio are insignificant, maintains. We follow Fleming et al. (2003) to study the economic value of the scaled portfolio by performance fee. Consistent with the statistics of performance, economic value of scaled portfolio is not statistically significant unequal to 0.

The structure of Chapter 2 is as follows: Section 2.2 describes some related studies. Section 2.3 introduces our data and methodology. Section 2.4 reports our results and findings. Section 2.5 presents some potential explanations. Finally, Section 2.6 concludes.

2.2 Literature Review

Our work enriches the study of volatility-managed strategy especially in commodity future market. Barroso and Santa-Clara (2015) confirm that volatility-managed strategy which scales the portfolio after its formation by the inverse of portfolio volatility can reduce downside risk and improve Sharpe ratios. Moreira and Muir (2017) apply a similar method to many market factors, including momentum and currency carry, and document scaled portfolios outperform the original ones. Harvey et al. (2018) study more than 60 assets and point that volatility-managed strategy reduces downside risk and increase Sharpe ratios for risk assets. However, Liu et al. (2019) and Bongaerts et al. (2020) state that conventional volatility-managed strategy cannot consistently succeed and improvements from the strategies in Moreira and Muir (2017) and Harvey et al. (2018) are driven by look-ahead bias.

Marshall et al. (2008) point that commodity futures have lower transaction costs, and it is easier to take short positions. Therefore, investors can manipulate a variety of strategies in the commodity futures market. Daniel and Moskowitz

(2016) investigate many kinds of markets, including the commodity futures market, and show that adjusted momentum strategy by the forecast of portfolio mean and variance can significantly improve the strategy performance. Besides momentum, Boons and Prado (2019) explore the character of the futures term structure and put forward a basis-momentum strategy. Kang and Kwon (2021) investigate the performance of Moreira and Muir (2017) methodology in momentum and basis-momentum in commodity futures markets.[1] We contribute to the debate about the efficiency of volatility-managed strategy in commodity futures markets and add to the literature on the efficiency in different portfolio strategies.

Moskowitz et al. (2012) use volatility-managed strategy to scale time-series momentum before its formation and find that scaled portfolio outperforms cross-sectional momentum. Kim et al. (2016) claim that volatility-managed strategy makes scaled time-series momentum outstanding, and the unscaled portfolio has no significant difference with a buy-and-hold portfolio. The intuition of a volatility-managed strategy reduces the risk exposure when volatility is high and leverages up risk exposure when volatility is low. There is a gap in the literature that which timing of managing the risk exposure, before or after the portfolio formation, is more efficient. We fill it in this study.

[1] Compared with the parallel and independent study of Kang and Kwon (2021), our study differs from it in following aspects. First, our study focuses on the difference in managing timing. Second, we choose a different scaled methodology to alleviate the potential look-ahead bias, which is explained by Liu et al. (2019). Third, we provide a comprehensive analysis of performance and focus on the improvement of methodology to explain the failure of volatility management.

Barroso and Santa-Clara (2015) point that there exists a negative relation between the volatility and return of momentum portfolio, so the return can be improved by adjusting volatility. However, Barroso and Maio (2019) present that most other factors have a positive volatility-return relation. Bongaerts et al. (2020) claim that the weakly negative relation between volatility and return can explain the poor performance of the conventional volatility-managed strategy. They find that the negative relation usually happens in extreme volatility states. Kang and Kwon (2021) use the simulation analysis to confirm the negative risk-return relation and explain the failure of volatility-managed strategy. Our study adds to the empirical literature on negative volatility-return relation.

Our work is related to the broad literature on the bias of volatility forecasting and volatility estimates. Moreira and Muir (2017) point that the efficiency of volatility-managed strategy is affected by the accuracy of volatility estimates. Han et al. (2021) state that bias of volatility forecasting in volatility-managed strategy may increase the volatility of the portfolio. Barroso and Santa-Clara (2015) use the average of historical volatility information over the past 6 months to estimate the volatility in the next month. Daniel and Moskowitz (2016) employ the GJR-GARCH model to forecast volatility in the next period. Bollerslev et al. (2018) compare several forecasting models and find that inaccurate volatility estimate makes the volatility of portfolio depart from the constant target level. They conclude that the more accurate the volatility forecasting is, the more efficient the scaled portfolio is.

2.3 Data and Methodology

2.3.1 Data

We obtain daily settlement prices for 22 commodity futures from the Commodity Research Bureau (CRB). Data are available for different contracts with different sample periods, and our sample period starts from January 1986 to February 2015. For every month, the number of available contracts ranges from 19 to 22. These 22 futures contracts are all liquid commodities and actively traded. These futures markets represent 7 different commodity sectors: energy (Brent oil, WTI oil, heating oil, natural gas), grains (corn, oats, rice, wheat), industrials (cotton, lumber), meats (live cattle, lean hogs), metals (gold, copper, silver), oilseeds (soy oil, soybeans, soy meal) and softs (cocoa, orange, coffee, sugar). Table 2.1 reports the details of these 22 contracts, such as contract names, contract tickers, futures exchanges and maturity for each commodity futures market.

Following Szymanowska et al. (2014), the rollover day is the last trading day of the month before the expiration month. This rollover practice helps us avoid the occurrence of unusual price behaviour when the contracts are close to expiration. Similar to Boons and Prado (2019), our studies focus on the first- and second-nearby contracts which are more liquid and stable. Thus the second-nearby futures contract becomes the first-nearby contract after the rollover day. In order to get the time-series of excess returns of a specific nearby, we compute the returns based on its time-series prices after rollover. That means the calculation of the returns which is the ratio of the current price over the same order nearby contract or the next order nearby depends on whether it is the day just after a rollover. For every commodity futures, we calculate the excess daily returns on a fully collateralized futures position which is the common practice in the commodity studies (e.g. Boons and Prado, 2019 and Paschke et al., 2020):

$$R_{t+1}^{(m,i)} = \begin{cases} \frac{F_{t+1}^{(m,i)}}{F_t^{(m,i)}} - 1, \text{ if the day t is not the rollover day} \\ \frac{F_{t+1}^{(m,i)}}{F_t^{(m,i+1)}} - 1, \text{ otherwise} \end{cases} \tag{2.3.1}$$

where $R_{t+1}^{(m,i)}$ is the simple excess return of the commodity m i^{th} futures contracts realized at $t+1$ day. $F_{t+1}^{(m,i)}$ denotes the price of the commodity m i^{th} futures contracts at $t+1$ day. Similarly, $F_{t+1}^{(m,i)}$ denotes the price of the commodity m $(i+1)^{th}$ futures contracts at $t+1$ day.

By adopting the methods, we get the daily time-series excess returns of every commodity first- and second-nearby futures contracts. Since our strategies focus on the performance of monthly returns, we use the prices of the last trading day of that month to get the monthly returns. Table 2.1 presents the percentage of annualized mean and standard deviations of the first and second nearby contracts excess returns for each commodity markets. We can see that the volatility of the first nearby futures contracts ranges from 13.70 to 39.34 while that of the second nearby futures contracts ranges from 11.72 to 34.93. It confirms that commodity markets are very heterogeneous.

2.3.2 Methodology

Trading Strategy

Momentum Following Miffre and Rallis (2007), we employ the cross-sectional momentum strategy and consider the first nearby futures contracts for every commodity. Our study only analyzes the momentum strategy with a ranking period of 12 months and a holding period of 1 month without skipping. We rebalance our momentum strategy at the end of each month.[2] Following Jegadeesh and Titman (1993), we compute the compound return of the first nearby of each commodity futures market over the previous 12 months to proxy its performance. At the end of each month, we rank the first nearby of each futures markets in ascending order of their performance to obtain the trading signal for the momentum strategy. Considering the small observations in the cross-section of our commodity sample, we form our momentum strategy by buying the top 5 commodities (winners) and selling the bottom 5 commodities (losers).[3] Our approach narrows the difference

[2]In Kenneth R. French data library, the daily momentum return is obtained by the daily rebalanced strategy. However, Daniel and Moskowitz (2016) study the monthly and daily momentum strategies that are rebalanced at the end of each month. Our empirical approach is similar in spirit.

[3]Miffre and Rallis (2007) study momentum strategies based on a cross-section of 31 commodity futures markets with the number of available contracts ranging from 22 to 27 at each

between the performance of long and short futures contracts by taking half of commodity futures markets into account. However, we also diversify the system risk by adding more futures to our momentum strategy.[4] The realized excess return of the momentum strategy is as follows:

$$R_{XS-MOM,t+1} = \sum_{i=1}^{5} \omega_{XS-MOM,t}^{(i,1)} R_{t+1}^{(i,1)} - \sum_{j=1}^{5} \omega_{XS-MOM,t}^{(j,1)} R_{t+1}^{(j,1)} \tag{2.3.2}$$

where

$$\begin{aligned}
\omega_{XS-MOM,t}^{(i,1)} &= 0.2, \text{ if } rank(-M_t^{(i,1)}) \leq 5 \\
\omega_{XS-MOM,t}^{(j,1)} &= 0.2, \text{ if } rank(M_t^{(j,1)}) \leq 5 \\
M_t^{(m,1)} &= \prod_{s=t-11}^{t} (1 + R_s^{(m,1)}) - 1
\end{aligned}$$

$R_{XS-MOM,t+1}$ is the excess return of momentum strategy at the end of month $t+1$, $\omega_{XS-MOM,t}^{(i,1)}$ is the weight of long positions in the commodity futures market i in our momentum strategy, $\omega_{XS-MOM,t}^{(j,1)}$ is the weight of short positions in the commodity futures market j, $R_{t+1}^{(i,1)}$ and $R_{t+1}^{(j,1)}$ is the monthly excess return of the first nearby futures contracts of market i or j. The futures contracts in top and bottom 5 are equally weighted. The weights in long positions and short positions

point in time. They form the strategy by trading the top and bottom quintiles to alleviate the small size of the sample. Similarly, Bakshi et al. (2019) choose 5 commodities for the long or short side to form the momentum strategy.

[4]In section 2.5.2, we also check our results in the momentum benchmark with different weights.

both add up to 1 each. $rank(\cdot)$ is the rank operator in ascending orders. $M_t^{(m,1)}$ is the average compound return of the first nearby of commodity futures market m at the end of time t over the past 12 months and $-M_t^{(m,1)}$ is the opposite number of $M_t^{(m,1)}$.

Basis Momentum Following Boons and Prado (2019), we also employ the difference between the momentum returns of the first- and second-nearby futures as the basis of performance for our basis momentum strategy. At the end of every month, we sort all the differences between the first- and second-nearby futures contracts momentum returns in ascending orders and then get the trading signal for the basis momentum strategy in the next month. Consistent with the previous momentum strategy, we also consider the momentum returns based on the past 12 months and hold for one month. Similarly, the long and short sides are both chosen from the top and bottom 5 orders based on their basis-momentum performance. The excess return of the basis momentum strategy is as follows:

$$R_{BASMOM,t+1} = \sum_{i=1}^{5} \omega_{BASMOM,t}^{(i,1)} R_{t+1}^{(i,1)} - \sum_{j=1}^{5} \omega_{BASMOM,t}^{(j,1)} R_{t+1}^{(j,1)} \tag{2.3.3}$$

where

$$
\begin{aligned}
\omega_{BASMOM,t}^{(i,1)} &= 0.2, \text{ if } rank(-BM_t^{(i,1)}) \leq 5 \\
\omega_{BASMOM,t}^{(j,1)} &= 0.2, \text{ if } rank(BM_t^{(j,1)}) \leq 5 \\
BM_t^{(m,1)} &= \prod_{s=t-11}^{t} (1 + R_s^{(m,1)}) - \prod_{s=t-11}^{t} (1 + R_s^{(m,2)})
\end{aligned}
$$

$R_{BASMOM,t+1}$ is the excess return of basis momentum strategy at the end of month $t+1$, $\omega_{BASMOM,t}^{(i,1)}$ and $\omega_{BASMOM,t}^{(j,1)}$ is the weight of long and short positions in the commodity futures market i and j, respectively, for the basis momentum strategy. $BM_t^{(m,1)}$ is the difference between the momentum returns of the first and second nearby futures contracts. $R_s^{(m,1)}$ and $R_s^{(m,2)}$ is the monthly excess return of the first and second nearby futures contract for the commodity market m at the end of month s, respectively. All other variables are defined as previously.

Carry The carry strategy is based on the difference between the spot and futures prices. It profits from the shape of the forward curve. Following the popular methods in commodity futures studies, we employ the nearest-to-maturity futures prices rather than the spot price since the commodity spot markets are illiquid. Bakshi et al. (2019) use the ratio of the price of first over second nearby futures contract to determine the trading signals of carry strategy. However, there exist seasonal fluctuations in the prices of many commodity futures contracts, e.g. Sørensen (2002) and Hevia et al. (2018). Following Paschke et al. (2020), we employ the ratio of the price of the first nearby futures contract over the price of a futures contract with an expiration of 12 months after the expiration of the first nearby contract as our carry signal. For every commodity futures contract, we take advantages of all the prices information about the time-to-maturity of each nearby futures contract. We then use linear interpolation to obtain the price of the futures contract with an expiration of 12 months after the expiration of the first nearby contract. We get the carry trading signal by sorting the ratio performance in ascending order. Next, the top and bottom 5 commodities are chosen and equally weighted to form the carry strategy. The excess return of the carry strategy is as follows:

$$R_{XS-CRY,t+1} = \sum_{i=1}^{5} \omega_{XS-CRY,t}^{(i,1)} R_{t+1}^{(i,1)} - \sum_{j=1}^{5} \omega_{XS-CRY,t}^{(j,1)} R_{t+1}^{(j,1)} \tag{2.3.4}$$

where

$$\begin{aligned}
\omega_{XS-CRY,t}^{(i,1)} &= 0.2, \text{ if } rank(-CRY_t^{(i,1)}) \leq 5 \\
\omega_{XS-CRY,t}^{(j,1)} &= 0.2, \text{ if } rank(CRY_t^{(j,1)}) \leq 5 \\
CRY_t^{(m,1)} &= \frac{R_t^{(m,1),s}}{R_t^{m,s+12}}
\end{aligned}$$

$R_{XS-CRY,t+1}$ is the excess return of carry strategy at the end of month $t+1$, $\omega_{XS-CRY,t}^{(i,1)}$ and $\omega_{XS-CRY,t}^{(j,1)}$ are the weights of long and short positions in the commodity futures market i and j, respectively, for our carry strategy. $CRY_t^{(m,1)}$ is the ratio of the price of first nearby futures contract over the price of the contract with expiration of next 12 months. $R_t^{(m,1),s}$ is the monthly excess return of the first nearby futures contracts market m at the end of month t and its expiration time is at month s. $R_t^{m,s+12}$ is the excess return of the futures contracts market m at the end of month t expiring at month $s+12$. All other variables are defined as previously.

Volatility-Managed Strategies

We construct two types of volatility-managed portfolios. We scale the excess return rather than the total return for focusing on the risk by filtering the time value of money.

Scaled by Portfolio Volatility The first scaling strategy consists of scaling the portfolio after the formation of the strategy. Barroso and Santa-Clara (2015) apply the volatility-managed strategy to the momentum portfolio in the equity market and present that it significantly enhances the performance of momentum returns, especially during periods where momentum crashes. They scale the excess return of the momentum portfolio by the conditional volatility and then require the managed portfolio to have the constant and target risk over time. Moreira and Muir (2017) also employ the inverse of conditional volatility of the portfolio to scale the excess return and then use a constant to maintain the unconditional volatility is the same as the original portfolio. However, the choice of the constant is determined by all the sample information, and it is challenging to implement the forecasting process.

We follow Barroso and Santa-Clara (2015) and also use the average of historical daily volatility over the past 6 months to forecast the volatility for the next month.[5] To be more specific, the volatility-managed strategy (henceforth, we call "BS strategy") is as follows:

$$R^{BS}_{k,t} = \frac{\sigma^{BS}_{target}}{\hat{\sigma}_{k,t}} \times R_{k,t} \tag{2.3.5}$$

where

$$\hat{\sigma}_{k,t} = \frac{\sum_{i=0}^{125} R^2_{k,d_{t-1}-i}}{126} \times 21 \tag{2.3.6}$$

$R^{BS}_{k,t}$ is the monthly excess return of the strategy k (in our study, it can relate to momentum, basis momentum or carry strategy) scaled by BS strategy at the end of month t, $R_{k,t}$ represents the original monthly excess return of the strategy k at the end of month t and σ_{target} is a constant target volatility. $\hat{\sigma}_{k,t}$ is the monthly forecasting volatility of the strategy k for month t estimated at the end of month $t-1$. $R_{k,d_{t-1}-i}$ represents the daily excess return of strategy k on the day $d_{t-1}-i$ and d_{t-1} is the date of last day on month $t-1$. In BS strategy, the portfolios keep self-financing by the scaling which simultaneously and equally changes the weights of long and short legs. Moreover, the mean

[5]In section 2.5.1, we discuss the alternative volatility forecasts and study the effect of the accuracy of volatility forecasts on our main results.

and volatility of the scaled portfolio both change proportionally to the scaling. Barroso and Santa-Clara (2015) and Moreira and Muir (2017) point that the choice of σ_{target} has no effect on the Sharpe ratio of the portfolio. Barroso and Santa-Clara (2015) choose an annualized volatility of 12% as the target level. Considering the summary statistics of the commodity futures contracts, we pick the target level of annualized volatility of 18%, which is marginally higher and closer to that of the original portfolio. The target level makes it more convenient to compare with the benchmark portfolio.

Scaled by Commodity Volatility The second scaling strategy is scaling the excess return of each commodity market by its volatility and then constructing the portfolios for the interested strategy. Moskowitz et al. (2012) scale every asset by the inverse of its volatility forecast and employ the scaled asset to form the time-series momentum portfolio. Kim et al. (2016) document the good performance of time-series momentum is due to volatility-managed portfolios rather than the trend of time-series momentum. They find that there is no significant difference between the performance of the unscaled time-series momentum portfolio and a buy-and-hold portfolio. Inspiring by these studies, we study the performance of the volatility-scaling portfolios before the formation of the strategy. The managed portfolio (henceforth, we call "MOP strategy") is as follows:

$$R_{k,t}^{MOP} = \sigma_{target}^{MOP} \times \left(\sum_{i=1}^{5} \omega_{k,t}^{(i,1)} \frac{z_{L,t}}{\hat{\sigma}_{i,t}} \times R_t^{(i,1)} - \sum_{j=1}^{5} \omega_{k,t}^{(j,1)} \frac{z_{S,t}}{\hat{\sigma}_{j,t}} \times R_t^{(j,1)} \right) \tag{2.3.7}$$

$R_{k,t}^{MOP}$ is the monthly excess return of the strategy k scaled by MOP strategy at the end of month t. $z_{L,t}$ ($z_{S,t}$) is the scaling coefficient to make sure the summation of weights on long (short) positions is 1. $\omega_{k,t}^{(i,1)}$ is the original weight of commodity i in the strategy k for the month t. $\hat{\sigma}_{i,t}$ represents the monthly volatility forecast of commodity i for month t estimated at the end of month $t-1$. Consistent with the BS strategy, we use the Equation (2.3.6) to forecast the volatility of the commodity i by the information of daily excess return over past 6 months. $R_t^{(i,1)}$ is the monthly return of the commodity i. Moskowitz et al. (2012) point that the choice of the target level is inconsequential since this method is scaling each position. They choose an annualized volatility of 40% as the target level so that the annualized volatility of the scaled equal-weighted time-series momentum portfolio is 12%, which is comparable with the volatility of other factors. Our interested original strategies are all long-short strategy and self-financing. We scale the original portfolio and keep the summation of long or short positions is 1. Thus the target level σ_{target}^{MOP} in our study cannot change the shape of the distribution of scaled portfolios and helps us adjust the level of the annualized volatility. Considering the different summary statistics of the three strategies we study, we choose the target level, σ_{target}^{MOP}, 3.6% to make the statistics of results comparable.

2.4 Main Results

This section shows the comparison of the performance of these strategies. Some studies, e.g. Moreira and Muir (2017) and Han et al. (2021), show that the BS volatility-managed strategy performs better than the original strategy. However, there is very little literature comparing the performance of MOP and BS strategy. We study whether the BS strategy still works in the commodity markets and whether the MOP strategy can provide better performance.

2.4.1 Performance Statistics

Table 2.2 presents the statistics of the performance of these three different portfolios: original portfolio (R_k), the portfolio scaled by BS strategy (R_k^{BS}) and the portfolio scaled by MOP strategy (R_k^{MOP}). We also show the Sharpe ratio and maximum drawdown to reflect the return compared to the risk of the portfolio and the downside risk, respectively.[6] We follow Cederburg et al. (2020) and employ JK-statistic to check whether the difference of Sharpe ratio is statistically significant or not.[7]

[6] Liu et al. (2019) claim that alpha is a less informative measure than Sharpe ratio, which can reflect the investment value.

[7] Cederburg et al. (2020) calculate the test statistics as:

$$z = \frac{\sigma_j \mu_i - \sigma_i \mu_j}{\sqrt{\theta}} \text{ where } \theta = \frac{1}{T}\left(2\sigma_i^2\sigma_j^2 - 2\sigma_i\sigma_j\sigma_{i,j} + \frac{1}{2}\mu_i^2\sigma_j^2 + \frac{1}{2}\mu_j^2\sigma_i^2 - \frac{\mu_i\mu_j}{\sigma_i\sigma_j\sigma_{i,j}^2}\right)$$

μ_i and μ_j are the mean of excess return for portfolio i and j, respectively. σ_i and σ_j are the standard deviation of excess return for portfolio i and j,respectively. $\sigma_{i,j}$ is the covariance between the excess returns of portfolio i and j, the statistic z asymptotically follows a standard

Momentum Panel A reports the performance of strategies for the momentum portfolio. We analyze the portfolio (Long-Short) at first. The skewness of the original momentum portfolio in commodity markets is positive, and the kurtosis is mild. By Jarque–Bera test, we can statistically reject the null hypothesis that the excess return is normally distributed (p-stat=0.35%). Moreover, we can also statistically reject at null hypothesis for the distributions of scaled portfolios R^{BS}_{XS-MOM} and R^{MOP}_{XS-MOM} (p-stat=0.00% and p-stat=0.79%). Comparing the performance of these portfolios, we can notice that the BS and MOP strategy both reduce standard deviations and maximum drawdown, although the improvement by MOP is very weak. For the mean of excess return, the overall ranking is: R^{MOP}_{XS-MOM}, R_{XS-MOM} and R^{BS}_{XS-MOM}, in decreasing order. Not surprisingly, BS and MOP strategy both improve Sharpe ratios, although we cannot statistically reject the null hypothesis that the Sharpe ratios are equal (z-stat=1.130 and z-stat=1.018). Turning to the performance of long and short legs, we notice that the excess returns of momentum portfolios are all mainly from long legs. BS and MOP strategy both change the distributions of long and short legs marginally and maintain their positive skewness.

Basis Momentum Panel B presents the performance of strategies for the basis momentum portfolio. The skewness of the original basis momentum portfolio is negative, suggesting the left tail is longer. BS and MOP strategy change the

normal distribution. The null hypothesis is that the Sharpe ratios of portfolio i and j are equal.

skewness of excess return more negative and increase the kurtosis. The ranking of absolute value of maximum drawdown is: R^{MOP}_{BASMOM}, R_{BASMOM} and R^{BS}_{BASMOM} in decreasing order. It suggests that the BS strategy slightly decreases the downside risk while the MOP strategy increases it. The means and Sharpe ratios of R^{BS}_{BASMOM} and R^{MOP}_{BASMOM} are both higher than that of R_{BASMOM}. However, we still cannot statistically reject the null hypothesis that the Sharpe ratios are equal (z-stat=0.363 and z-stat=0.739). Again, BS and MOP strategy both change the distributions of long and short legs slightly.

Carry Focusing on the performance of strategies for carry portfolio, Panel C shows that BS and MOP strategy both increase the tail risk and downside risk by more negative skewness and maximum drawdown. Moreover, the ranking of mean is: R_{XS-CRY}, R^{BS}_{XS-CRY} and R^{MOP}_{XS-CRY} in decreasing order. BS and MOP strategy both decrease Sharpe ratios, but the difference of Sharpe ratios are not statistically significant (z-stat=-0.677 and z-stat=-1.425). In detail, the two scaled strategies both decrease the means of excess returns in long and short legs.

Overall, BS and MOP strategy do not significantly improve the performance of momentum, basis momentum and carry portfolios in commodity markets. The performance of BS cannot be improved by MOP strategy. Barroso and Santa-Clara (2015) show that BS strategy can significantly improve the equity momentum performance and alter its distribution which has a very large kurtosis and a significant negative skewness. Cederburg et al. (2020) and Bongaerts et al. (2020) point that BS strategy cannot provide consistently better performance than the original portfolios. Our results support the conclusion of Cederburg et al. (2020) and Bongaerts et al. (2020). Furthermore, we show that there is no significant difference between the volatility-managed portfolio scaled by the volatility of the original portfolio after the formation of the portfolio and the volatility-managed portfolio scaled by the volatility of each commodity before the formation of the portfolio.

2.4.2 Performance under Economic Conditions

The excess returns of original portfolios are affected by the market states and easily experience drawdowns in bear markets. One aim of the volatility-managed strategy is to reduce the downside risk, especially in economic downturns. Barroso and Santa-Clara (2015) and Moreira and Muir (2017) state that the volatility-managed portfolio decreases risk and maintains stable performance in recessions. Moreover, momentum crashes in market turning points and the BS strategy can almost eliminate the crash of the original portfolio. Although the two kinds of volatility-managed portfolios have no significant better performance than the original portfolio, it is meaningful to investigate whether BS and MOP strategy could help the portfolios hedge the risk in different economic conditions.

We classify months into three states: non-turning, recession to expansion and expansion to recession, using the data from Federal Reserve Bank of St. Loius website.[8] 2.3 presents the performance statistics of the original portfolio, portfolio scaled by BS strategy and portfolio scaled by MOP strategy during different economic states. Panel A reports the performance of momentum portfolios, Panel B presents the performance of basis momentum portfolios, and Panel C reports the results of carry portfolios. Overall, we notice that the original portfolios perform the best when the market in the turning point, from expansion to recession. In contrast, the original portfolios perform the worst when the market in the turning point, from recession to expansion. In detail, the excess returns of original portfolios are all negative in turning point recession to expansion, while those are all positive in turning point expansion to recession. Moreover, the excess return of the portfolio arises mainly from the long leg. For the risk, there exists little difference of standard deviations of original portfolios for momentum and carry strategy. For basis momentum, the risk in turning point expansion to recession is more than twice of that in turning point recession to expansion. Not surprisingly, the skewness of portfolios are all positive in turning point expansion to recession, while most of them are negative in turning point recession to expansion.

Turning to the performance of scaled portfolios, R_k^{BS} and R_k^{MOP}, we can see

[8]We employ the data from the file named as "OECD based Recession Indicators for the United States from the Peak through the Trough" to identify the months states. See `https://fred.stlouisfed.org/series/USARECM`. We define month as the recession to expansion state when the indicator on that month changes from 1 to 0, month as the expansion to recession state when the indicator on that month changes from 0 to 1 and the other months as the non-turning state.

that under the different economic condition, the BS and MOP strategy do not significantly improve upon the original portfolios. Consistent with the original portfolio, most of the mean of R_k^{BS} and R_k^{MOP} comes from the portfolio in turning point expansion to recession and the excess return is mainly from the long leg. We employ the JK-statistics to formally evaluate the difference of the Sharpe ratios under different economic conditions. We cannot reject the null hypotheses that the Sharpe ratios scaled by BS or MOP strategy is equal to the original portfolio. We keep the summation of long and short positions equal, so it is not surprising to note that the scaled long or short legs are both not significantly different from the original long or short legs, respectively. Statistically, original portfolio, portfolio scaled by BS strategy and portfolio scaled by MOP strategy, these strategies have no significant difference under different economic conditions.

2.5 Potential Explanations

2.5.1 Alternative Volatility Forecasting

Until now, we forecast the volatility of the strategy and commodity itself by the historical average of the daily volatility over past 6 months. However, the poor forecasting performance of this model may materially affect our conclusions. Moreira and Muir (2017) point out that more sophisticated volatility forecasting models can improve the performance of the volatility managed portfolio. Bollerslev et al. (2018) show that the more accurate the volatility forecast is, the better the volatility-managed strategy performs. To shed light on whether the poor performance of BS and MOP strategy is due to the performance of the volatility estimates, we repeat our study with the volatility forecasts from alternative forecasting models.

GJR-GARCH model Considering that shocks with different signs have asymmetric effects on volatility and volatility is clustering, we employ the GJR-GARCH model proposed by Glosten et al. (1993). Daniel and Moskowitz (2016) use the GJR-GARCH model to forecast the volatility of the momentum portfolio and improve the performance of the conventional momentum portfolio when applying the volatility forecast to dynamic weighting strategy. The GJR-GARCH model is defined as:

$$\begin{aligned} r_t = \mu + \epsilon_t; \qquad \epsilon_t \sim N(0, \sigma^2_{GJR,t}); \\ \sigma^2_{GJR,t} = \omega + (\alpha + \gamma I_{\{\epsilon_{t-1}<0\}})\epsilon^2_{t-1} + \beta\sigma^2_{GJR,t-1} \end{aligned} \tag{2.5.1}$$

where r_t is the daily return of the strategy portfolio or commodity futures contracts at date t, μ is the mean of the return series, ϵ_t is the residuals and also represents the price innovations following a normal distribution with mean zero and variance $\sigma^2_{GJR,t}$. $I_{\{\epsilon_{t-1}<0\}}$ is an indicator function which equals 1 (0) when the previous residual ϵ_{t-1} is negative (positive). Lamoureux and Lastrapes (1993) find that the estimation for parameters of GARCH model by the recursive window has a better performance than that by the rolling window. Consistent with the previous historical average method, we estimate the parameters by the recursive window from 126 observations.[9]

HAR model We consider Heterogeneous Autoregressive (HAR) model which proposed by Corsi (2009) and is a simple but efficient forecasting model. The original HAR model is based on the high-frequency data to obtain the past realized volatilities over different horizons. However, Bollerslev et al. (2018) point that daily data can be used in HAR model. The HAR model in our study is defined as:

$$\sigma^2_{HAR,t} = \beta_0 + \beta_D \sigma^2_{t-1,D} + \beta_W \sigma^2_{t-1,W} + \beta_M \sigma^2_{t-1,M} + \epsilon_t \tag{2.5.2}$$

where

$$\begin{aligned}
\sigma^2_{t-1,D} &= R^2_{d_{t-1}} \\
\sigma^2_{t-1,W} &= \frac{1}{5}\sum_{i=0}^{4} R^2_{d_{t-1-i}} \\
\sigma^2_{t-1,M} &= \frac{1}{21}\sum_{i=0}^{20} R^2_{d_{t-1-i}}
\end{aligned}$$

[9]In Table of A2 in Section Appendix, we provide the results based on the rolling window with 126 observations.

$\sigma^2_{HAR,t}$ is the monthly forecasting volatility of the strategy or commodity, $R_{d_{t-1}}$ is the daily excess return of the corresponding strategy or commodity and d_{t-1} is the date of last day on month $t-1$. Consistently, we use the recursive window from 126 observations to estimate the parameters of HAR model.[10]

To compare the accuracy of the forecasts by different models, we employ two loss functions: the mean squared error (MSE) and the quasi-likelihood (QLIKE) to assess the performance of these competing forecasts. Following Patton (2011b), these two loss functions are robust to the noise in the proxy of the realized volatility.[11] The two loss functions are defined as follows:

$$MSE = \frac{1}{n}\sum_{t=1}^{n}(RV_t - f_t)^2 \tag{2.5.3}$$

$$QLIKE = \frac{1}{n}\sum_{t=1}^{n}\left[\log(f_t) + \frac{RV_t}{f_t}\right] \tag{2.5.4}$$

where n is the total number of the forecast, RV_t is the monthly realized volatility of the strategy or commodity at month t, and f_t is the corresponding forecasts estimated by previous forecasting models for the month t.

Table 2.4 reports the difference of volatility forecasting errors. It shows that

[10] In Table A2, we also provide the results produced by the rolling window with 126 observations.

[11] Intuitively, the object of interest, i.e. the realized volatility, is not directly observable. As a result, it can only be computed empirically, thus introducing measurement errors. The MSE and QLIKE loss functions are robust to this noise (Patton, 2011b).

by recursive window GJR-GARCH model provides the smallest forecasting errors, and HAR model performs better than the forecasts by the benchmark historical volatility over the past 6 months in both MSE and QLIKE criterion.

We further analyze whether the performance of scaled portfolios is improved by the more accurate volatility forecasting. Table 2.5 presents the performance statistics of scaled portfolios. Overall, the results are consistent with our main finding that BS and MOP strategies do not significantly improve the performances of the original portfolios in our study. Interestingly, the Sharpe ratios of portfolios scaled by volatility forecasting from GJR-GARCH model are generally the lowest among portfolios scaled by volatility forecasting from HAR and average models. It seems that portfolios scaled by more accurate volatility forecasting have lower standard deviations and lower excess returns. Our results suggest that the failure of BS and MOP strategy is not due to poor volatility forecasts.[12]

2.5.2 Construction of Benchmark Portfolios

Our main analysis focuses on the equal-weighted portfolio and our volatility-managed strategy is also based on an equal-weighted portfolio. As previously mentioned, an equal-weighted portfolio with half of commodity futures narrows the difference between the long legs and short legs. We employ alternative weight by ranking for the original portfolio to enlarge the long-short difference. The

[12]In Table A2, the results are consistent with our main findings, and the accuracy of volatility forecasting is not the reason for the failure of volatility-managed portfolios.

portfolio is formed as described in Section 2.3.2 and we just change the weight to:

$$\omega_{k,t}^{(i,1)} = 0.3 - (rank(-K_t^{(i,1)}) - 1) \times 0.05, \text{ if } rank(-K_t^{(i,1)}) \leq 5$$
$$\omega_{k,t}^{(j,1)} = -0.3 + (rank(K_t^{(j,1)}) - 1) \times 0.05, \text{ if } rank(K_t^{(j,1)}) \leq 5$$

where $\omega_{k,t}^{(i,1)}$ is the weight of long positions in the commodity futures market i in our K strategy (momentum, basis momentum or carry), $\omega_{k,t}^{(j,1)}$ is the weight of short positions in the commodity futures market i, $K_t^{(i,1)}$ represents $M_t^{(i,t)}$, $BM_t^{(i,t)}$, or $CRY_t^{(i,t)}$. All other variables are defined as previously.

Table 2.6 reports the performance of conventional and scaled portfolios by the alternative benchmark. By putting more weight on the asset with a high or low ranking, we observe that means of excess returns of momentum and basis momentum are larger than the equal-weighted portfolios while that of carry is smaller than the equal-weighted portfolio. Accordingly, the scaled portfolios of momentum and basis momentum with alternative weight are larger than the scaled portfolios with equal-weighted portfolios. Yet, the results are consistent with our main finding that BS and MOP do not statistically significantly improve the performance of the original portfolio.

2.5.3 Alternative Performance Evaluations

So far, we consider the performance statistics of volatility-managed portfolios but ignore the measurement of economic value.

Performance Fee

The volatility-managed strategy is motivated by the problem of the mean-variance trade-off. In the mean-variance framework, we follow Fleming et al. (2003) to calculate the performance fee (Δ) that investors are willing to pay for switching between two investment strategies. We assume an investor has a mean-variance utility function:

$$U(R^i_{k,t}) = R^i_{k,t} - \frac{\gamma}{2} Var(R^i_{k,t}) \tag{2.5.5}$$

where $R^i_{k,t}$ is the excess return of the portfolio k by scaled strategy i and γ is the risk aversion level of the investor. Thus the performance fee is calculated as:

$$\frac{1}{T}\sum_{t=1}^{T}[(R^i_{k,t} - \Delta) - \frac{\gamma}{2} Var(R^i_{k,t})] = \frac{1}{T}\sum_{t=1}^{T}[R^j_{k,t} - \frac{\gamma}{2} Var(R^j_{k,t})] \tag{2.5.6}$$

where T is the number of periods, $Var(R^i_{k,t}) = (R^i_{k,t} - \overline{R^i_k})^2$, $\overline{R^i_k}$ is the mean of $R^i_{k,t}$ over periods $[0, T]$. We use the t-test to test the null hypothesis that the performance fee is equal to zero.

Panel A in Table 2.7 reports the performance fee. Investors with all levels of risk aversion are mostly willing to pay extra fees for switching from the original portfolio to the BS or MOP scaled portfolio except for carry portfolios. The results are consistent with our main finding that scaled carry portfolios both have a smaller Sharpe ratio than the original portfolio. Moreover, for R^{BS}_{BASMOM}, investors with very high risk aversion levels need to get some benefits for switching from the original portfolio. Considering the performance statistics, we notice that R^{BS}_{BASMOM} is the only scaled portfolio that has a larger standard deviation than the original portfolio. Our utility function penalizes the risk heavily and most of the scaled portfolios reduce the risk, so the performance fee increases with the increasing risk aversion levels. Consistently, the performance fees are not statistically significant except for R^{BS}_{XS-MOM} when investors have a high risk aversion level. The information on economic values generally supports our main findings.

Turnover

Although the performance of BS and MOP strategy is not statistically significant better than the original portfolio, we still wonder whether the scaled portfolios have lower turnover ratio and reduce the transaction costs of scaled portfolios. We calculate the turnover ratio as follows:

$$Turnover = \frac{1}{T}\sum_{t=1}^{T}\sum_{j=1}^{N}(\mid w_{j,t+1} - w_{j,t} \mid) \tag{2.5.7}$$

where $w_{j,t}$ is the actual weight of commodity j at time t, T is the number of periods and N is the total number of commodities in portfolio.

Panel B of Table 2.7 reports turnover ratios. The turnover ratios of BS and MOP scaled portfolios are all larger than the turnover ratio of the original portfolio except for R^{BS}_{XS-MOM}. Moreover, MOP scaled portfolios have larger turnover ratios than BS scaled portfolios. It confirms that the volatility-managed portfolio does not outperform the original portfolio.

2.6 Conclusion

We study volatility-managed volatility strategy in commodity futures markets. Consistent with a growing literature, we document that the conventional volatility-managed strategy fails in commodity markets. Furthermore, we analyze the timing of volatility-managed and find that the volatility-managed strategy which scales the portfolio before its formation has no significant difference with conventional volatility-managed strategy. We consider different potential reasons and find that, alone, economic conditions, alternative volatility, forecasting models, and alternative methods to compute the portfolio cannot explain the performance of the volatility timing strategies.

Our results state that scaling portfolios before or after their formation both fail to improve the performance of the original portfolio in commodity markets. In short, our results suggest that volatility scaling does not lead to consistent improvement in the performance of the conventional commodity strategies. In future works, it would be interesting to extend our analysis to other asset classes, e.g. international equity futures.

2.7 Tables and Appendices

Table 2.1: Summary of Commodity Markets

This table reports summary information of the commodity futures contracts. It lists the sectors that the commodity belongs to, the commodity markets, the corresponding ticker, the exchange where the commodity contract trades (ICE represents the International Exchange and CME stands for the Chicago Mercantile Exchange) and the expiration month of each commodity contracts. Columns 6 and 7 report the percentage of annualized mean ($Mean^{(1)}$) and standard deviation ($SD^{(1)}$) of the first nearby futures contracts for each commodity market, respectively. Columns 8 and 9 presents the percentage of annualized mean ($Mean^{(2)}$) and standard deviation ($SD^{(2)}$) of the second nearby futures contracts for each commodity market, respectively.

Sector	Commodity	Ticker	Exchange	Maturity	$Mean^{(1)}$(%)	$SD^{(1)}$(%)	$Mean^{(2)}$(%)	$SD^{(2)}$(%)
Energy	Brent Oil	CB	ICE	JAN-DEC	12.47	31.42	13.20	30.21
	WTI Oi	CL	CME	JAN-DEC	10.60	32.13	10.64	30.54
	Heating Oil	HO	CME	JAN-DEC	8.99	30.25	9.52	28.82
	Natural Gas	NG	CME	JAN-DEC	-3.26	39.34	0.37	34.93
Grains	Corn	C-	CME	Jan, Mar, May, Jul, Sep, Nov, Dec	-3.91	24.58	-1.57	23.75
	Oats	O-	CME	Mar, May, Jul, Sep, Dec	-1.01	29.49	0.37	27.01
	Rice	RR	CME	Jan, Mar, May, Jul, Sep, Nov	-5.85	22.86	-0.92	21.64
	Wheat	W-	CME	Mar, May, Jul, Sep, Dec	-3.20	26.66	-0.55	25.17
Industrials	Cotton	CT	CME	Mar, May, Jul, Oct, Dec	0.76	24.80	2.33	23.50
	Lumber	LB	CME	Jan, Mar, May, Jul, Sep, Nov	-5.46	26.29	-1.29	22.58
Meats	Live Cattle	LC	CME	Feb, Apr, Jun, Aug, Oct, Dec	3.65	13.70	4.83	11.72
	Lean Hogs	LH	CME	Feb, Apr, Jun, Jul, Aug, Oct, Dec	-0.86	22.18	5.88	19.39
Metals	Gold	GC	CME	Feb, Apr, Jun, Aug, Oct, Dec	2.17	16.44	2.26	16.44
	Copper	HG	CME	Mar, May, Jul, Sep, Dec	12.49	27.07	12.81	26.50
	Silver	SI	CME	Mar, May, Jul, Sep, Dec	3.56	29.08	3.64	29.00
Oilseeds	Soy Oil	BO	CME	Jan, Mar, May, Jul, Aug, Sep, Oct, Dec	-2.35	22.90	-1.36	22.47
	Soybeans	S-	CME	Jan, March, May, Jul, Aug, Sep, Nov	4.70	22.35	5.19	22.17
	Soy Meal	SM	CME	Jan, Mar, May, Jul, Aug, Sep, Oct, Dec	11.85	24.53	10.48	24.05
Softs	Cocoa	CC	ICE	Mar, May, Jul, Sep, Dec	-2.66	29.08	-1.92	27.48
	Orange	JO	ICE	Jan, Mar, May, Jul, Sep, Nov	-0.41	28.50	-0.62	26.05
	Coffee	KC	ICE	Mar, May, Jul, Sep, Dec	-3.73	36.33	-4.03	33.16
	Sugar	SB	ICE	Mar, May, Jul, Oct, Dec	8.45	32.46	8.19	28.84

Table 2.2: Strategy Comparison: Performance Statistics

This table reports statistics of portfolios performance. The portfolio formation is presented in Section 2.3.2. Columns under "Mean(%)", "SD(%)", "Skew", "Kurt" report the mean of monthly excess return of portfolio in percentage, monthly standard deviation in percentage, skewness and kurtosis, respectively. "JB(%)" reports the Jarque-Bera p-value in percentage of the test that the excess return is normal distribution. "MDD" is the maximum drawdown. "SR" is the Sharpe ratio and "ΔSR" is the difference between the Sharpe ratio of the scaled portfolio and the Sharpe ratio of the unscaled portfolio. "JK Stat" is the statistic value calculated as described in footnote 6 and follows a standard normal distribution. If we choose 5% significant level, the corresponding value of the "JK Stat" should be 1.96.

	Variables	Mean(%)	SD(%)	Skew	Kurt	JB(%)	MDD	SR	ΔSR	JK Stat
				Panel A: Momentum						
R_{XS-MOM}	Long	0.824	5.678	0.159	5.096	0.00	-2.063	0.145		
	Short	-0.476	4.924	0.514	4.919	0.00	-2.629	-0.097		
	Long-Short	1.301	6.333	0.006	3.906	0.35	-1.830	0.205		
R^{BS}_{XS-MOM}	Long	0.747	4.910	0.432	5.833	0.00	-1.989	0.152	0.007	0.684
	Short	-0.458	4.199	0.239	3.898	0.08	-2.620	-0.109	-0.012	-1.053
	Long-Short	1.205	5.528	0.202	4.525	0.00	-1.770	0.218	0.013	1.130
R^{MOP}_{XS-MOM}	Long	0.828	5.555	0.046	4.942	0.00	-2.045	0.149	0.004	0.349
	Short	-0.530	4.931	0.531	4.731	0.00	-2.707	-0.107	-0.011	-1.047
	Long-Short	1.358	6.199	-0.031	3.836	0.79	-1.827	0.219	0.014	1.018
				Panel B: Basis Momentum						
R_{BASMOM}	Long	0.845	4.853	-0.394	4.835	0.00	-2.901	0.174		
	Short	-0.438	4.783	1.428	14.820	0.00	-1.757	-0.092		
	Long-Short	1.283	5.708	-0.510	6.418	0.00	-4.921	0.225		
R^{BS}_{BASMOM}	Long	0.863	4.832	-0.073	4.194	0.00	-2.024	0.179	0.004	0.383
	Short	-0.468	4.884	1.667	17.160	0.00	-1.661	-0.096	-0.004	-0.423
	Long-Short	1.332	5.808	-0.598	7.078	0.00	-4.900	0.229	0.005	0.363
R^{MOP}_{BASMOM}	Long	0.892	4.737	-0.451	5.444	0.00	-2.933	0.188	0.014	1.167
	Short	-0.440	4.668	1.938	21.000	0.00	-1.574	-0.094	-0.003	-0.189
	Long-Short	1.332	5.638	-0.789	8.226	0.00	-5.030	0.236	0.011	0.739
				Panel C: Carry						
R_{XS-CRY}	Long	0.410	5.423	0.221	5.061	0.00	-6.370	0.076		
	Short	-0.247	5.046	0.733	6.507	0.00	-1.600	-0.049		
	Long-Short	0.657	6.139	-0.085	5.528	0.00	-3.953	0.107		
R^{BS}_{XS-CRY}	Long	0.380	5.111	0.276	5.179	0.00	-6.598	0.074	-0.001	-0.119
	Short	-0.205	4.848	1.053	8.576	0.00	-1.425	-0.042	0.007	0.627
	Long-Short	0.585	5.868	-0.337	6.471	0.00	-4.821	0.100	-0.007	-0.677
R^{MOP}_{XS-CRY}	Long	0.350	5.235	0.002	4.300	0.00	-6.275	0.067	-0.009	-0.758
	Short	-0.178	5.138	1.030	8.718	0.00	-1.537	-0.035	0.014	1.325
	Long-Short	0.528	6.049	-0.590	6.409	0.00	-5.272	0.087	-0.020	-1.425

Table 2.3: Strategy Comparison: Performance under Economic Conditions

This table reports statistics of portfolios performance. The portfolio formation is presented in Section 2.3.2. Columns under “Mean(%)”, “SD(%)”, “Skew”, “Kurt” report the mean of monthly excess return of portfolio in percentage, monthly standard deviation in percentage, skewness and kurtosis, respectively. “MDD” is the maximum drawdown. “SR” is the Sharpe ratio and “ΔSR” is the difference between the Sharpe ratio of the scaled portfolio and the Sharpe ratio of the unscaled portfolio. “JK Stat” is the statistic value calculated as described in footnote 6 and follows a standard normal distribution. If we choose 5% significant level, the corresponding value of the “JK Stat” should be 1.96. The economic condition: recession and expansion is defined by the NBER recession variable obtained from Federal Reserve Bank of St. Loius website.

(a) Panel A: Performance of Momentum

	VARIABLES	Mean(%)	SD(%)	Skew	Kurt	Sharpe	ΔSR	JK-stat
				Non-turning				
	Long	0.828	5.640	0.129	5.177	0.147		
R_{XS-MOM}	Short	-0.517	4.977	0.526	4.862	-0.104		
	Long-Short	1.345	6.330	-0.019	3.946	0.212		
	Long	0.747	4.879	0.433	5.994	0.153	0.006	0.602
R^{BS}_{XS-MOM}	Short	-0.503	4.231	0.247	3.860	-0.119	-0.015	-1.264
	Long-Short	1.250	5.527	0.195	4.591	0.226	0.014	1.201
	Long	0.831	5.526	0.028	5.007	0.150	0.004	0.297
R^{MOP}_{XS-MOM}	Short	-0.556	4.993	0.541	4.652	-0.111	-0.007	-0.756
	Long-Short	1.387	6.212	-0.037	3.839	0.223	0.011	0.788
				Recession to Expansion				
	Long	-0.810	7.012	-0.208	2.010	-0.116		
R_{XS-MOM}	Short	2.011	3.074	0.956	2.558	0.654		
	Long-Short	-2.820	5.958	0.417	2.174	-0.473		
	Long	0.178	7.036	-0.037	2.238	0.025	0.141	2.057
R^{BS}_{XS-MOM}	Short	2.334	3.357	0.944	2.540	0.695	0.041	2.371
	Long-Short	-2.155	6.184	0.556	2.221	-0.348	0.125	1.469
	Long	-0.967	6.883	-0.477	1.965	-0.140	-0.025	-0.321
R^{MOP}_{XS-MOM}	Short	1.287	2.000	-0.619	1.715	0.644	-0.011	-0.028
	Long-Short	-2.254	5.657	-0.603	2.474	-0.398	0.075	0.436
				Expansion to Recession				
	Long	2.213	7.798	1.375	3.081	0.284		
R_{XS-MOM}	Short	-0.356	1.260	1.114	2.777	-0.283		
	Long-Short	2.569	6.701	1.260	2.921	0.383		
	Long	1.339	5.823	1.316	3.006	0.230	-0.054	-1.973
R^{BS}_{XS-MOM}	Short	-0.359	0.950	1.260	2.904	-0.378	-0.095	-1.552
	Long-Short	1.698	4.990	1.171	2.828	0.340	-0.043	-1.451
	Long	2.484	6.908	1.390	3.098	0.360	0.076	2.703
R^{MOP}_{XS-MOM}	Short	-0.656	1.944	0.312	1.823	-0.337	-0.055	-0.261
	Long-Short	3.141	5.576	1.121	2.730	0.563	0.180	1.540

Table 2.3: Strategy Comparison: Performance under Economic Conditions

(b) Panel B: Performance of Basis Momentum

	VARIABLES	Mean(%)	SD(%)	Skew	Kurt	Sharpe	ΔSR	JK-stat
				Non-turning				
	Long	0.906	4.850	-0.404	4.911	0.187		
R_{BASMOM}	Short	-0.453	4.800	1.457	15.04	-0.094		
	Long-Short	1.359	5.669	-0.579	6.705	0.240		
	Long	0.926	4.826	-0.086	4.267	0.192	0.005	0.423
R_{BASMOM}^{BS}	Short	-0.491	4.893	1.717	17.55	-0.100	-0.006	-0.570
	Long-Short	1.417	5.739	-0.695	7.478	0.247	0.007	0.567
	Long	0.959	4.722	-0.460	5.562	0.203	0.016	1.317
R_{BASMOM}^{MOP}	Short	-0.452	4.694	1.975	21.17	-0.096	-0.002	-0.131
	Long-Short	1.411	5.584	-0.878	8.694	0.253	0.013	0.808
				Recession to Expansion				
	Long	-3.957	3.729	-1.453	3.188	-1.061		
R_{BASMOM}	Short	0.312	2.602	0.766	2.252	0.120		
	Long-Short	-4.269	3.451	-0.153	1.450	-1.237		
	Long	-4.167	3.002	-1.127	2.868	-1.388	-0.327	-1.778
R_{BASMOM}^{BS}	Short	0.836	3.164	0.937	2.410	0.264	0.144	2.300
	Long-Short	-5.003	3.779	-0.007	1.732	-1.324	-0.087	-0.315
	Long	-4.422	3.781	-1.373	3.058	-1.170	-0.108	-0.838
R_{BASMOM}^{MOP}	Short	0.565	2.637	0.907	2.227	0.214	0.094	0.978
	Long-Short	-4.987	3.399	-0.294	1.742	-1.467	-0.230	-1.738
				Expansion to Recession				
	Long	1.727	4.184	-0.234	1.560	0.413		
R_{BASMOM}	Short	-0.222	6.034	0.135	1.774	-0.037		
	Long-Short	1.950	8.096	0.661	1.717	0.241		
	Long	1.838	4.553	-0.027	1.622	0.404	-0.009	-0.187
R_{BASMOM}^{BS}	Short	-0.333	6.397	-0.085	1.818	-0.052	-0.015	-0.334
	Long-Short	2.171	9.069	0.818	2.048	0.239	-0.001	-0.030
	Long	1.862	4.006	-0.112	2.112	0.465	0.052	0.428
R_{BASMOM}^{MOP}	Short	-0.688	5.165	-0.230	1.415	-0.133	-0.096	-0.641
	Long-Short	2.550	7.981	0.636	1.829	0.320	0.079	1.156

Table 2.3: Strategy Comparison: Performance under Economic Conditions

(c) Panel C: Performance of Carry

	VARIABLES	Mean(%)	SD(%)	Skew	Kurt	Sharpe	ΔSR	JK-stat
				Non-turning				
	Long	0.422	5.408	0.212	5.074	0.078		
R_{XS-CRY}	Short	-0.264	5.095	0.751	6.449	-0.052		
	Long-Short	0.686	6.133	-0.093	5.618	0.112		
	Long	0.395	5.121	0.275	5.201	0.077	-0.001	-0.094
R^{BS}_{XS-CRY}	Short	-0.237	4.899	1.069	8.505	-0.048	0.003	0.309
	Long-Short	0.632	5.884	-0.354	6.560	0.107	-0.004	-0.406
	Long	0.359	5.226	0.013	4.292	0.069	-0.009	-0.810
R^{MOP}_{XS-CRY}	Short	-0.197	5.172	1.063	8.737	-0.038	0.014	1.245
	Long-Short	0.557	6.034	-0.602	6.562	0.092	-0.020	-1.400
				Recession to Expansion				
	Long	-2.332	5.504	-1.268	2.950	-0.424		
R_{XS-CRY}	Short	0.126	4.480	-1.181	2.874	0.028		
	Long-Short	-2.457	7.013	-0.047	2.347	-0.350		
	Long	-1.734	4.795	-0.983	2.644	-0.362	0.062	0.918
R^{BS}_{XS-CRY}	Short	1.003	3.619	-0.844	2.423	0.277	0.249	2.238
	Long-Short	-2.737	5.362	0.018	2.193	-0.510	-0.160	-2.494
	Long	-2.149	6.024	-1.177	2.795	-0.357	0.067	0.720
R^{MOP}_{XS-CRY}	Short	0.362	5.538	-1.216	2.928	0.065	0.037	1.847
	Long-Short	-2.511	8.144	0.157	2.446	-0.308	0.042	0.620
				Expansion to Recession				
	Long	2.349	6.475	1.406	3.125	0.363		
R_{XS-CRY}	Short	0.462	1.626	-0.151	1.459	0.284		
	Long-Short	1.887	6.037	1.042	2.743	0.313		
	Long	1.537	5.177	1.266	2.948	0.297	-0.066	-1.288
R^{BS}_{XS-CRY}	Short	0.658	1.792	0.350	1.851	0.367	0.083	0.601
	Long-Short	0.879	5.337	0.532	2.479	0.165	-0.148	-1.556
	Long	2.298	5.214	1.311	2.986	0.441	0.078	1.551
R^{MOP}_{XS-CRY}	Short	0.535	2.456	0.285	1.599	0.218	-0.066	-0.644
	Long-Short	1.763	5.114	0.238	2.420	0.345	0.032	0.252

Table 2.4: Difference of Forecasting Errors

This table presents results of forecasting errors from competing forecasts for SPX, USO, GLD, SLV, GDX and XLE sectors and each panel corresponds to a different sector. Column "Method" reports forecasting methods: average of historical volatility over past 6 months (Average), GJR-GARCH model (GJR) and HAR model (HAR). MSE and Qlike denote the forecasting errors in the corresponding criterion. For BS strategy, we forecast the volatility of strategy: Momentum, Basis Momentum and Carry. For MOP strategy, we forecast the volatility of each commodity. The forecast horizon is one month, 21 trading days in our study. We use a recursive window starting with 126 observations to get the forecasts.

	Method	MSE	QLIKE
	Average	2.363	2.782
Momentum	GJR	1.176	2.772
	HAR	1.537	2.778
	Average	1.379	2.613
Basis Momentum	GJR	0.842	2.606
	HAR	1.016	2.609
	Average	2.333	2.676
Carry	GJR	0.988	2.664
	HAR	1.365	2.670
	Average	4.578	2.903
Commodity	GJR	2.000	2.890
	HAR	2.231	2.893

Table 2.5: Performance Statistics: Alternative Volatility Forecasting

This table reports statistics of portfolios performance. The portfolio formation is presented in Section 2.3.2. Columns under "Mean(%)", "SD(%)", "Skew", "Kurt" report the mean of monthly excess return of portfolio in percentage, monthly standard deviation in percentage, skewness and kurtosis, respectively. "JB(%)" reports the Jarque-Bera p-value in percentage of the test that the excess return is normal distribution. "MDD" is the maximum drawdown. "SR" is the Sharpe ratio and "ΔSR" is the difference between the Sharpe ratio of the scaled portfolio and the Sharpe ratio of the unscaled portfolio. "JK Stat" is the statistic value calculated as described in footnote 6 and follows a standard normal distribution. If we choose 5% significant level, the corresponding value of the "JK Stat" should be 1.96. Panel A reports the results about scaled portfolios by volatility forecasting from GJR-GARCH model in recursive window. Panel B reports the results linked to volatility-managed portfolios based on the HAR model estimated using a recursive window.

	Variables	Mean(%)	SD(%)	Skew	Kurt	JB(%)	MDD	SR	ΔSR	JK stat
					Panel A: GJR					
R^{BS}_{XS-MOM}	Long	0.726	4.831	0.248	5.506	0.00	-2.034	0.150	0.005	0.620
	Short	-0.410	4.221	0.407	4.102	0.00	-2.610	-0.097	0.000	-0.058
	Long-Short	1.137	5.485	-0.002	4.421	0.00	-1.805	0.207	0.002	0.222
R^{MOP}_{XS-MOM}	Long	0.821	5.541	-0.021	4.750	0.00	-9.526	0.148	0.003	0.234
	Short	-0.492	4.901	0.591	5.064	0.00	-2.808	-0.100	-0.004	-0.352
	Long-Short	1.314	6.132	-0.105	3.833	0.62	-7.124	0.214	0.009	0.586
R^{BS}_{BASMOM}	Long	0.886	4.759	-0.182	3.653	2.11	-2.261	0.186	0.012	1.442
	Short	-0.417	4.952	2.006	19.88	0.00	-1.703	-0.084	0.007	0.968
	Long-Short	1.303	5.837	-0.725	7.923	0.00	-4.760	0.223	-0.002	-0.207
R^{MOP}_{BASMOM}	Long	0.871	4.722	-0.502	5.701	0.00	-2.848	0.184	0.010	0.779
	Short	-0.413	4.604	1.612	17.47	0.00	-1.525	-0.090	0.002	0.126
	Long-Short	1.285	5.555	-0.688	7.184	0.00	-4.733	0.231	0.007	0.396
R^{BS}_{XS-CRY}	Long	0.353	4.821	0.150	4.636	0.00	-6.611	0.073	-0.002	-0.312
	Short	-0.244	4.617	0.693	5.891	0.00	-1.581	-0.053	-0.004	-0.545
	Long-Short	0.597	5.534	-0.185	5.110	0.00	-4.436	0.108	0.001	0.115
R^{MOP}_{XS-CRY}	Long	0.321	5.201	-0.022	4.286	0.00	-3.314	0.062	-0.014	-0.987
	Short	-0.149	4.996	0.716	6.673	0.00	-1.644	-0.030	0.019	1.720
	Long-Short	0.469	5.826	-0.369	5.172	0.00	-3.631	0.081	-0.027	-1.651

Table 2.5: Performance Statistics: Alternative Volatility Forecasting

	Variables	Mean(%)	SD(%)	Skew	Kurt	JB(%)	MDD	SR	ΔSR	JK stat
					Panel B: HAR					
R^{BS}_{XS-MOM}	Long	0.699	4.842	0.010	5.866	0.00	-2.381	0.144	-0.001	-0.120
	Short	-0.380	4.172	0.485	4.559	0.00	-2.711	-0.091	0.006	0.985
	Long-Short	1.079	5.473	-0.134	4.742	0.00	-2.074	0.197	-0.008	-1.137
R^{MOP}_{XS-MOM}	Long	0.807	5.534	-0.035	4.814	0.00	-2.108	0.146	0.001	0.047
	Short	-0.503	4.965	0.567	4.990	0.00	-2.852	-0.101	-0.005	-0.507
	Long-Short	1.310	6.182	-0.086	3.879	0.40	-60.048	0.212	0.006	0.478
R^{BS}_{BASMOM}	Long	0.888	4.823	-0.211	3.731	0.73	-2.413	0.184	0.010	1.341
	Short	-0.435	4.983	1.921	18.98	0.00	-1.665	-0.087	0.004	0.615
	Long-Short	1.323	5.883	-0.684	7.646	0.00	-5.597	0.225	0.000	0.008
R^{MOP}_{BASMOM}	Long	0.890	4.719	-0.493	5.604	0.00	-2.837	0.189	0.014	1.209
	Short	-0.435	4.650	1.698	18.39	0.00	-1.591	-0.094	-0.002	-0.148
	Long-Short	1.324	5.623	-0.742	7.712	0.00	-4.756	0.235	0.011	0.731
R^{BS}_{XS-CRY}	Long	0.372	4.789	0.155	4.502	0.00	-6.716	0.078	0.002	0.353
	Short	-0.227	4.587	0.724	6.099	0.00	-1.567	-0.049	-0.001	-0.118
	Long-Short	0.599	5.518	-0.195	5.157	0.00	-4.431	0.109	0.002	0.295
R^{MOP}_{XS-CRY}	Long	0.336	5.179	-0.015	4.258	0.00	-5.093	0.065	-0.011	-0.836
	Short	-0.161	5.032	0.694	6.386	0.00	-1.653	-0.032	0.017	1.681
	Long-Short	0.497	5.835	-0.337	5.001	0.00	-4.592	0.085	-0.022	-1.494

Table 2.6: Performance Statistics: Alternative Portfolio Construction

This table reports statistics of portfolios performance. The portfolio formation is presented in Section 2.3.2 and the weight in formation equations are all in Section 2.5.2. Columns under "Mean(%)", "SD(%)", "Skew", "Kurt" report the mean of monthly excess return of portfolio in percentage, monthly standard deviation in percentage, skewness and kurtosis, respectively. "JB(%)" reports the Jarque-Bera p-value in percentage of the test that the excess return is normal distribution. "MDD" is the maximum drawdown. "SR" is the Sharpe ratio and "ΔSR" is the difference between the Sharpe ratio of the scaled portfolio and the Sharpe ratio of the unscaled portfolio. "JK Stat" is the statistic value calculated as described in footnote 6 and follows a standard normal distribution. If we choose 5% significant level, the corresponding value of the "JK Stat" should be 1.96.

	Variables	Mean(%)	SD(%)	Skew	Kurt	JB(%)	MDD	SR	ΔSR	JK statis
				Momentum						
R_{XS-MOM}	Long	0.749	6.383	0.340	5.377	0.00	-2.113	0.117		
	Short	-0.580	5.158	0.476	4.634	0.00	-2.710	-0.112		
	Long-Short	1.329	7.120	0.137	3.811	0.64	-1.844	0.187		
R^{BS}_{XS-MOM}	Long	0.661	5.512	0.644	6.626	0.00	-2.036	0.120	0.003	0.252
	Short	-0.542	4.469	0.238	4.049	0.01	-2.467	-0.121	-0.009	-0.748
	Long-Short	1.203	6.207	0.252	4.484	0.00	-1.831	0.194	0.007	0.647
R^{MOP}_{XS-MOM}	Long	0.773	6.195	0.211	5.111	0.00	-2.081	0.125	0.007	0.699
	Short	-0.633	5.118	0.497	4.375	0.00	-3.057	-0.124	-0.011	-1.047
	Long-Short	1.406	6.874	0.109	3.615	5.32	-1.830	0.205	0.018	1.369
				Basis Momentum						
R_{BASMOM}	Long	0.954	5.128	-0.222	5.113	0.00	-2.546	0.186		
	Short	-0.439	4.755	0.620	6.766	0.00	-1.642	-0.092		
	Long-Short	1.393	6.036	-0.0524	4.424	0.00	-5.125	0.231		
R^{BS}_{BASMOM}	Long	0.981	5.113	0.224	5.008	0.00	-2.133	0.192	0.006	0.468
	Short	-0.466	4.875	0.785	7.426	0.00	-1.561	-0.096	-0.003	-0.313
	Long-Short	1.448	6.183	-0.020	5.171	0.00	-5.320	0.234	0.003	0.252
R^{MOP}_{BASMOM}	Long	1.006	4.939	-0.401	5.986	0.00	-2.818	0.204	0.018	1.420
	Short	-0.446	4.613	0.848	9.198	0.00	-1.498	-0.097	-0.004	-0.297
	Long-Short	1.452	5.835	-0.241	4.720	0.00	-4.350	0.249	0.018	1.169
				Carry						
R_{XS-CRY}	Long	0.438	5.891	0.219	5.069	0.00	-2.622	0.074		
	Short	-0.179	5.376	0.975	7.992	0.00	-1.493	-0.033		
	Long-Short	0.617	6.760	-0.237	5.685	0.00	-4.201	0.091		
R^{BS}_{XS-CRY}	Long	0.412	5.548	0.355	5.283	0.00	-2.571	0.074	0.000	-0.006
	Short	-0.147	5.272	1.365	11.04	0.00	-1.349	-0.028	0.005	0.516
	Long-Short	0.559	6.462	-0.527	7.057	0.00	-4.522	0.086	-0.005	-0.455
R^{MOP}_{XS-CRY}	Long	0.384	5.686	0.0479	4.502	0.00	-2.628	0.068	-0.007	-0.611
	Short	-0.123	5.534	1.375	11.05	0.00	-1.439	-0.022	0.011	1.044
	Long-Short	0.507	6.738	-0.776	7.602	0.00	-5.219	0.075	-0.016	-1.217

Table 2.7: Alternative Performance Evaluations

Panel A reports performance fees (Δ) of portfolios. γ is the risk aversion level. Δ is the performance fee which investors are willing to pay for switching between the two investment strategies. It reports in basis point. "t-stat" reports the t test associated with the null hypothesis that the performance fee is equal to zero. Panel B reports the monthly turnover ratio of the portfolio.

Panel A: Performance Fee

		Momentum		Basis Momentum		Carry	
	γ	Δ	t-stat	Δ	t-stat	Δ	t-stat
BS strategy	1	-0.048	0.538	0.043	0.517	-0.055	0.394
	2	0.000	0.995	0.037	0.560	-0.039	0.546
	3	0.047	0.553	0.031	0.612	-0.023	0.726
	4	0.095	0.244	0.025	0.674	-0.007	0.920
	5	0.142	0.089	0.020	0.745	0.009	0.892
	6	0.190	0.029	0.014	0.820	0.026	0.724
	7	0.237	0.009	0.008	0.897	0.042	0.582
	8	0.285	0.003	0.002	0.971	0.058	0.469
	9	0.333	0.001	-0.003	0.960	0.074	0.381
	10	0.380	0.000	-0.009	0.898	0.091	0.313
MOP strategy	1	0.066	0.425	0.053	0.544	-0.123	0.143
	2	0.074	0.369	0.057	0.522	-0.117	0.166
	3	0.083	0.321	0.061	0.504	-0.112	0.197
	4	0.091	0.280	0.065	0.488	-0.106	0.236
	5	0.099	0.247	0.069	0.476	-0.101	0.280
	6	0.108	0.219	0.073	0.466	-0.096	0.329
	7	0.116	0.197	0.077	0.458	-0.090	0.382
	8	0.124	0.179	0.081	0.452	-0.085	0.436
	9	0.133	0.165	0.084	0.448	-0.079	0.490
	10	0.141	0.154	0.088	0.445	-0.074	0.543

Panel B: Turnover

	Momentum			Basis Momentum			Carry		
Variables	R_{XS-MOM}	R^{BS}_{XS-MOM}	R^{MOP}_{XS-MOM}	R_{BASMOM}	R^{BS}_{BASMOM}	R^{MOP}_{BASMOM}	R_{XS-CRY}	R^{BC}_{XS-CRY}	R^{MOP}_{XS-CRY}
Turnover	0.879	0.838	1.122	0.772	0.886	0.936	0.995	1.056	1.223

2.7.1 Appendix

Table A1: Difference of Forecasting Errors (Rolling Window)

This table presents results of forecasting errors from competing forecasts. Column "Method" reports forecasting methods: GJR-GARCH model (GJR) and HAR model (HAR). MSE and QLIKE denote the forecasting errors in the corresponding criterion. For BS strategy, we forecast the volatility of the strategy: [name in row] Momentum, Basis Momentum and Carry. For MOP strategy, we forecast the volatility of each commodity. The forecast horizon is one month, 21 trading days in our study. We use a rolling window of 126 observations to get the forecasts.

	Method	MSE	QLIKE
Momentum	GJR	1.912	2.777
	HAR	3.007	2.792
Basis Momentum	GJR	1.098	2.607
	HAR	1.789	2.624
Carry	GJR	1.960	2.671
	HAR	3.057	2.689
Commodity	GJR	3.835	2.895
	HAR	5.549	2.924

Table A2: Performance Statistics: Alternative Volatility Forecasting (Rolling Window)

This table reports statistics of portfolios performance. The portfolio formation is presented in Section 2.3.2. Columns under "Mean(%)", "SD(%)", "Skew", "Kurt" report the mean of monthly excess return of portfolio in percentage, monthly standard deviation in percentage, skewness and kurtosis, respectively. "JB(%)" reports the Jarque-Bera p-value in percentage of the test that the excess return is normal distribution. "MDD" is the maximum drawdown. "SR" is the Sharpe ratio and "ΔSR" is the difference between the Sharpe ratio of the scaled portfolio and the Sharpe ratio of the unscaled portfolio. "JK Stat" is the statistic value calculated as described in footnote 6 and follows a standard normal distribution. If we choose 5% significant level, the corresponding value of the "JK Stat" should be 1.96. Panel A reports the results linked to the volatility managed portfolio based on the GJR-GARCH model in rolling window of 126 observations. Panel B reports the results linked to the volatility managed portfolio based on the HAR model estimated using a rolling window of 126 observations.

Panel A: GJR

	Variables	Mean	SD	Skew	Kurt	JB	MDD	Sharpe	ΔSR	JK stat
R^{BS}_{XS-MOM}	Long	0.743	4.786	0.220	4.655	0.00	-1.945	0.155	0.010	0.923
	Short	-0.436	4.214	0.273	3.992	0.02	-2.636	-0.103	-0.007	-0.536
	Long-Short	1.179	5.451	0.044	4.130	0.01	-1.709	0.216	0.011	0.915
R^{MOP}_{XS-MOM}	Long	0.805	5.559	0.046	5.003	0.00	-4.483	0.145	0.000	-0.027
	Short	-0.514	4.897	0.571	5.015	0.00	-2.699	-0.105	-0.008	-0.717
	Long-Short	1.319	6.183	-0.029	3.840	0.75	-4.620	0.213	0.008	0.524
R^{BS}_{BASMOM}	Long	0.879	4.736	-0.154	3.877	0.260	-2.451	0.186	0.011	0.917
	Short	-0.450	4.945	1.673	16.530	0.00	-1.666	-0.091	0.001	0.050
	Long-Short	1.329	5.820	-0.614	7.116	0.00	-4.805	0.228	0.004	0.271
R^{MOP}_{BASMOM}	Long	0.852	4.713	-0.473	5.526	0.00	-3.009	0.181	0.007	0.471
	Short	-0.407	4.587	1.705	18.400	0.00	-1.677	-0.089	0.003	0.190
	Long-Short	1.258	5.530	-0.680	7.297	0.00	-4.585	0.227	0.003	0.161
R^{BS}_{XS-CRY}	Long	0.351	4.929	0.010	4.163	0.00	-6.499	0.071	-0.004	-0.356
	Short	-0.273	4.805	0.973	8.651	0.00	-1.425	-0.057	-0.008	-0.665
	Long-Short	0.623	5.764	-0.532	6.094	0.00	-4.745	0.108	0.001	0.092
R^{MOP}_{XS-CRY}	Long	0.299	5.186	0.045	4.332	0.01	-2.988	0.058	-0.018	-1.351
	Short	-0.177	5.033	0.804	7.239	0.00	-1.607	-0.035	0.014	1.200
	Long-Short	0.476	5.879	-0.334	5.280	0.00	-4.442	0.081	-0.026	-1.752

Table A2: Performance Statistics: Alternative Volatility Forecasting(Rolling Window)

	Panel B: HAR									
	Variables	Mean	SD	Skew	Kurt	JB	MDD	Sharpe	ΔSR	JK stat
R^{BS}_{XS-MOM}	Long	0.790	5.050	0.571	7.714	0.00	-2.388	0.156	0.011	0.925
	Short	-0.455	4.208	0.242	3.903	0.07	-2.689	-0.108	-0.011	-0.899
	Long-Short	1.246	5.628	0.244	5.437	0.00	-2.080	0.221	0.016	1.223
R^{MOP}_{XS-MOM}	Long	0.823	5.523	0.027	4.971	0.00	-1.990	0.149	0.004	0.236
	Short	-0.495	4.889	0.531	4.850	0.00	-2.764	-0.101	-0.005	-0.395
	Long-Short	1.318	6.176	0.033	3.852	0.67	-2.016	0.213	0.008	0.459
R^{BS}_{BASMOM}	Long	0.806	5.073	0.095	5.462	0.00	-2.378	0.159	-0.015	-1.084
	Short	-0.444	5.046	1.633	16.22	0.00	-1.605	-0.088	0.004	0.300
	Long-Short	1.250	6.041	-0.839	7.413	0.00	-5.597	0.207	-0.018	-1.294
R^{MOP}_{BASMOM}	Long	0.885	4.788	-0.482	5.672	0.00	-2.934	0.185	0.011	0.790
	Short	-0.434	4.686	1.897	20.68	0.00	-1.511	-0.093	-0.001	-0.060
	Long-Short	1.319	5.698	-0.823	8.247	0.00	-5.122	0.231	0.007	0.377
R^{BS}_{XS-CRY}	Long	0.398	5.236	0.333	4.961	0.00	-6.515	0.076	0.000	0.030
	Short	-0.206	4.916	0.999	8.224	0.00	-1.389	-0.042	0.007	0.554
	Long-Short	0.604	5.925	-0.314	6.279	0.00	-5.252	0.102	-0.005	-0.404
R^{MOP}_{XS-CRY}	Long	0.309	5.181	-0.097	4.236	0.00	-5.241	0.060	-0.016	-0.973
	Short	-0.166	5.084	1.008	8.837	0.00	-1.529	-0.033	0.016	1.361
	Long-Short	0.475	5.982	-0.599	6.238	0.00	-6.138	0.079	-0.028	-1.572

Chapter 3

Volatility Risk Premium and Volatility Forecasting In Commodity-related ETFs

3.1 Introduction

Volatility plays a central role in finance. Understandably, voluminous literature focuses on the accurate modelling of volatility. Generally, these studies belong to two streams. The first one uses historical information to generate volatility forecasts. The most popular representatives by using past information in literature are Exponentially Weighted Moving Average (EWMA), Autoregressive Moving Average (ARMA), (Generalized) Autoregressive Conditional Heteroscedasticity (ARCH/GARCH), Heterogeneous Autoregressive model of Realized Volatility (HAR-RV).

The second approach extracts market estimates of future volatility from traded option prices, and implied volatility is referred to realized volatility. Intuitively, this method is based on the assumption that the volatility expected under the risk-neutral measure is equal to the volatility under the physical measure. However, Carr and Wu (2008), Trolle and Schwartz (2010) and Prokopczuk et al. (2017) show that there exists a significant difference between the implied variance obtained under the risk-neutral measure Q and the realized variance observed under the physical measure P. As a result, there is a significant bias if we directly use implied variance to proxy realized variance. Therefore, if one is interested in using the implied volatility to predict the future volatility, it is important to adjust the implied volatility by considering the market price of volatility risk. Since we refer to the square root of the variance to volatility, it is necessary to take the market price of volatility risk into account and employ it to adjust the implied volatility.

Prokopczuk and Wese Simen (2014) use the historical average of relative variance risk premium to adjust the model-free implied volatility (MFIV) on three energy markets. Kourtis et al. (2016) also employ the historical average of relative variance risk premium to adjust the MFIV and check the performance in international equity indices. They all conclude that the MFIV adjusted by the historical average of the relative variance risk premium is superior to the MFIV and GARCH-type models. Prokopczuk and Wese Simen (2014), Kourtis et al. (2016) and a growing literature prove the necessity of correcting the implied volatility, and their suggestion is simple but effective. This paper aims to investigate whether more elaborated methods can help reduce the bias in the implied volatility.

By definition, we know that the volatility risk premium (VRP)[1] is the difference between implied volatility and realized volatility. Thus, we can get a better volatility forecast if we can get a more accurate VRP forecast. To the best of our knowledge, we are the first to specifically investigate the time-series models for VRP forecasts and their implications for volatility forecasting. We make several contributions to the literature. First, we propose different models for the (log) VRP and assess their empirical performance. To do this, we use implied volatility indices computed by the Chicago Board Options Exchange (CBOE). Since ETFs are rapidly growing financial investment products, we focus on ETFs by which investors can take the risk of a relative physical good or stock index. Given that commodities are good diversifiers for traditional equity investments and a hedge against inflation, we analyze commodity-related ETF. These include

[1]Volatility risk premium reflects the difference between implied and realized volatility while variance risk premium is defined as the difference between implied and realized variance. Absolutely, they can both measure the difference between risk-neutral and physical measure. In Chapter 3, we focus on volatility, which is more popular for investors to measure the risk and volatility risk premium is the relative term. We following DeMiguel (2013) and Prokopczuk and Wese Simen (2014) to employ volatility risk premium to adjust implied volatility. In Section 3.5.2, we also consider the format of variance risk premium. By comparison of equation (3.5.2) and equation (3.5.3), volatility risk premium is more simple and straightforward in our sample.

United States Oil Fund (USO), SPDR Gold Shares (GLD), iShares Silver Trust (SLV), VanEck Vectors Gold Miners ETF (GDX), Energy Select Sector SPDR Fund (XLE) and S&P 500 Index (SPX).

We then analyze the implications of different forecasting models for volatility forecasting. Consistent with our insights, we present some evidence to suggest that a better model of the VRP helps improve the accuracy of volatility forecasts. Indeed, We find that $AMFIV^{ir}$ delivers in-sample volatility forecasts that are superior to those of its competitors, which include the MFIV and its adjusted version following Prokopczuk and Wese Simen (2014). Out-of-sample, the mean squared errors (MSE) and the QLIKE loss functions indicated that this adjustment ($AMFIV^{ir}$) delivers more accurate volatility forecasts than its rivals. We implement several additional tests to evaluate the robustness of our main findings. We first choose alternative proxies of the realized volatility. Second, we employ different VRP functional forms rather logarithm to repeat our analysis and compare the performance of forecasts by competing models. In addition, we consider the forecasts RMFIV as Prokopczuk and Wese Simen (2014) and Kourtis et al. (2016) used to be another benchmark and we find that $AMFIV^{ir}$ is better than it. Finally, we also consider an estimation window containing 484 trading days rather than 232 days and our message is the same.

The remainder of the chapter is organized as follows: Section 3.2 describes some related studies. Section 3.3 provides the data and methodology. Section

3.4 reports our findings. Section 3.5 presents some robustness checks. Finally Section 3.6 concludes.

3.2 Literature Review

3.2.1 Volatility Forecasting

A voluminous literature focuses on forecasting volatility. Most existing studies can be put into two categories. The first category uses historical data to forecast volatility, while the second category derives the market estimates of future volatility from traded option prices.

Time-Series Forecasting Model

The time-series models use historical data. It contains the Random Walk model, the Historical Average method, the Moving Average (MA) method, and the Exponentially Weighted Moving Average (EWMA) method, which is favoured by RiskMetrics and places greater weights on the more recent estimates. These methods are different in the number of observations and weights assigned to them. If we formulate volatility by past values and error terms, we get the Autoregressive Moving Average (ARMA) model. Another main volatility modelling group of time series is the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model (Bollerslev (1986)), which extends the ARCH model of Engle (1982) to capture the clustering of volatility. EWMA is a non-stationary case of the GARCH(1,1) model where shocks of prices introduce permanent impacts on volatility and the persistence parameters sum to 1. Inspired by the success of GARCH model, Nelson (1991) proposes the Exponential GARCH (EGARCH) to relax the restriction of nonnegative constraints in the linear GARCH model. GJR-GARCH model proposed by Glosten et al. (1993) and Threshold GARCH (TGARCH) are also models reflecting asymmetric effects of positive and negative returns. Based on these studies, more GARCH-type models are developed, such as the integrated GARCH (IGARCH), the Quadratic GARCH (QGARCH), the regime-switching GARCH (RS-GARCH).

Implied Volatility Forecasting Model

The implied volatility is introduced by Black-Scholes (B&S) model since it can be easily derived by the standard deviation when option traded price is observable, and the other parameters are known. Latane and Rendleman Jr (1976) use the weighted average of implied volatility in B&S call options and show that the volatility forecasts from weighted implied standard deviations are superior to those from the historical model. In subsequent studies, Chiras and Manaster (1978), Jorion (1995), Christensen and Prabhala (1998) and Fleming (1998) all extract the implied volatility from the B&S constant volatility option model and confirm the finding that the implied volatility outperforms historical forecasts. In contrast, Canina and Figlewski (1993) use the binomial model to get the implied volatility from S&P 100 index option and find that historical forecasts perform better. They also show that the implied volatility of near the money options lead to superior forecasts compared to deep in or out of the money options. Christensen and Prabhala (1998) and Fleming (1998) forcefully argue that the findings of Canina and Figlewski (1993) suffer from overlapping observation biases. Charoenwong et al. (2009) use high-frequency data to report that implied volatility forecasts are superior to time-series forecasts, regardless of the trading venue. Szakmary et al. (2003) document that at-the-money (ATM) implied volatility forecasts are superior to forecasts from GARCH and MA models throughout the maturity of the contract in the commodity market. Contrary to the study of Szakmary et al. (2003), Agnolucci (2009) reach a different conclusion in the crude oil market. They find that the predictive power of ATM implied volatility is inferior to that of a set of GARCH-type models. They also show that the forecasts from models combined GARCH-based and IV-based can be improved, which means that implied volatility forecasts contain some information that is not contained in the time series models.

Jiang and Tian (2005) build on the work of Britten-Jones and Neuberger (2000) to propose the model-free implied volatility that does not depend on any specific options pricing model and any particular strike prices. They show that the model-free implied volatility (MFIV) subsumes the information of the Black and Scholes ATM IV from the B&S model and historical volatility. However, Taylor et al. (2010) report that ATM IV outperform MFIV by analyzing options of individual firms. Finally, they show that option forecasts are more informative than historical forecasts for the month ahead estimation.

Lamoureux and Lastrapes (1993) derive ATM IV from the Hull and White (1987) model, which assumes that volatility risk is diversifiable and there is no volatility risk premium. They document that the bias in the IV forecasts may be due to ignorance of pricing of volatility risk. Jorion (1995) and Fleming (1998) also find that IV estimates are upward-biased. However, it is unclear why implied volatility is biased. Poteshman (2000) uses the Heston (1993) model, which takes a predetermined volatility risk premium into account to estimate IV and report a lower bias. He presents that high-frequency futures data and consideration of volatility risk premium are helpful for bias reduction. Chernov (2007) models the volatility risk premium as an affine function of the latent spot volatility, and reports that volatility risk premium leads to the bias of volatility estimates in theoretically and empirically. Kang et al. (2010) use investor risk preferences and higher-order risk-neutral moments to estimate the disparity based on the presence of volatility risk premium. Based on the assumption that volatility risk premium is proportional to the latent spot volatility, DeMiguel et al. (2013) adjust the MFIV estimates by the ratio of the average MFIV and realized volatility over the past year. Prokopczuk and Wese Simen (2014) employ a similar adjustment which uses the MFIV divided by the average of the relative volatility risk premium in the energy sector. They find that the adjusted MFIV is superior to other models, including raw MFIV. Kourtis et al. (2016) use the adjustment of Prokopczuk and Wese Simen (2014) and provide a comprehensive performance of adjusted MFIV in different equity markets. They report that the HAR-RV model outperforms others at the daily horizon, and the adjusted MFIV performs best at the monthly horizon.

3.2.2 Volatility Risk Premium

Volatility risk premium (VRP) is the difference between risk-neutral and physical volatility. Regarding the model of the volatility risk premium, there are a few papers to investigate the forecasting. Bollerslev et al. (2011) show that VRP is time-varying and employ an augmented AR(1) process to predict the VRP. They document that a set of five macro-finance variables contribute to time-variations of the volatility risk premium of the S&P 500 index after testing 29 macro-finance variables and prove that VRP is driven by realized volatility, Moody AAA bond spread, Housing start, S&P500 P/E ratio, industrial production, producer price index and payroll employment. Chabi-Yo (2012) demonstrate that investor's risk aversion has a positive effect on the value of price of market variance risk and then has a positive effect on the volatility risk premium. Garg and Vipul (2015) use daily data to study VRP forecast on Indian options market and use AR(3) to predict VRP. They gradually increase the numbers of lag VRP and present after AR(3) the residuals have no serial correlation. Chen et al. (2016) use investor sentiment, which is measured by the bull-bear spread to explain the sign of VRP.

Some studies focus on the variance risk premium (VRP^2). Since variance risk premium is defined as the difference between the risk-neutral and physical variance, the VRP is a nonlinear transformation of VRP^2 and we also analyze some findings on VRP^2 forecast. Bollerslev et al. (2009) use a general equilibrium model to show that the variance risk premium is related to the volatility of volatility of the consumption growth process. Bekaert et al. (2013) decompose the squared VIX into a proxy for risk aversion, which is the variance risk premium and a measure of economic uncertainty, which is the physical variance. They find that lax monetary policy affects these two components and more strongly for variance risk premium. Konstantinidi and Skiadopoulos (2016) investigate the variance risk premium of the S&P 500 index in four specification predictive models: variation in the volatility of the S&P 500 returns, stock market conditions, economic conditions and trading activity. They find that the trading activity model performs best among them.

3.3 Data and Methodology

3.3.1 Data

Chicago Board Options Exchange (CBOE) applied its volatility index methodology to different markets and assets to compute the 30-day volatility implied. In this paper, we focus on the S&P 500 index volatility index (VIX) for S&P 500 Index (SPX), the crude oil volatility index (OVX) for United States Oil Fund (USO), the gold volatility index (GVZ) for SPDR Gold Shares (GLD), the silver volatility index (VXSLV) for iShares Silver Trust (SLV), the VXGDX for VanEck Vectors Gold Miners ETF (GDX), the VXXLE for Energy Select Sector SPDR Fund (XLE).[2] Since 2003, the CBOE uses the model-free method to construct a new and more robust VIX, and we choose the time period of VIX from 2004/01/01 to 2018/09/30.[3][4] The dataset is available from 2007/05/10 and 2008/06/03 for the OVX and GVZ, respectively. As VXSLV, VXGDX and VXXLE have been calculated and published from March 2011, the implied volatility index samples for these three sectors are all from 2011/03/16 to 2018/09/30. All implied volatility indexes data are based on daily closing data from CBOE. All the underlying prices are dividend-adjusted closing data obtained from the Bloomberg database. The sample periods of the underlying assets are aligned with those of implied

[2] They all use the VIX methodology to measure the implied volatility.

[3] In 1993, CBOE create the old VIX, which is the expected implied volatility for the next 30 days by the option prices of the at-the-money S&P 100 index (OEX Index). The old VIX calculation is based on an average of implied volatility calculated from the Black and Scholes model. This implied volatility is based on eight near-the-money options of the two nearest maturities. From September 22, 2003, the CBOE changed to a new methodology to calculate VIX based on model-free implied volatility, which relaxes the need for options with near-the-money strikes and contains more options with a wide range of strike prices. Another change of VIX is that the new VIX refers to the S&P 500 index instead of the S&P 100 index.

[4] Although Chapter 3 focuses on commodity-related ETFs, our study includes SPY as a benchmark. Kourtis et al. (2016) show that adjusted VIX outperforms the time-series forecasting model in the monthly forecast horizon. In Table 3.1 we can find that the summary statistics of SPY is close to those of commodity-related ETFs. Since SPY is very popular and has an influence on commodity-related ETFs, it is interesting to see whether our conclusions work in SPY. We use daily data to compute the realized volatility while Kourtis et al. (2016) use 5-min data. It means that SPY in our study can also test whether the success of adjusted VIX is due to high frequency.

volatility data. We complement this dataset with the opening, daily high and daily low prices of the underlying assets from Bloomberg.

Table 3.1 reports the summary statistics of SPX and ETFs. It reports the Newey-West t-statistics on the significance of the mean volatility risk premiums computed with 2 lags. Overall, the sample averages of volatility risk premium are all positive, and most of them are statistically significant. Our results are consistent with Tee and Ting (2017) which confirms that there exists a significant difference between physical and risk-neutral measure in the commodity ETFs market. Moreover, the averages of lag 1 autocorrelations of SPX, USO, and GDX are all larger than 0.18, and it shows that future VRP can be partly reflected by its past.

3.3.2 Realized Volatility, Implied Volatility and Volatility Risk Premium

Realized Volatility Since it is widely known that volatility itself cannot be observed, a popular way to proxy volatility is obtained by the square root of the sum of daily squared returns. Andersen and Bollerslev (1998) convincingly argue that realized volatility calculated using intraday data is a more efficient proxy of the realized variance. Barndorff-Nielsen and Shephard (2002) show that when the sampling frequency increases to infinity, the sum of squared intraday returns asymptotically converges to the truly realized variance under some ideal conditions such as continuous and frictionless prices. The choice of data frequency involves a careful analysis of the microstructure noise induced by factors such as nonsynchronous trading and bid-ask bounce. A thorough review of the effect of microstructures on realized volatility can be found in the paper by McAleer and Medeiros (2008).

Throughout this paper, we focus on the monthly forecasting horizon. Since we collect daily returns, we employ daily returns to get monthly realized variance which means the realized volatility computed over a horizon of 21 trading days. Following Jorion (1995) and Prokopczuk and Wese Simen (2014), we use the square root of the sum of daily log returns to calculate the realized volatility over 21-day post windows. It means that the realized volatility between t and $t + \tau$, $RV_{t,t+\tau}$ is measured:

$$RV_{t,t+\tau} = \sqrt{\frac{252}{\tau}\Big[\sum_{i=t+1}^{t+\tau}\Big(100 \times \log\frac{P_i}{P_{i-1}}\Big)^2\Big]} \tag{3.3.1}$$

where P_i is the closing price of the underlying asset on trading day i and τ is 21 trading days in our analysis.

Model-Free Implied Volatility Building on the work of Britten-Jones and Neuberger (2000), Jiang and Tian (2005) show how to compute the model-free implied variance, which does not depend on any specific option pricing model and any particular strike prices. They extend the work of Britten-Jones and

Neuberger (2000) to asset price processes with jumps and they demonstrate that:

$$\mathbb{E}_t^Q(V_{t,T}^2) = MFIV_{t,T}^2 = \frac{2e^{r_t(T-t)}}{T-t}\left[\int_0^{F_{t,T}} \frac{P(t,K,T)}{K^2}dK + \int_{F_{t,T}}^{+\infty} \frac{C(t,K,T)}{K^2}dK\right] \tag{3.3.2}$$

where $\mathbb{E}_t^Q(V_{t,T}^2)$ and $MFIV_{t,T}^2$ denote the risk-neutral expectation of variance and model-free implied variance between t and T, respectively. r_t is risk-free rate and $F_{t,T}$ refer to the time t futures contract expiring at T. $P(t,K,T)$ and $C(t,K,T)$ refer to the put and call European options price at time t and expiring at T with strike price K.

CBOE created the old version of VIX in 1993 and based on the $B\&S$ model and get the average of implied volatility by each of 8 options which are near-the-money. In 2003, CBOE uses the model-free method, which is similar to the Equation (3.3.2) to calculate the new VIX. They truncate the two integrals at the lowest and highest strike prices for a given maturity and then employ the out-the-money call and put options to get the implied volatility of the S&P 500 index. In recent years, the CBOE has applied the VIX methodology to compute the volatility indices of different securities. In this paper, we directly use the following implied volatility indexes: VIX, OVX, GVZ, VXSLV, VXGDX and VXXLE, from CBOE as model-free implied volatility for our study.

Volatility Risk Premium According to Della Corte et al. (2016) and Fan et al. (2016), we define the volatility risk premium as:

$$VRP_{t,t+\tau} = \mathbb{E}^{Q}(V_{t,t+\tau}) - \mathbb{E}^{P}(V_{t,t+\tau}) \tag{3.3.3}$$

where $VRP_{t,t+\tau}$ denotes the volatility risk premium between t and $t+\tau$ and we use the one month horizon. $\mathbb{E}^{Q}(V_{t,t+\tau})$ is the ex ante expectation of volatility under risk-neutral measure and $\mathbb{E}^{P}(V_{t,t+\tau})$ is the ex ante expectation of volatility under the physical measure.[5] Following Bollerslev et al. (2009), we use the VIX index and the other implied volatility index to proxy for the $MFIV_{t,t+\tau}$. Following Prokopczuk and Wese Simen (2014), we use the annualized volatility of the underlying asset daily log returns over 21-day post window as realized volatility to proxy $RV_{t,t+\tau}$ which is the measurement of $\mathbb{E}^{P}(V_{t,t+\tau})$. Then we can get the formula of measuring $VRP_{t,t+\tau}$ as:[6]

$$VRP_{t,t+\tau} = MFIV_{t,t+\tau} - RV_{t,t+\tau} \tag{3.3.4}$$

[5]Empirical studies on quantifying the VRP usually belong to three methods. The first is calculated by deriving volatility from a pricing model. The model-free method is developed to measure the VRP to overcome these gaps. Thus, the measurement of VRP reduces to quantifying realized volatility and risk-neutral volatility, which can be calculated by the model-free method.

[6]Since VIX is the annualized 100 times monthly implied volatility of the S&P 500 index, we also annualize and multiply by 100 the monthly realized volatility accordingly. See CBOE VIX White Paper for more details.

where $MFIV_{t,T}$ is the annualized 30-day implied volatility which is proxied by VIX, OVX, GVZ, VXSLV, VXGDX or VXXLE. $RV_{t,T}$ is the ex post annualized realized volatility of the next month, computed using Equation (3.3.1). By analyzing Equation (3.3.4), we can infer that the MFIV is a good and unbiased proxy for the future realized volatility if the VRP is zero. However, if the VRP is time-varying, it confounds the information content of the MFIV. Chernov (2007) shows that VRP is a main bias for the realized volatility estimator. Carr and Wu (2008) and Bollerslev et al. (2011) present that the VRP is non-zero and time-varying, supporting MFIV is a biased estimator. Inspired by them, we need to have a model for the time-varying future VRP in order to purge the MFIV from these time variations.

3.3.3 Volatility Forecasting Models

Our aim is to reduce the bias in the implied volatility by the expectation of volatility risk premium. Thus the adjusted implied volatility can be used to predict the realized volatility. Clearly, predicting VRP is a key point to estimating physical volatility by the method deriving from future implied volatility.

Forecasts by Model Free Implied Volatility Forecasts (MFIV)

By the definition of VRP, its forecast is added to the implied volatility forecast to obtain the realized volatility forecast. In this part, we check whether the adjusted implied volatility has a good performance in commodity sectors. We focus on the role of the volatility risk premium and its implication for realized volatility forecasting.

Chernov (2007) indicates that the volatility risk premium is the primary bias of volatility forecast. Intuitively, the difference between the implied volatility for the next period and the volatility risk premium forecast yields the realized volatility forecast. Since the forecast of volatility under risk-neutral is proxied by implied volatility indexes from CBOE, expected realized volatility can be expressed as:

$$\mathbb{E}(RV_{t,t+\tau}) = MFIV_{t,t+\tau} - \mathbb{E}(VRP_{t,t+\tau}) \tag{3.3.5}$$

where $MFIV_{t,t+\tau}$ is the annualized next 30-day expected implied volatility which is proxied by VIX, OVX, GVZ, VXSLV, VXGDX or VXXLE in this study; $\mathbb{E}(VRP_{t,t+\tau})$ is the volatility risk premium forecast for the next period and $\mathbb{E}(RV^2_{t,t+\tau})$ is the realized volatility forecast.

Carr and Wu (2008) indicate that the distribution of log variance risk premium is closer to normality and more suitable for ordinary least squares (OLS) regression. Inspired by them, we use the log volatility risk premium format to compare the performance of different estimating models.

The log volatility risk premium is defined as:

$$LVRP_{t,t+\tau} = \ln \mathbb{E}^{Q}(V_{t,t+\tau}) - \ln \mathbb{E}^{P}(V_{t,t+\tau}) \tag{3.3.6}$$

where $\mathbb{E}^Q(V_{t,t+\tau})$ is the ex ante expectation of volatility under the risk-neutral measure and $\mathbb{E}^P(V_{t,t+\tau})$ is the ex ante expectation of volatility under the physical measure. The adjusted implied volatility by log volatility risk premium which can proxy the realized volatility forecast and is denoted as $AMFIV_{t,t+\tau}$ is as follow:

$$AMFIV_{t,t+\tau} = \exp\left(\ln(MFIV_{t,t+\tau}) - \mathbb{E}(LVRP_{t,t+\tau})\right) \tag{3.3.7}$$

If we take VRP into account to get a decent realized volatility forecast, predicting VRP is a crucial point to estimating physical volatility by the method deriving from future implied volatility.

In this study, we focus on different time series models to forecast VRP. By employing different VRP forecasts, we compare their impact for volatility forecasting.

$LVRP$ Forecasts by Historical Averages Prokopczuk and Wese Simen (2014) and Kourtis et al. (2016) show that model-free implied volatility adjusted by historical relative volatility risk premium, which is the average values over one past year, outperforms many other volatility forecasting models at the monthly horizon. We employ the historical average as the $LVRP$ forecast and is expressed as:

$$HLVRP_{t-252,t-\tau} = \frac{1}{252-\tau}\sum_{i=t-252}^{t-\tau} LVRP_{i,i+\tau} \tag{3.3.8}$$

where $HLVRP_{t-252,t-\tau}$ is the average log volatility risk premium between $t-252$

and $t-\tau$; τ denotes the forecasting horizon which is one month, 21 trading days in this study. We applied the simple time series method for forecasting log volatility risk premium and the forecast is proxied by $HLVRP_{t-252,t-\tau}$. The adjusted implied volatility by historical averages $AMFIV^{h}_{t,t+\tau}$ for the period t to $t+\tau$ is:

$$AMFIV^{h}_{t,t+\tau} = \exp\left(\ln(MFIV_{t,t+\tau}) - HLVRP_{t-252,t-\tau}\right) \tag{3.3.9}$$

$LVRP$ **Forecasts by AR(1)** Garg and Vipul (2015) employ an AR(3) time-series specification to model daily VRP. We use the AR(1) model to capture the persistence of the LVRP and forecast the log volatility risk premium for the next period.[7] Our specification is as follows:

$$LVRP_{t-\tau,t} = \alpha + \beta * LVRP_{t-2\tau,t-\tau} + \epsilon_t \tag{3.3.10}$$

Given information set $I_t = \{LVRP_{t-252,t-252+\tau}, LVRP_{t-251,t-251+\tau}, ..., LVRP_{t-\tau,t}\}$, the forecast by autoregressive model is:

$$ALVRP_{t,t+\tau} = \mathbb{E}(LVRP_{t,t+\tau}|I_t) = \alpha + \beta * LVRP_{t-\tau,t} \tag{3.3.11}$$

[7] Prokopczuk and Wese Simen (2014) employ an ARMA(1,1) model as a robustness check to predict VRP in commodity futures market. However, we use ARMA(1,1) model and get an insignificant coefficient for moving average term. This is not necessarily inconsistent with the results of them. They analyze options on commodity futures, whereas we study options on ETFs. It indicates that ARMA(1,1) is not suitable for commodity ETFs indexes.

where α and β are obtained from the past one year information of $LVRP$ by the Equation (3.3.10), τ denotes the forecasting horizon which is one month, 21 trading days in this study.

We estimate the above model using a rolling window of 232 observations. Then we apply the α and β from Equation (3.3.10) to Equation (3.3.11). After knowing the forecasts of log volatility risk premium by AR(1), we can get the adjusted implied volatility $AMFIV^{ar}_{t,t+\tau}$ which is calculated by the following equation.

$$AMFIV^{ar}_{t,t+\tau} = \exp\left(\ln(MFIV_{t,t+\tau}) - ALVRP_{t,t+\tau}\right) \tag{3.3.12}$$

$LVRP$ **Forecasts by EWMA** The historical model in Equation 3.3.8 assigns equal weight to past data. One may argue that more recent data should receive more weight. As a result, we use the exponentially weighted moving average forecast is a weighted average (EWMA). Consistent with the forecasting window of previous models, we estimate the weighted parameter on a rolling window of 232 observations. We choose the smoothing parameter by minimizing the mean squared forecast errors and then combine past information by exponentially decreasing weights to indicate the forecast for the next 21 trading days. The forecasts of $LVRP$ by EWMA is:

$$ELVRP_{t,t+\tau} = \lambda \sum_{i=0}^{252-\tau} (1-\lambda)^i LVRP_{t-i-\tau,t-i} + (1-\lambda)^t LVRP_0 \tag{3.3.13}$$

$$LVRP_0 = \frac{1}{252-\tau} \sum_{j=t-252}^{t-\tau} LVRP_{j,j+\tau} \tag{3.3.14}$$

where $LVRP_{t-i}$ is the log volatility risk premium for the period $t-i-\tau$ to $t-i$, $LVRP_0$ is the average log volatility risk premium between $t-252$ and $t-\tau$ where τ is 21 trading days in our study. λ which is the smoothing parameter to minimize the mean squared forecast errors satisfies the following equation:

$$\min_{0\leq\lambda\leq 1} \sum_{k=0}^{t-\tau} (LVRP_{t-k-\tau,t-k} - ELVRP_{t-k-\tau,t-k})^2 \tag{3.3.15}$$

where $ELVRP_{t-k-\tau,t-k}$ is calculated in Equation (3.3.13).[8] We always employ a rolling sample of the latest 232 observations, which means that we use the information of $LVRP$ of past 232 trading days to get the λ. After that, we use the Equation (3.3.13) step by step to forecast $LVRP$ for next 21 trading days. Equipped with the EWMA forecasts of log variance risk premium, we compute the adjusted implied volatility $AMFIV^e_{t,t+\tau}$ as follows.

$$AMFIV^e_{t,t+\tau} = \exp\left(\ln(MFIV_{t,t+\tau}) - ELVRP_{t,t+\tau}\right) \tag{3.3.16}$$

[8] In our sample, the mean of λ for SPX over the whole period, 0.9371. λ fluctuates from 0.6897 to 0.9998. The standard deviation of λ for SPX is 0.0630. The means of λ for USO, GLD, SLV, GDX and XLE are 0.9884, 0.9922, 0.9947, 0.9509 and 0.9723, respectively. The λ for USO varies from 0.8301 to 0.9998, λ for GLD changes from 0.8439 to 0.9998 and that for SLV varies from 0.8392 to 0.9998. The standard deviation of λ for USO, GLD and SLV are 0.0238, 0.0216 and 0.0200. λ for GDX oscillates from 0.5423 to 0.9998 and the standard deviation is as high as 0.1196. λ for XLE fluctuates from 0.7425 to 0.9998 and the standard deviation is 0.0606.

$LVRP$ **Forecasts by RV and MFIV** We adopt a richer model that includes the implied volatility and the lagged realized volatility to forecast $LVRP$:

$$LVRP_{t-\tau,t} = \alpha_{ir} + \beta_1 * lnMFIV_{t-\tau,t} + \beta_2 * lnRV_{t-2\tau,t-\tau} + \epsilon_t \tag{3.3.17}$$

Given the information set

$$\begin{aligned} M_t = &\{RV_{t-252,t-252+\tau}, RV_{t-251,t-251+\tau}, ..., RV_{t-\tau,t}, \\ &MFIV_{t-252+\tau,t-252+2\tau}, MFIV_{t-251+\tau,t-251+2\tau}, ..., MFIV_{t,t+\tau}\}, \end{aligned}$$

the forecast is:

$$IRLVRP_{t,t+\tau} = \mathbb{E}(LVRP_{t,t+\tau}|M_t) = \alpha_{ir} + \beta_1 * lnMFIV_{t,t+\tau} + \beta_2 * lnRV_{t-\tau,t} \tag{3.3.18}$$

where α_{ir}, β_1 and β_2 are obtained from Equation (3.3.17) given information set M_t and τ is the forecasting horizon, 21 trading days. In comparison with other models, we employ the above model by a rolling window of 232 observations. After knowing the forecasts of log volatility risk premium by RV and $MFIV$, we obtain the adjusted implied volatility $AMFIV^{ir}_{t,t+\tau}$ is as follows.

$$AMFIV^{ir}_{t,t+\tau} = \exp\left(\ln(MFIV_{t,t+\tau}) - IRLVRP_{t,t+\tau}\right) \tag{3.3.19}$$

Forecasts From Realized Volatility by EWMA (ERV)

Ding and Meade (2010) indicate that EWMA performs better than GARCH in most cases and GARCH outperforms stochastic volatility (SV) in different volatility scenarios. Following them, we use EWMA to predict realized volatility and the forecasts for the next period which we denoted as $ERV_{t,t+\tau}$ is:[9]

$$ERV_{t,t+\tau} = \lambda_r \sum_{i=0}^{252-\tau} (1-\lambda_r)^i RV_{t-i-\tau,t-i} + (1-\lambda_r)^t RV_0 \tag{3.3.20}$$

$$RV_0 = \frac{1}{252-\tau} \sum_{j=t-252}^{t-\tau} RV_{j,j+\tau} \tag{3.3.21}$$

where the RV_0 is the average volatility of the past 232 trading days in our analysis, $RV_{t-i-\tau,t-i}$ are the historical realized volatility and λ_r is the smoothing parameter. Riskmetrics (1996) recommend to set $\lambda = 0.94$ while Mina et al. (2001) choose $\lambda = 0.97$. In this study, we use the smoothing parameter that minimizes the in sample sum-of-squared forecast errors in our analysis. It means that we choose

[9] We choose EWMA as our benchmark in several reasons. First, EWMA is a very simple but efficient way to forecast volatility. We also consider HAR model as another benchmark in Section 3.5.4 as a robustness test. Second, Ding and Meade (2010) point that EWMA outperforms when data comes from a high volatility of volatility scenarios. Part of our data covers 2008 financial crisis during which assets prices fluctuate. Third, their conclusions that EWMA is superior work in many different markets including commodity markets. We point that commodity ETFs track commodity prices in Section 3.4 so EWMA may perform well in commodity-related ETFs.

the parameter to satisfy the following equation:

$$\min_{0\leq\lambda_r\leq 1}\sum_{k=0}^{t-\tau}(RV_{t-k-\tau,t-k} - ERV_{t-k-\tau,t-k})^2 \tag{3.3.22}$$

where $ERV_{t-k-\tau,t-k}$ is calculated in Equation 3.3.20. We use the volatility of the past 232 trading days to get the λ_r and then use Equation (3.3.20) to forecast the next-period volatility.[10] We use this model as our benchmark.

3.4 Empirical Results

3.4.1 In-Sample Analysis

In this section, we evaluate the in-sample performance of our forecasting models: ERV, $MFIV$, $AMFIV^h$, $AMFIV^{ar}$, $AMFIV^e$ and $AMFIV^{ir}$. Mincer-Zarnowitz regressions are OLS regressions, and they are simple and typical methods to evaluate the biases of forecasts. They usually work by testing the joint hypothesis that the intercept is 0 and the slope is 1. A large number of studies, e.g. Andersen and Bollerslev (1998), Prokopczuk and Wese Simen (2014) and Kourtis et al. (2016), employ Mincer-Zarnowitz regression to examine bias in forecasts. Following them, we use Mincer-Zarnowitz regressions to evaluate the information content of volatility forecasts. We regress the monthly realized

[10] In our study, the mean of λ_r over the whole period is 0.9818 and λ_r ranges from 0.6661 to 0.9998. The standard deviation is 0.0376.

volatility on our volatility forecasts from the different models:

$$RV_{t,T} = \alpha + \beta f_{t,T} + \epsilon_T \tag{3.4.1}$$

where $RV_{t,T}$ is the monthly ex-post realized volatility from t to T, $f_{t,T}$ is either one monthly volatility forecast or a vector of competing forecasts at time t and ϵ_T is the error term. We employ Newey-West standard errors with 2 lags for all t-statistics and other tests. A forecast is unbiased and efficient if it has errors that are unforecastable on the basis of all available information at the time of the forecast. For univariate regressions, we use a Wald test to test the null hypothesis, which assumes that the values of α and β are jointly equal to zero and one, respectively. For encompassing regressions, we restrict the slope of alternative forecasts to zero to test whether the alternative one is more efficient than the baseline one.

Univariate Regressions The results of in-sample regressions are reported in Table 3.2. If the forecast is informative about future volatility, the slope will be statistically different from zero, and we will reject the null hypothesis. The table presents the coefficient estimates (β) along with the corresponding Newey-West t-statistics computed using 2 lags. We find that all slope coefficient estimates are positive and statistically significant, which means that these forecasts contain information about next month's volatility. We analyze the adjusted R-square which indicates the performance of the model so that we can evaluate the explanatory power of forecasts. We can observe that the slopes of forecasts from some implied variance related models are closer to one. In order to formally test the unbiasedness of forecasts, we employ the Wald test, which restricts the value of α and β jointly to zero and one, respectively. The corresponding p-values are presented below the Wald values, and p-values in bold show a rejection of the null hypothesis at 5% significant level, reporting that forecasts are biased.

In the S&P 500 market, we see that the slope of forecast from MFIV is 0.97 and gets very close to expected number 1 while the slope of EWMA is only 0.77. The results of the Wald test suggest that the MFIV forecasts are less biased than the benchmark model. This finding is consistent with Jiang and Tian (2005) and Kourtis et al. (2016), suggesting that it is quite necessary to adjust MFIV. We turn to check the performance of $AMFIV^h$ forecast proposed by Prokopczuk and Wese Simen (2014) and Kourtis et al. (2016). We notice that $AMFIV^h$ cannot reject the null hypothesis at 5% significant level by Wald test, and the explanatory power is equal to 0.59, indicating that the MFIV is a good predictor for next month volatility. Comparing $AMFIV^{ar}$, $AMFIV^e$ and $AMFIV^{ir}$, we find that $AMFIV^{ar}$ and $AMFIV^e$ are biased while $AMFIV^{ir}$ is not as evidenced by p-values of Wald test at 5% significant level. Furthermore, $AMFIV^{ir}$ provides the highest adjusted R-square value 0.67 among all the forecasts while $AMFIV^{ar}$ has the lowest value of 0.54. It is fairly to infer that $AMFIV^{ir}$ is the best forecast.

For the US oil market, we focus on USO, which is a commodity ETF reflecting prices of light and sweetcrude oil and trades like stocks. The value of USO is calculated on the price of near-month West Texas Intermediate (WTI) crude oil futures contracts traded on the New York Mercantile Exchange (NYMEX), and OVX is based on the options on USO. Agnolucci (2009) use options on futures on WTI and note that forecasts from GARCH-type models outperform implied volatility from the B&S model. However, Prokopczuk and Wese Simen (2014) indicate that in the crude oil and heating oil markets, MFIV and MFIV-adjusted forecasts are both perform better than time-series forecasts and also MFIV-based forecasts are less biased than time-series forecasts. In our results of this sector, the benchmark forecast, EWMA, performs worse than MFIV as shown by the smaller adjusted R-squared and smaller β than 1, suggesting that the time-series forecast is inferior to MFIV. We notice that in explanatory power, all the MFIV-related forecasts are better than EWMA, and for the Wald test, the values of MFIV-adjusted forecasts are much smaller than that of MFIV. These findings are consistent with Prokopczuk and Wese Simen (2014) and confirm that MFIV needs to be adjusted. We observe that the p-values of the Wald tests associated with $AMFIV^h$ $AMFIV^{ar}$ and $AMFIV^{ir}$ are all larger than 5% , confirming the unbiasedness of these forecasts. Moreover, $AMFIV^{ir}$ has the largest adjusted R-square value among all the forecasts, indicating $AMFIV^{ir}$ is superior to that of other forecasts.

We use gold ETF, SPDR Gold Shares, which invests in physical gold and almost keep track of the price of gold, to calculate the realized volatility. Its implied volatility index, GVZ, is based on the options on it. Compared with MFIV, EWMA performs worse, as evidenced by the smaller adjusted R-square. This finding is consistent with Szakmary et al. (2003). Not surprisingly, the MFIV is biased, and we cannot reject the unbiased null hypothesis by the Wald test. $AMFIV^h$ not only displays a high slope coefficient, but its forecast is also unbiased. As for $AMFIV^{ar}$ and $AMFIV^e$, their performance are worse than $AMFIV^h$. However, $AMFIV^{ir}$ is with the smaller intercept and larger coefficient of the slope than $AMFIV^h$, which reduces Wald value and maintains the rejection of the unbiased null hypothesis. Furthermore, $AMFIV^{ir}$ has a larger explanatory power than $AMFIV^h$. We can conclude that $AMFIV^{ir}$ outperforms all other forecasts.

We turn to the silver sector. SLV is short for ishares Silver Trust, which is silver ETF and invests in physical silver, so it almost follows the price of silver. Similar to the results in the previous sectors, EWMA is inferior to the MFIV. Although the explanatory power of $AMFIV^h$ is smaller than that of the MFIV that we cannot reject the unbiased null hypothesis. For MFIV-adjusted forecasts we propose, we find that $AMFIV^{ir}$ performs much better than $AMFIV^h$. The adjusted R-square of $AMFIV^{ir}$ is as high as 0.41, and the p-value of the Wald test is 0.40, which suggests it is an unbiased forecast. Our results support that the $AMFIV^{ir}$ performs best.

GDX is VanEck Vectors Gold Miners ETF which helps investors to gain exposure to gold miners. Since GDX invest shares in gold miners, it tracks the performance of the NYSE ARCA Gold Miners Index. In the gold miners sector, we see that EWMA is still inferior to MFIV, but MFIV is an unbiased forecast. Moreover, we cannot reject the null hypothesis, which is the value of α and β are jointly equal to zero and one, of $AMFIV^h$ and $AMFIV^{ar}$. $AMFIV^e$ performs worst among all the forecasts with the lowest adjusted R-square and highest Wald value. Consistent with the finding in previous sectors, $AMFIV^{ir}$ has the highest explanatory power and lowest Wald value, indicating that it is superior to all other forecasts.

Turning to the energy sector, XLE, which tracks the performance of the S&P Energy Select Sector Index. The index contains companies from the following industries: oil, gas and consumable fuels, and energy equipment and services. We notice that the MFIV improves upon the predictive performance of EWMA, and both of them are biased forecasts. The results that times-series forecast is biased and MFIV-related forecasts perform better in energy sector are in line with those of Szakmary et al. (2003) and Prokopczuk and Wese Simen (2014). Analyzing the adjusted-MFIV forecasts, we find that $AMFIV^{ir}$ is unbiased with 0.55 p-value of Wald test and has 0.47 adjusted R-square. We can conclude that $AMFIV^{ir}$ has the best performance among all the forecasts.

Taken together, we draw three conclusions from these univariate regressions. First, MFIV beats EWMA in all sectors, although both of them are biased. Second, in general, the MFIV-based forecasts yield more accurate forecasts than EWMA. Third, among adjusted MFIV models, we can conclude that $AMFIV^e$ performs worst and $AMFIV^{ir}$ dominates others. $AMFIV^h$ and $AMFIV^{ir}$ yield unbiased forecasts in every market.

Encompassing regressions We focus on encompassing regressions. We can conclude that one forecast provides information beyond another if its slope is statistically significant in encompassing regressions. In addition, we restrict the slope of EWMA to be equal to zero to further investigate if it adds any information relative to the other models. If the p-value is higher than 5%, we cannot reject the null hypothesis, which indicates that EWMA does not add any further information relative to the MFIV or its adjusted counterparts. Table 3.4 presents the results.

In SPX, the adjusted R-square ranges from 0.59 to 0.67 for univariate regression, while multivariate regression ranges from 0.60 to 0.67. All the coefficients of MFIV-related forecasts are significant from 0 and larger than that of EWMA except for $AMFIV^e$, suggesting that the forecasting performance is almost from baseline forecasts and the appropriate adjustment of MFIV is essential. Furthermore, the test statistics are generally larger than 5%, indicating that EWMA is statistically not more efficient than MFIV-adjusted forecasts. We can infer that

EWMA does not appear to incorporate any information beyond that of MFIV-related forecasts. For USO, adjusted R-square is almost not increased by EWMA, and the coefficients of the baseline forecast are all larger than that of EWMA. In addition, the slope of the baseline forecast is significant while that of EWMA is not. We check the values of Wald tests, and the null hypothesis cannot be rejected, strengthening the conclusion that the time-series forecast is less informative than MFIV-related forecasts. We turn to the study of relative efficiency in the gold and silver market, and their results are pretty similar. For GLD and SLV, the adjusted R-square is almost unchanged in encompassing regressions. The coefficients of MFIV $AMFIV^h$ and $AMFIV^{ir}$ are all significant, and that of their alternative forecast, EWMA, is not. It is easy to conclude that MFIV $AMFIV^h$ and $AMFIV^{ir}$ are more informational than EWMA, especially when we take their Wald test statistics which are all larger than 5% into account. In GDX, there is also no increase in explanatory power. The coefficients of MFIV, $AMFIV^h$, $AMFIV^{ar}$, and $AMFIV^{ir}$ are all significantly different from 0 and larger than that of the alternative forecast, EWMA. Apart from previous sectors, through the Wald test, only the result of $AMFIV^{ir}$ cannot reject the null hypothesis and contains more information than EWMA. In XLE, the explanatory power is still not improved by adding an alternative forecast. The coefficients of MFIV $AMFIV^h$ $AMFIV^{ar}$ and $AMFIV^{ir}$ are all significant, while that of EWMA are not. By the Wald test statistic, we get that the null hypothesis cannot be rejected in all encompassing regressions suggesting that all baseline forecasts are more informational than EWMA.

Overall, these results confirm that $AMFIV^{ir}$ subsumes the information in EWMA forecasts in all sectors. Furthermore, it generally provides the highest predictive power. Taking the results of our univariate and multivariate regressions together, we conclude that $AMFIV^{ir}$ outperforms all other forecasts.

3.4.2 Forecasting Accuracy

Until now, we have focused on the information content of volatility forecasts, in-sample performance. It is also important to assess the out-of-sample forecasting accuracy by using statistical loss functions to formally evaluate the competing models. As the realized volatility is not directly observable and our realized volatility is daily data. Following Patton (2011a), we employ two loss functions, MSE and QLIKE, to make our inference robust to the noise in the volatility series. The two loss functions are defined as follows:

$$MSE = \frac{1}{n}\sum_{t=1}^{n}(RV_{t,T} - f_{t,T})^2 \tag{3.4.2}$$

$$QLIKE = \frac{1}{n}\sum_{t=1}^{n}\left[\log(f_{t,T}) + \frac{RV_{t,T}}{f_{t,T}}\right] \tag{3.4.3}$$

where n is the number of forecasts, $RV_{t,T}$ is the realized volatility and $f_{t,T}$ is the corresponding forecasts, ERV, MFIV, $AMFIV^h$, $AMFIV^e$, $AMFIV^{ar}$, and $AMFIV^{ir}$, from forecasting model in Section 3.3. Thus the forecast horizon $T - t$ is 21 trading days and we use a rolling window of 232 observations to get the out-of-sample forecasts.[11] Since loss function measures the forecast error, it is obvious that the smaller the value of the loss function, the better performance of the forecasting model.

After analyzing the forecasting accuracy of the competing models, we assess whether the differences of forecast errors between competing volatility models are statistically significant. We calculate the differences between the forecast errors of model [name in row] and those of model [name in column]. In order to test whether the difference is significant, we employ Diebold-Mariano (DM) predictive accuracy test and non-parametric Wilcoxon signed rank test to assess the mean and median differences, respectively. Concerned with possible autocorrelation in overlapping forecast periods, we employ Newey-West estimators with 2 lags to calculate DM statistics. The figures in bold refer to statistical significance at 5% significant level.

All forecast errors measured by the two loss functions are reported in Table 3.5. We find that the rankings of models performance are consistent with our in-sample results. Starting with the MSE, we notice that the MSE of the EWMA

[11] In Section 3.5.3 we also consider a different rolling window as a robustness check.

is larger than that of the MFIV in most sectors. Generally, it is easy to infer that MFIV provides a more accurate forecast than the time-series model, EWMA. Consistent with Prokopczuk and Wese Simen (2014), the MSE of the $AMFIV^h$ is often smaller than that of the MFIV. Comparing all the forecasts in MSE criterion, $AMFIV^h$ is the second-best forecast in all areas except for GDX in which MFIV ranks second on accuracy order. $AMFIV^{ir}$ is the best forecast in all sectors.

Comparing EWMA and MFIV, we find that in all sectors, MFIV provides a smaller QLIKE than EWMA. Moreover, we can see that $AMFIV^h$ is more accurate than MFIV, confirming the study of Prokopczuk and Wese Simen (2014). Similarly, among MFIV-related forecasts, $AMFIV^{ir}$ beats $AMFIV^h$. Overall, $AMFIV^{ir}$ yields the best forecast. This is true for both the MSE and QLIKE criteria. These findings show that although it is necessary to adjust MFIV to forecast realized volatility, a decent model to forecast VRP is important and meaningful.

From previous tests, we observe that MFIV beats EWMA, $AMFIV^{ir}$ is superior to any other forecast. Now we turn to report whether these estimators from competing models have significant differences, and the test results are presented in Table 3.6. We can generally get several conclusions as follows. First, the differences between EWMA and MFIV are not statistically significant. Second, the $AMFIV^h$ indeed provides a more accurate forecast than MFIV, and the differences are statistically significant in most sectors. Third, the difference between $AMFIV^{ir}$ and $AMFIV^{h}$ not statistically significant.

3.5 Robustness Checks

In this section, we investigate the robustness of our findings by conducting several additional tests. First, we check whether our findings are robust when we use a more efficient estimator of realized volatility. Second, we study the robustness of our core results using the different functional forms of volatility risk premium rather than the log format. Third, we check whether our findings persist when we expand the length of our rolling window.

3.5.1 Alternative Estimator of Realized Volatility

Andersen and Bollerslev (1998) point out that it is quite important to pick a proper ex post evaluation criteria to assess variance forecasts. In multiple studies, including Bollerslev et al. (2009) and Bekaert and Hoerova (2014), it is standard to use 5-minute high frequency data to compute the realized variance to get a better estimator of variance. We follow Prokopczuk and Wese Simen (2014) and employ the range estimator developed by Garman and Klass (1980) and refined by Yang and Zhang (2000):

$$RV^{Z}_{t.T} = \sqrt{\frac{252}{T}\sum_{t=1}^{T}(\log O_t - \log C_{t-1})^2 + \frac{1}{2}(\log H_t - \log L_t)^2 - (2\log 2 - 1)(\log C_t - \log O_t)^2} \tag{3.5.1}$$

where O_t, H_t and L_t denote the opening, the daily high, and the daily low prices of the underlying on trading day t, respectively. C_{t-1} and C_t refer to the previous and current closing prices, respectively. The estimator includes the daily highest and daily lowest price information and also capture the overnight price. We repeat all the analyses with this more efficient estimator as a robustness check.

Table 3.7 shows the univariate regression findings. It presents results that are consistent with Table 3.2. It can be seen that MFIV performs better than EWMA in all sectors, although MFIV is a biased forecast. Among the MFIV-adjusted forecasts we propose in this study, we find that $AMFIV^{ir}$ consistently has the highest explanatory power in all the sectors, and the Wald test associated with the $AMFIV^{ir}$ does not lead to a rejection of the null hypothesis $\alpha = 0$ and $\beta = 1$ at 5% significant level. We thus conclude that the $AMFIV^{ir}$ is unbiased and performs the best.

Table 3.8 presents the values of the loss functions. Generally, MFIV beats EWMA, although the difference is small. After adjusting for the VRP, $AMFIV^{h}$, $AMFIV^{ar}$ and $AMFIV^{ir}$ are more accurate predictors of the future volatility than the MFIV. Among them, $AMFIV^{ir}$ yields the smallest errors in MSE and QLIKE criterion and performs best. In Table 3.9, we show the results of the statistical significance test of forecasting errors based on range estimator. Briefly, the values of the tests support the results that $AMFIV^{ir}$ is significantly better than EWMA, MFIV and $AMFIV^{e}$ and differences between $AMFIV^{h}$ and $AMFIV^{ar}$ are not significant.

3.5.2 Different Functional Form of the Volatility Risk Premium

Our study uses the format of log volatility risk premium, which is a nonlinear transformation of the volatility risk premium, and one may argue that the transformation may affect the statistical characteristics of VRP and introduce an upward bias. Since Chernov (2007) indicates that the volatility risk premium is the primary bias of volatility forecast, we use the level volatility risk premium directly to adjust the MFIV. However, volatility is less volatile than a variance. We repeat all the previous tests on level volatility risk premium and level variance risk premium in this robustness check sector. The adjusted-MFIV by level VRP format model is as follow:

$$AMFIV^{vol}_{t,t+\tau} = \max(MFIV_{t,t+\tau} - \mathbb{E}(VRP_{t,t+\tau}), 0) \qquad (3.5.2)$$

where $\mathbb{E}(VRP_{t,t+\tau})$ is the forecast of VRP at time t with forecasting horizon τ, and it can be estimated as discussed in Section 3.3.3 by equations (3.3.8), (3.3.11), (3.3.13) and (3.3.18) with the level VRP rather than $LVRP$. The adjusted-MFIV by level VRP^2 format model is as follow:

$$AMFIV_{t,t+\tau}^{VRP^2} =$$

$$\begin{cases} \sqrt{min(RV_{t-252,t}^2)} & \text{if } \mathbb{E}(VRP_{t,t+\tau}^2) \leq min(RV_{t-252,t}^2) \\ \sqrt{\max(MFIV_{t,t+\tau}^2 - \mathbb{E}(VRP_{t,t+\tau}^2), 0)} & \text{if } min(RV_{t-252,t}^2) \leq \mathbb{E}(VRP_{t,t+\tau}^2) \leq max(RV_{t-252,t}^2) \\ \sqrt{max(RV_{t-252,t}^2)} & \text{if } \mathbb{E}(VRP_{t,t+\tau}^2) \geq max(RV_{t-252,t}^2) \end{cases} \tag{3.5.3}$$

where $min(RV_{t-252,t}^2)$ and $max(RV_{t-252,t}^2)$ are the maximum and minimum realized variance over past 252 trading days respectively. $\mathbb{E}(VRP_{t,t+\tau}^2)$ is the forecast of VRP^2 at time t with forecasting horizon τ, and it can be estimated as models in Section 3.3.3 by Equations (3.3.8), (3.3.11), (3.3.13) and (3.3.18) with the level VRP^2 format rather than $LVRP$.

Prokopczuk and Wese Simen (2014) choose relative variance risk premium to decrease the dependence on the level of variance and show that the MFIV adjusted by the average relative variance risk premium is superior to the forecasts based on the GIR-GARCH forecast, ATM IV forecast, and MFIV. Kourtis et al. (2016) present that at the monthly horizon, the MFIV adjusted by the average relative variance risk premium is the best among HAR forecast, GJR-GARCH forecast, lagged realized volatility and MFIV. Inspired by them, we choose the MFIV adjusted by the average relative variance risk premium as one of the benchmarks to compare with other forecasts and the forecast is as follows:

$$RMFIV_{t,t+\tau} = \frac{MFIV_{t,t+\tau}}{\sqrt{ARVRP^2_{t,t+\tau}}} \tag{3.5.4}$$

where

$$ARVRP^2_{t,t+\tau} = \frac{1}{252-\tau} \sum_{i=t-252}^{t-\tau} \frac{MFIV^2_{i,i+\tau}}{RV^2_{i,i+\tau}} \tag{3.5.5}$$

We report the univariate regression results in the Table 3.10. It is easy to conclude that our main findings are consistent with a different format of volatility risk premium. In Table 3.10 for univariate regressions, the explanatory power of forecasts are quite similar with them in Table 3.2, indicating that the format of VRP has little effect on the performance of forecast. In line with previous findings, MFIV performs better than EWMA. $AMFIV^h$ can maintain the prediction power as MFIV and significantly reduce the Wald test values to make the forecast unbiased. $AMFIV^{ir}$ is the best among the other forecasts in an alternative format. It is also better than $RMFIV$ in all the sectors. In the Wald test, we can see that $AMFIV^{vol,ir}$ and $AMFIV^{VRP^2,ir}$ obviously decrease the Wald values compared with EWMA and MFIV. In most cases, $AMFIV^{vol,ir}$ and $AMFIV^{VRP^2,ir}$ have the lowest Wald values in relative format, confirming $AMFIV^{ir}$ is less biased.

Table 3.11 shows the forecast errors, and the results are of the same magnitude as those of Table 3.5. $AMFIV^{vol,ir}$ and $AMFIV^{VRP^2,ir}$ offer the smallest errors in all the sectors under MSE and QLIKE criteria in corresponding format forecasts. The difference of the forecasts from the same model in a different format is small. Table 3.12 and Table 3.13 report the difference of forecasting errors for forecasts obtained by level VRP format and VRP^2 format, respectively. In all the sectors under both criteria, the mean errors between $AMFIV^e$ and other forecasts in an upper triangle are all negative, while those between $AMFIV^{ir}$ and other forecasts are all positive for the two formats. In general, the forecasting error differences between $AMFIV^{ir}$ and others are significant, suggesting $AMFIV^{vol,ir}$ and $AMFIV^{VRP^2,ir}$ statistically dominate the other competing forecasts. Overall, we find that $AMFIV^{ir}$ beats its competitors.

3.5.3 Different Rolling Windows

So far, we use a rolling window of 232 trading days to estimate the value of $LVRP$ for the next period. Since the choice of 232 trading days may bring contingent findings, we expand our rolling windows to 484 trading days. We repeat all the tests by the alternative estimation periods and report the results in Table 3.14 3.15 and 3.16. Generally, the performance of the MFIV is superior to that of EWMA, suggesting that the time-series forecast is inferior to the model-free implied volatility. In line with Prokopczuk and Wese Simen (2014) and Kourtis et al. (2016), MFIV is biased and $AMFIV^h$ is unbiased. Our core conclusion that $AMFIV^{ir}$ is better than EWMA and any other MFIV-based forecasts are not driven by the choice of a specific rolling window, indicating that our adjustment is the best and robust.

3.5.4 Alternative benchmark

Kourtis et al. (2016) show that forecast by HAR model is superior than adjusted MFIV at the daily horizon. Although HAR model proposed by Corsi (2009) needs high-frequency data, Bollerslev et al. (2018) show that HAR model can be adjusted to daily data. The HAR model in our study is defined as:

$$RV_{t,t+\tau}^{HAR} = \beta_0 + \beta_D RV_{t-1,D} + \beta_W RV_{t-1,W} + \beta_M RV_{t-1,M} + \epsilon_t \tag{3.5.6}$$

where

$$\begin{aligned} RV_{t-1,D} &= \sqrt{R^2_{d_{t-1}}} \\ RV_{t-1,W} &= \sqrt{\frac{1}{5}\sum_{i=0}^{4} R^2_{d_{t-1}-i}} \\ RV_{t-1,M} &= \sqrt{\frac{1}{21}\sum_{i=0}^{20} R^2_{d_{t-1}-i}} \\ R^2_{d_{t-1}} &= \left(100 \times \log \frac{P_{d_{t-1}}}{P_{d_{t-1}-1}}\right)^2 \end{aligned}$$

$RV_{t,t+\tau}^{HAR}$ is the monthly forecasting volatility for next period τ. $RV_{t-1,D}$,$RV_{t-1,W}$ and $RV_{t-1,M}$ are realized volatility over different horizons. d_{t-1} is the date of last day on month $t-1$. All other variables are defined as previously. Consistently, we use the rolling window of 232 trading days to estimate the parameters of HAR model. We forecast realized volatility by HAR model and report the results in Table 3.17. Comparing Table 3.17 with Table 3.2 and 3.5, we can conclude that the performance of the forecast by HAR is generally inferior to that by EWMA and confirm that time-series forecast is inferior to the model-free implied volatility. Our core conclusion, that $AMFIV^{ir}$ is better than time-series forecasts and any other MFIV-based forecasts, keeps.

3.6 Conclusions

This chapter investigates how to model the volatility risk premium to correct the model-free implied volatility to forecast realized volatility. Many studies show that the gap between the implied volatility and realized volatility is informative about the bias for implied volatility forecast, and our study confirms this point. We employ four different kinds of time-series models to predict VRP and then use the VRP forecast to adjust MFIV to reduce the bias. Our analysis is carried out for 6 kinds of the index and show consistent findings. In general, MFIV beats EWMA, confirming the view that this time-series forecast is inferior to the model-free implied volatility. MFIV-based forecasts subsume EWMA information. The performance of $AMFIV^{ir}$ significantly dominates that of any other competitor, indicating that our adjustment of the MFIV improves the forecasting accuracy of the model-free implied volatility.

3.7 Tables and Appendices

Table 3.1: Summary Statistics

This table reports summary statistics of RV (realized volatility), IV (implied volatility) and VRP (volatility risk premium) and each panel corresponds to a different sector (SPX, USO, GLD, SLV, GDX and XLE sectors).Columns under Obs, Mean, SD(%), Skew, Kurt, Auto1, Auto2 report the sample observations, average, standard deviation in percentage, skewness, and kurtosis, lag1 autocorrelation, lag2 autocorrelation, respectively. Columns under t report the Newey-West t-statistics of the mean risk premiums computed with 2 lags.

Var	Obs	Mean	SD(%)	Skew	Kurt	Auto1	Auto2	t-stats
				SPX				
RV	166	14.92	10.57	3.17	17.13	0.74	0.57	11.84
IV	166	18.64	8.42	2.17	8.74	0.85	0.71	17.80
VRP	166	3.73	6.63	-3.19	21.20	0.27	0.04	6.16
				USO				
RV	126	30.88	14.62	1.41	5.44	0.79	0.66	15.03
IV	126	36.19	13.87	1.33	5.21	0.91	0.79	17.70
VRP	126	5.30	7.51	-0.73	3.81	0.18	0.06	6.99
				GLD				
RV	113	14.86	5.84	1.53	6.08	0.42	0.36	20.14
IV	113	18.05	4.92	0.80	4.18	0.76	0.60	25.09
VRP	113	3.18	4.86	-2.48	16.49	-0.04	0.07	6.98
				SLV				
RV	79	21.91	8.34	1.71	7.06	0.39	0.44	17.36
IV	79	27.09	6.64	0.45	2.59	0.79	0.67	22.95
VRP	79	5.17	7.14	-2.47	15.80	-0.09	0.22	6.35
				GDX				
RV	79	35.88	14.22	0.52	2.49	0.69	0.53	14.87
IV	79	36.93	9.57	0.29	2.25	0.82	0.64	21.62
VRP	79	1.06	9.65	-1.30	5.26	0.22	0.06	0.84
				XLE				
RV	79	18.19	7.42	1.13	3.90	0.61	0.48	14.90
IV	79	21.35	5.09	1.07	3.97	0.72	0.55	24.42
VRP	79	3.16	5.44	-1.27	5.06	0.13	0.12	4.61

Table 3.2: Univariate Regressions for Realized Volatility

This table presents results from univariate regressions of realized volatility on competing forecasts for SPX, USO, GLD, SLV, GDX and XLE sectors and each panel corresponds to a different sector. Each columns reports the regression results for a particular forecast in the sector. α and β denote the intercept and the slope coefficients, respectively. We present in brackets the Newey-West test statistic computed with 2 lags. Wald reports the Wald test statistics and p_wald reports the corresponding p-value of Wald test in testing the null hypothesis that α and β are jointly equal to zero and one, respectively. DW and Obs denote the Durbin-Watson test statistic and the number of observations, respectively.

	EWMA	MFIV	$AMFIV^h$	$AMFIV^{ar}$	$AMFIV^e$	$AMFIV^{ir}$		EWMA	MFIV	$AMFIV^h$	$AMFIV^{ar}$	$AMFIV^e$	$AMFIV^{ir}$
			SPX							**USO**			
α	3.50***	-3.21*	1.41	2.57***	5.38***	1.83*	α	6.52***	-1.99	3.10*	3.24*	8.64***	3.25**
	(3.26)	(-1.67)	(0.99)	(3.74)	(6.09)	(1.67)		(3.22)	(-1.03)	(1.75)	(1.78)	(4.53)	(2.43)
β	0.77***	0.97***	0.93***	0.87***	0.61***	0.89***	β	0.80***	0.91***	0.92***	0.91***	0.72***	0.90***
	(8.87)	(7.72)	(7.45)	(16.75)	(9.34)	(9.85)		(11.04)	(16.08)	(14.56)	(13.58)	(10.99)	(20.24)
Adj. R^2	0.59	0.61	0.59	0.54	0.64	0.67	Adj. R^2	0.62	0.74	0.73	0.71	0.65	0.77
Wald	5.88	41.95	1.37	7.04	19.13	1.80	Wald	5.34	25.05	1.83	1.82	10.27	2.97
p_wald	0.00	0.00	0.26	0.00	0.00	0.17	p_wald	0.01	0.00	0.16	0.17	0.00	0.06
DW	2.17	1.42	1.36	1.57	2.26	1.47	DW	2.14	1.62	1.58	1.49	2.42	1.52
Obs	166	166	166	166	166	166	Obs	126	126	126	126	126	126
			GLD							**SLV**			
α	8.00***	1.96	3.71**	4.74***	10.18***	3.14**	α	13.77***	2.62	6.28*	8.04**	15.72***	2.34
	(4.94)	(1.26)	(2.35)	(2.78)	(6.55)	(2.22)		(4.09)	(0.80)	(1.84)	(2.57)	(4.80)	(0.90)
β	0.47***	0.72***	0.78***	0.71***	0.31***	0.81***	β	0.37***	0.71***	0.73***	0.66***	0.28**	0.91***
	(4.88)	(9.19)	(7.96)	(7.13)	(3.48)	(8.60)		(2.65)	(5.93)	(4.58)	(4.43)	(2.12)	(6.16)
Adj. R^2	0.20	0.36	0.30	0.24	0.20	0.34	Adj. R^2	0.11	0.31	0.25	0.22	0.12	0.41
Wald	16.72	38.80	2.77	4.24	34.97	2.46	Wald	10.46	22.11	1.81	3.36	16.77	0.93
p_wald	0.00	0.00	0.07	0.02	0.00	0.09	p_wald	0.00	0.00	0.17	0.04	0.00	0.40
DW	2.23	2.02	1.84	1.51	2.24	1.73	DW	2.13	2.11	1.86	1.39	2.18	1.50
Obs	113	113	113	113	113	113	Obs	79	79	79	79	79	79
			GDX							**XLE**			
α	9.90***	-4.62	5.33	6.93*	15.63***	3.27	α	6.88***	-3.02	1.21	2.92	9.58***	1.68
	(3.50)	(-0.97)	(1.50)	(1.89)	(4.46)	(1.31)		(4.19)	(-1.23)	(0.61)	(1.62)	(5.27)	(0.93)
β	0.73***	1.10***	0.87***	0.82***	0.55***	0.93***	β	0.64***	0.99***	0.98***	0.87***	0.48***	0.93***
	(10.24)	(8.85)	(8.90)	(8.35)	(6.53)	(12.67)		(6.78)	(8.06)	(7.93)	(8.29)	(4.86)	(8.31)
Adj. R^2	0.50	0.54	0.51	0.51	0.48	0.60	Adj. R^2	0.35	0.46	0.45	0.43	0.32	0.47
Wald	7.44	0.67	1.14	1.82	15.91	0.97	Wald	8.80	11.96	1.04	1.48	14.76	0.60
p_wald	0.00	0.51	0.33	0.17	0.00	0.38	p_wald	0.00	0.00	0.36	0.23	0.00	0.55
DW	2.17	1.62	1.44	1.58	2.27	1.61	DW	2.08	1.66	1.57	1.66	2.07	1.56
Obs	79	79	79	79	79	79	Obs	79	79	79	79	79	79

Table 3.3: Encompassing Regressions for Realized Volatility

This table presents results from encompassing regressions of realized volatility on competing forecasts for SPX, USO, GLD, SLV, GDX and XLE sectors and each panel corresponds to a different sector. Columns report regression results for a particular forecast in the sector. EWMA and IV denote the slope coefficient of the forecast EWMA and the other MFIV-related forecast as reported in the column, respectively. α denote the intercept and in brackets we present the Newey-West test statistic computed with 2 lags. Wald reports the Wald test statistics and p_wald reports the corresponding p-value of Wald test in which we restrict the slope of EWMA to be equal to zero. DW and Obs denote the Durbin-Watson test statistic and the number of observations, respectively.

Var	EWMA+MFIV	EWMA+$AMFIV^h$	EWMA+$AMFIV^{ar}$	EWMA+$AMFIV^e$	EWMA+$AMFIV^{ir}$
			SPX		
EWMA	0.37*	0.41**	0.25	0.59	0.16*
	(1.68)	(2.07)	(1.09)	(1.60)	(1.97)
IV	0.55***	0.48***	0.44**	0.24	0.74***
	(2.81)	(2.89)	(2.10)	(0.63)	(7.00)
α	-0.89	1.86**	4.44***	2.80***	1.81*
	(-0.83)	(2.02)	(5.53)	(3.85)	(1.68)
Adj. R^2	0.63	0.62	0.65	0.60	0.67
Wald	2.81	4.27	1.19	2.57	3.90
p_wald	0.10	0.04	0.28	0.11	0.05
DW	1.82	1.84	2.34	2.04	1.62
Obs	166	166	166	166	166
			USO		
EWMA	-0.07	-0.06	0.26	0.16	0.07
	(-0.55)	(-0.49)	(1.57)	(1.51)	(0.66)
IV	0.97***	0.97***	0.50***	0.75***	0.84***
	(7.23)	(8.10)	(2.94)	(6.66)	(8.63)
α	-2.30	3.14*	7.36***	3.01*	3.05**
	(-1.16)	(1.74)	(4.14)	(1.66)	(2.11)
Adj. R^2	0.74	0.73	0.66	0.72	0.77
Wald	0.30	0.24	2.46	2.29	0.44
p_wald	0.59	0.62	0.12	0.13	0.51
DW	1.56	1.53	2.42	1.64	1.60
Obs	126	126	126	126	126
			GLD		
EWMA	-0.02	0.08	0.20	0.26***	0.08
	(-0.27)	(1.00)	(0.91)	(2.83)	(0.73)
IV	0.74***	0.69***	0.19	0.50***	0.73***
	(6.41)	(5.40)	(1.02)	(4.28)	(4.85)
α	1.93	3.72**	9.03***	3.94***	3.07**
	(1.23)	(2.33)	(5.42)	(2.71)	(2.20)
Adj. R^2	0.35	0.30	0.20	0.27	0.33
Wald	0.07	1.00	0.84	8.00	0.53
p_wald	0.79	0.32	0.36	0.01	0.47
DW	1.98	1.96	2.29	1.98	1.86
Obs	113	113	113	113	113

Table 3.3: Encompassing Regressions for Realized Volatility

Var	EWMA+MFIV	EWMA+$AMFIV^h$	EWMA+$AMFIV^{ar}$	EWMA+$AMFIV^e$	EWMA+$AMFIV^{ir}$
			SLV		
EWMA	0.02	**0.03**	0.02	-0.02	0.05
	(-0.68)	(0.11)	(1.01)	(2.17)	(0.41)
IV	0.77***	0.73***	0.16	0.55***	0.88***
	(5.35)	(4.26)	(0.90)	(4.83)	(5.11)
α	2.61	6.27*	14.58***	6.10*	1.98
	(0.79)	(1.81)	(4.59)	(1.96)	(0.74)
Adj. R^2	0.31	0.24	0.11	0.24	0.40
Wald	0.47	0.01	1.03	4.72	0.17
p_wald	0.50	0.91	0.31	0.03	0.68
DW	1.99	1.88	2.20	1.79	1.59
Obs	79	79	79	79	79
			GDX		
EWMA	0.28**	0.38***	0.49**	0.37***	0.11
	(2.34)	(2.74)	(2.26)	(2.66)	(0.92)
IV	0.73***	0.48***	0.20	0.45***	0.82***
	(3.69)	(2.94)	(0.99)	(2.79)	(6.44)
α	-1.14	5.67*	11.01***	6.86**	3.41
	(-0.24)	(1.77)	(3.82)	(2.09)	(1.38)
Adj. R^2	0.55	0.53	0.51	0.53	0.59
Wald	5.49	7.49	5.09	7.06	0.85
p_wald	0.02	0.01	0.03	0.01	0.36
DW	1.88	1.87	2.30	1.94	1.71
Obs	79	79	79	79	79
			XLE		
EWMA	0.10	0.11	0.46*	0.15	0.11
	(0.63)	(0.67)	(1.79)	(0.84)	(0.68)
IV	0.88***	0.86***	0.15	0.71***	0.82***
	(4.60)	(4.15)	(0.77)	(3.58)	(4.05)
α	-2.38	1.44	7.27***	2.97	1.71
	(-1.00)	(0.75)	(3.89)	(1.66)	(0.95)
Adj. R^2	0.45	0.44	0.34	0.43	0.47
Wald	0.39	0.45	3.22	0.71	0.46
p_wald	0.53	0.50	0.08	0.40	0.50
DW	1.74	1.68	2.13	1.79	1.67
Obs	79	79	79	79	79

Table 3.4: Encompassing Regressions for Realized Volatility

This table presents results from encompassing regressions of realized volatility on competing forecasts for SPX, USO, GLD, SLV, GDX and XLE sectors and each panel corresponds to a different sector. Columns report regression results for a particular forecast in the sector. EWMA and IV denote the slope coefficient of the forecast EWMA and the other MFIV-related forecast as reported in the column, respectively. α denote the intercept and in brackets we present the Newey-West test statistic computed with 2 lags. Wald reports the Wald test statistics and p_wald reports the corresponding p-value of Wald test in which we restrict the slope of EWMA to be equal to zero. DW and Obs denote the Durbin-Watson test statistic and the number of observations, respectively.

Var	EWMA+MFIV	EWMA+$AMFIV^h$	EWMA+$AMFIV^{ar}$	EWMA+$AMFIV^e$	EWMA+$AMFIV^{ir}$	Var	EWMA+MFIV	EWMA+$AMFIV^h$	EWMA+$AMFIV^{ar}$	EWMA+$AMFIV^e$	EWMA+$AMFIV^{ir}$
			SPX						**USO**		
EWMA	0.37*	0.41**	0.25	0.59	0.16*	EWMA	-0.07	-0.06	0.26	0.16	0.07
	(1.68)	(2.07)	(1.09)	(1.60)	(1.97)		(-0.55)	(-0.49)	(1.57)	(1.51)	(0.66)
IV	0.55***	0.48***	0.44**	0.24	0.74***	IV	0.97***	0.97***	0.50***	0.75***	0.84***
	(2.81)	(2.89)	(2.10)	(0.63)	(7.00)		(7.23)	(8.10)	(2.94)	(6.66)	(8.63)
α	-0.89	1.86**	4.44***	2.80***	1.81*	α	-2.30	3.14*	7.36***	3.01*	3.05**
	(-0.83)	(2.02)	(5.53)	(3.85)	(1.68)		(-1.16)	(1.74)	(4.14)	(1.66)	(2.11)
Adj. R^2	0.63	0.62	0.65	0.60	0.67	Adj. R^2	0.74	0.73	0.66	0.72	0.77
Wald	2.81	4.27	1.19	2.57	3.90	Wald	0.30	0.24	2.46	2.29	0.44
p_wald	0.10	0.04	0.28	0.11	0.05	p_wald	0.59	0.62	0.12	0.13	0.51
DW	1.82	1.84	2.34	2.04	1.62	DW	1.56	1.53	2.42	1.64	1.60
Obs	166	166	166	166	166	Obs	126	126	126	126	126
			GLD						**SLV**		
EWMA	-0.02	0.08	0.20	0.26***	0.08	EWMA	-0.07	0.01	0.17	0.19**	0.05
	(-0.27)	(1.00)	(0.91)	(2.83)	(0.73)		(-0.68)	(0.11)	(1.01)	(2.17)	(0.41)
IV	0.74***	0.69***	0.19	0.50***	0.73***	IV	0.77***	0.73***	0.16	0.55***	0.88***
	(6.41)	(5.40)	(1.02)	(4.28)	(4.85)		(5.35)	(4.26)	(0.90)	(4.83)	(5.11)
α	1.93	3.72**	9.03***	3.94***	3.07**	α	2.61	6.27*	14.58***	6.10*	1.98
	(1.23)	(2.33)	(5.42)	(2.71)	(2.20)		(0.79)	(1.81)	(4.59)	(1.96)	(0.74)
Adj. R^2	0.35	0.30	0.20	0.27	0.33	Adj. R^2	0.31	0.24	0.11	0.24	0.40
Wald	0.07	1.00	0.84	8.00	0.53	Wald	0.47	0.01	1.03	4.72	0.17
p_wald	0.79	0.32	0.36	0.01	0.47	p_wald	0.50	0.91	0.31	0.03	0.68
DW	1.98	1.96	2.29	1.98	1.86	DW	1.99	1.88	2.20	1.79	1.59
Obs	113	113	113	113	113	Obs	79	79	79	79	79
			GDX						**XLE**		
EWMA	0.28**	0.38***	0.49**	0.37***	0.11	EWMA	0.10	0.11	0.46*	0.15	0.11
	(2.34)	(2.74)	(2.26)	(2.66)	(0.92)		(0.63)	(0.67)	(1.79)	(0.84)	(0.68)
IV	0.73***	0.48***	0.20	0.45***	0.82***	IV	0.88***	0.86***	0.15	0.71***	0.82***
	(3.69)	(2.94)	(0.99)	(2.79)	(6.44)		(4.60)	(4.15)	(0.77)	(3.58)	(4.05)
α	-1.14	5.67*	11.01***	6.86**	3.41	α	-2.38	1.44	7.27***	2.97	1.71
	(-0.24)	(1.77)	(3.82)	(2.09)	(1.38)		(-1.00)	(0.75)	(3.89)	(1.66)	(0.95)
Adj. R^2	0.55	0.53	0.51	0.53	0.59	Adj. R^2	0.45	0.44	0.34	0.43	0.47
Wald	5.49	7.49	5.09	7.06	0.85	Wald	0.39	0.45	3.22	0.71	0.46
p_wald	0.02	0.01	0.03	0.01	0.36	p_wald	0.53	0.50	0.08	0.40	0.50
DW	1.88	1.87	2.30	1.94	1.71	DW	1.74	1.68	2.13	1.79	1.67
Obs	79	79	79	79	79	Obs	79	79	79	79	79

Table 3.5: Forecasting Errors

This table presents results of forecasting errors from competing forecasts for SPX, USO, GLD, SLV, GDX and XLE sectors and each panel corresponds to a different sector. MSE and QLIKE denote the forecasting loss functions. Obs denotes the number of observations. The forecast horizon is one month, 21 trading days in our study. We use a rolling window of 232 observations to get the out-of-sample forecasts.

Var	EWMA	MFIV	$AMFIV^h$	$AMFIV^{ar}$	$AMFIV^e$	$AMFIV^{ir}$
			SPX			
MSE	50.69	57.50	45.50	52.84	69.02	37.91
QLIKE	3.64	3.63	3.61	3.62	3.64	3.60
Obs	166	166	166	166	166	166
			USO			
MSE	87.98	84.13	57.83	62.27	94.23	51.29
QLIKE	4.38	4.37	4.36	4.36	4.38	4.36
Obs	126	126	126	126	126	126
			GLD			
MSE	35.92	33.56	24.52	27.28	62.80	22.96
QLIKE	3.71	3.69	3.68	3.69	3.72	3.67
Obs	113	113	113	113	113	113
			SLV			
MSE	84.68	77.05	53.91	57.98	118.89	40.43
QLIKE	4.11	4.09	4.08	4.09	4.12	4.06
Obs	79	79	79	79	79	79
			GDX			
MSE	112.32	93.07	99.79	102.20	167.48	81.07
QLIKE	4.55	4.54	4.54	4.54	4.56	4.53
Obs	79	79	79	79	79	79
			XLE			
MSE	41.56	39.15	30.54	31.50	58.33	28.59
QLIKE	3.89	3.88	3.87	3.87	3.89	3.86
Obs	79	79	79	79	79	79

Table 3.6: Difference of Forecasting Errors

This table presents differences of forecasting errors from competing forecasts for SPX, USO, GLD, SLV, GDX and XLE sectors under MSE and QLIKE criterion, respectively. Each panel corresponds to a different sector. We calculate the differences between the loss functions of model [name in row] and those of model [name in column]. The upper triangular matrices and lower triangular matrices report the mean and median difference of forecasting errors, respectively. For the upper triangular matrices, the values in bold indicate that the mean differences are statistically significant at the 5% level in the Diebold-Mariano (DM) test. Similarly, values in bold in lower triangular matrices indicate that the median differences are statistically significant at 5% level in the non-parametric Wilcoxon signed rank test.

Panel A: MSE

	EWMA	MFIV	$AMFIV^h$	$AMFIV^{ar}$	$AMFIV^e$	$AMFIV^{ir}$
			SPX			
EWMA		-6.81	5.19	-2.15	-18.32	**12.78**
MFIV	**15.53**		**12.00**	4.66	-11.52	**19.59**
$AMFIV^h$	**-2.82**	**-18.34**		-7.34	-23.52	7.59
$AMFIV^{ar}$	**-2.65**	**-18.18**	0.17		-16.18	14.93
$AMFIV^e$	2.57	**-12.96**	**5.39**	**5.22**		**31.11**
$AMFIV^{ir}$	**-4.20**	**-19.73**	-1.39	-1.55	**-6.77**	
			USO			
EWMA		3.85	**30.15**	**25.72**	-6.25	**36.69**
MFIV	8.87		**26.30**	**21.86**	-10.10	**32.84**
$AMFIV^h$	**-11.82**	**-20.69**		-4.44	**-36.40**	6.54
$AMFIV^{ar}$	**-8.53**	**-17.40**	3.29		**-31.97**	**10.98**
$AMFIV^e$	0.38	-8.50	**12.19**	**8.90**		**42.94**
$AMFIV^{ir}$	**-14.41**	**-23.28**	-2.59	**-5.88**	**-14.79**	
			GLD			
EWMA		2.36	**11.40**	**8.64**	-26.87	**12.96**
MFIV	**4.25**		**9.04**	6.28	-29.24	**10.60**
$AMFIV^h$	**-5.70**	**-9.95**		-2.76	-38.27	1.56
$AMFIV^{ar}$	**-5.77**	**-10.02**	-0.08		-35.52	4.31
$AMFIV^e$	-2.15	-6.40	**3.55**	**3.63**		39.83
$AMFIV^{ir}$	**-6.69**	**-10.94**	**-0.99**	**-0.92**	**-4.54**	
			SLV			
EWMA		7.62	**30.77**	26.70	-34.21	44.25
MFIV	8.24		**23.15**	19.07	-41.84	**36.62**
$AMFIV^h$	**-9.67**	**-17.92**		-4.07	-64.98	13.48
$AMFIV^{ar}$	**-8.16**	**-16.40**	1.51		-60.91	17.55
$AMFIV^e$	8.39	0.15	**18.06**	**16.55**		78.46
$AMFIV^{ir}$	**-9.76**	**-18.00**	-0.08	**-1.60**	**-18.15**	
			GDX			
EWMA		19.25	12.53	10.12	-55.16	**31.25**
MFIV	-12.05		-6.72	-9.13	-74.41	12.00
$AMFIV^h$	-21.38	-9.33		-2.41	-67.69	**18.72**
$AMFIV^{ar}$	-23.20	-11.15	-1.82		-65.28	**21.13**
$AMFIV^e$	-13.38	-1.33	7.99	9.81		**86.41**
$AMFIV^{ir}$	**-34.40**	-22.35	**-13.02**	**-11.20**	**-21.02**	
			XLE			
EWMA		2.41	**11.02**	**10.06**	-16.77	**12.97**
MFIV	6.46		8.61	7.65	-19.18	10.56
$AMFIV^h$	**-7.69**	**-14.16**		-0.96	-27.79	1.95
$AMFIV^{ar}$	**-6.02**	**-12.48**	1.67		-26.83	2.91
$AMFIV^e$	-1.88	-8.34	**5.82**	**4.15**		29.74
$AMFIV^{ir}$	**-8.07**	**-14.53**	-0.37	-2.05	**-6.19**	

Table 3.6: Difference of Forecasting Errors

Panel B: QLIKE

	EWMA	MFIV	$AMFIV^h$	$AMFIV^{ar}$	$AMFIV^e$	$AMFIV^{ir}$
			SPX			
EWMA		0.00	**0.03**	0.02	-0.01	**0.03**
MFIV	**0.07**		**0.02**	0.02	-0.01	**0.03**
$AMFIV^h$	**-0.02**	**-0.09**		-0.01	**-0.03**	**0.01**
$AMFIV^{ar}$	**-0.03**	**-0.10**	-0.01		-0.03	0.01
$AMFIV^e$	0.01	-0.06	**0.03**	**0.04**		**0.04**
$AMFIV^{ir}$	**-0.02**	**-0.09**	0.00	**0.01**	**-0.03**	
			USO			
EWMA		0.00	**0.01**	**0.01**	-0.01	**0.02**
MFIV	-0.01		0.01	0.01	-0.01	**0.01**
$AMFIV^h$	**0.00**	**0.00**		0.00	**-0.02**	**0.00**
$AMFIV^{ar}$	**-0.02**	**-0.01**	-0.02		**-0.02**	**0.01**
$AMFIV^e$	0.01	0.02	**0.02**	**0.03**		**0.03**
$AMFIV^{ir}$	**-0.01**	**-0.01**	-0.01	**0.01**	**-0.02**	
			GLD			
EWMA		0.02	**0.02**	0.02	-0.01	**0.03**
MFIV	0.00		0.01	0.00	-0.03	**0.02**
$AMFIV^h$	**-0.03**	**-0.03**		-0.01	-0.04	0.01
$AMFIV^{ar}$	**-0.03**	**-0.03**	0.00		-0.03	0.02
$AMFIV^e$	-0.02	-0.02	**0.01**	**0.01**		0.05
$AMFIV^{ir}$	**-0.03**	**-0.03**	**0.00**	**0.00**	**-0.01**	
			SLV			
EWMA		0.02	**0.03**	0.02	-0.02	0.05
MFIV	0.02		0.01	0.00	-0.04	**0.03**
$AMFIV^h$	**-0.01**	**-0.04**		-0.01	-0.05	0.02
$AMFIV^{ar}$	**-0.01**	**-0.04**	0.00		-0.04	0.03
$AMFIV^e$	0.01	-0.01	**0.02**	**0.02**		0.06
$AMFIV^{ir}$	**-0.01**	**-0.04**	0.00	**0.00**	**-0.02**	
			GDX			
EWMA		0.01	0.00	0.00	-0.01	**0.01**
MFIV	0.00	0.00	-0.02	0.01		
$AMFIV^h$	0.01	0.02		0.00	-0.02	**0.01**
$AMFIV^{ar}$	0.00	0.01	-0.01		-0.01	**0.01**
$AMFIV^e$	0.00	0.01	0.00	0.01		**0.03**
$AMFIV^{ir}$	**-0.01**	0.00	**-0.01**	**0.00**	**-0.01**	
			XLE			
EWMA		0.01	**0.03**	**0.02**	0.00	**0.03**
MFIV	0.01		0.01	0.01	-0.02	0.02
$AMFIV^h$	**-0.01**	**-0.02**		0.00	**-0.03**	0.00
$AMFIV^{ar}$	**-0.01**	**-0.02**	0.00		**-0.03**	0.00
$AMFIV^e$	0.00	-0.01	**0.02**	**0.02**		**0.03**
$AMFIV^{ir}$	**-0.01**	**-0.02**	0.00	0.00	**-0.02**	

Table 3.7: Univariate Regressions: Alternative Realized Volatility

This table presents results from univariate regressions of realized volatility on competing forecasts for SPX, USO, GLD, SLV, GDX and XLE sectors and each panel corresponds to a different sector. Realized volatility is calculated by Equation 3.5.1. Each columns reports the regression results for a particular forecast in the sector. α and β denote the intercept and the slope coefficients, respectively. We present in brackets the Newey-West test statistic computed with 2 lags. Wald reports the Wald test statistics and p_wald reports the corresponding p-value of Wald test in testing the null hypothesis that α and β are jointly equal to zero and one, respectively. DW and Obs denote the Durbin-Watson test statistic and the number of observations, respectively.

Var	EWMA	MFIV	$AMFIV^h$	$AMFIV^{ar}$	$AMFIV^e$	$AMFIV^{ir}$	Var	EWMA	MFIV	$AMFIV^h$	$AMFIV^{ar}$	$AMFIV^e$	$AMFIV^{ir}$
			SPX							**USO**			
α	3.17***	-1.30	1.22	1.64**	4.39***	0.70	α	4.17**	-4.34**	1.37	1.41	6.85***	1.97*
	(4.84)	(-0.86)	(1.09)	(2.33)	(5.77)	(0.53)		(2.28)	(-2.34)	(0.89)	(0.96)	(3.95)	(1.97)
β	0.75***	0.73***	0.92***	0.89***	0.62***	0.96***	β	0.87***	0.99***	0.97***	0.97***	0.78***	0.94***
	(11.39)	(7.48)	(7.90)	(11.50)	(8.97)	(7.36)		(13.03)	(17.36)	(16.95)	(17.79)	(12.82)	(26.42)
Adj. R^2	0.56	0.61	0.61	0.57	0.63	0.68	Adj. R^2	0.75	0.82	0.81	0.80	0.75	0.84
Wald	11.93	174.83	1.35	3.89	16.80	0.66	Wald	3.12	32.11	0.70	0.73	8.17	1.95
p_wald	0.00	0.00	0.26	0.02	0.00	0.52	p_wald	0.05	0.00	0.50	0.48	0.00	0.15
DW	1.96	1.39	1.42	1.54	2.17	1.34	DW	2.04	1.63	1.53	1.58	2.36	1.49
Obs	166	166	166	166	166	166	Obs	126	126	126	126	126	126
			GLD							**SLV**			
α	6.05***	3.20***	4.22***	5.19***	9.12***	2.49**	α	10.02***	5.68***	7.07***	8.14***	14.19***	3.30*
	(5.15)	(2.67)	(3.56)	(3.78)	(8.02)	(2.12)		(4.60)	(2.93)	(3.37)	(3.55)	(6.60)	(1.85)
β	0.60***	0.65***	0.73***	0.66***	0.38***	0.84***	β	0.57***	0.65***	0.71***	0.66***	0.38***	0.85***
	(8.13)	(10.33)	(9.44)	(8.05)	(5.79)	(10.46)		(6.88)	(10.67)	(8.70)	(7.72)	(5.21)	(10.56)
Adj. R^2	0.34	0.44	0.41	0.33	0.33	0.45	Adj. R^2	0.31	0.43	0.41	0.36	0.27	0.49
Wald	15.16	53.18	6.55	8.48	48.52	2.25	Wald	14.81	57.91	6.54	8.24	50.90	1.71
p_wald	0.00	0.00	0.00	0.00	0.00	0.11	p_wald	0.00	0.00	0.00	0.00	0.00	0.19
DW	2.19	1.83	1.72	1.54	2.22	1.67	DW	2.19	1.85	1.76	1.48	2.17	1.61
Obs	113	113	113	113	113	113	Obs	79	79	79	79	79	79
			GDX							**XLE**			
α	8.04***	-1.39	3.45	4.82	12.83***	3.54	α	6.21***	-2.59	0.65	2.46	9.49***	0.03
	(3.45)	(-0.40)	(1.10)	(1.58)	(4.46)	(1.29)		(3.95)	(-0.99)	(0.30)	(1.22)	(5.56)	(0.02)
β	0.76***	0.94***	0.91***	0.86***	0.61***	0.91***	β	0.68***	1.01***	1.01***	0.89***	0.49***	1.02***
	(11.56)	(9.98)	(9.70)	(9.78)	(7.86)	(10.51)		(8.23)	(7.53)	(7.71)	(7.81)	(5.83)	(8.79)
Adj. R^2	0.57	0.62	0.58	0.60	0.55	0.63	Adj. R^2	0.44	0.49	0.49	0.49	0.40	0.54
Wald	6.46	7.44	0.64	1.27	13.66	1.01	Wald	7.98	9.17	0.77	0.94	17.77	0.15
p_wald	0.00	0.00	0.53	0.29	0.00	0.37	p_wald	0.00	0.00	0.47	0.40	0.00	0.86
DW	1.97	1.53	1.34	1.49	2.24	1.44	DW	2.04	1.64	1.60	1.85	2.09	1.73
Obs	79	79	79	79	79	79	Obs	79	79	79	79	79	79

Table 3.8: Forecasting Errors: Alternative Realized Volatility

This table presents results of forecasting errors from competing forecasts for SPX, USO, GLD, SLV, GDX and XLE sectors and each panel corresponds to a different sector. Realized volatility is calculated by Equation 3.5.1. Columns report regression results for a particular forecast in the sector. MSE and QLIKE denote the forecasting loss functions. Obs denote the number of observations. The forecast horizon is one month, 21 trading days in our study. We use a rolling window of 232 observations to get the out-of-sample forecasts.

Variables	EWMA	MFIV	$AMFTV^h$	$AMFTV^{ar}$	$AMFTV^e$	$AMFTV^{ir}$
			SPX			
MSE	69.88	30.80	24.16	26.81	37.66	19.85
QLIKE	3.50	3.44	3.43	3.43	3.44	3.42
Obs	166	166	166	166	166	166
			USO			
MSE	62.26	61.31	43.15	46.77	71.00	37.74
QLIKE	4.39	4.38	4.38	4.38	4.39	4.38
Obs	126	126	126	126	126	126
			GLD			
MSE	25.17	18.37	14.65	17.09	35.47	12.87
QLIKE	3.70	3.70	3.69	3.69	3.71	3.68
Obs	113	113	113	113	113	113
			SLV			
MSE	43.73	35.74	27.44	30.34	59.80	21.69
QLIKE	4.14	4.14	4.13	4.13	4.15	4.12
Obs	79	79	79	79	79	79
			GDX			
MSE	61.55	62.46	55.17	53.25	87.14	47.86
QLIKE	4.48	4.48	4.48	4.47	4.48	4.47
Obs	79	79	79	79	79	79
			XLE			
MSE	32.47	34.20	26.87	26.72	53.16	23.95
QLIKE	3.91	3.91	3.90	3.90	3.92	3.90
Obs	79	79	79	79	79	79

Table 3.9: Difference of Forecasting Errors: Alternative Realized Volatility

This table presents differences of forecasting errors from competing forecasts for SPX, USO, GLD, SLV, GDX and XLE sectors under MSE and QLIKE criterion, respectively. Realized volatility is calculated based on Equation (3.5.1). Each panel corresponds to a different sector. We calculate the differences between the loss functions of model [name in row] and those of model [name in column]. The upper triangular matrices and lower triangular matrices report the mean and median difference of forecasting errors, respectively. For the upper triangular matrices, the values in bold indicate that the mean differences are statistically significant at the 5% level in the Diebold-Mariano (DM) test. Similarly, values in bold in lower triangular matrices indicate that the median differences are statistically significant at 5% level in the non-parametric Wilcoxon signed rank test.

Panel A: MSE

Variables	EWMA	MFIV	$AMFIV^h$	$AMFIV^{ar}$	$AMFIV^e$	$AMFIV^{ir}$
SPX						
EWMA		**-39.08**	**6.65**	3.99	-6.85	**10.95**
MFIV	**35.10**		**45.73**	**43.07**	**32.23**	**50.03**
$AMFIV^h$	0.03	**-35.07**		-2.66	-13.50	4.30
$AMFIV^{ar}$	**-0.22**	**-35.32**	-0.25		-10.84	6.96
$AMFIV^e$	0.17	**-34.93**	0.14	0.39		17.80
$AMFIV^{ir}$	**-0.72**	**-35.82**	**-0.75**	**-0.50**	-0.89	
USO						
EWMA		-0.95	**18.16**	14.54	-9.70	**23.57**
MFIV	**22.51**		**19.11**	15.48	-8.75	**24.52**
$AMFIV^h$	**-4.31**	**-26.82**		-3.62	**-27.86**	5.41
$AMFIV^{ar}$	**-0.96**	**-23.47**	3.35		**-24.23**	9.04
$AMFIV^e$	6.87	-15.64	**11.18**	**7.83**		**33.27**
$AMFIV^{ir}$	**-1.79**	**-24.30**	2.52	-0.83	**-8.66**	
GLD						
EWMA		**-6.79**	**3.72**	1.29	-17.09	**5.51**
MFIV	**7.53**		**10.51**	**8.08**	-10.30	**12.30**
$AMFIV^h$	**-1.77**	**-9.30**		-2.43	**-20.82**	1.79
$AMFIV^{ar}$	-1.80	**-9.34**	-0.03		**-18.38**	**4.22**
$AMFIV^e$	1.24	**-6.30**	**3.01**	**3.04**		**22.60**
$AMFIV^{ir}$	**-1.85**	**-9.38**	-0.08	**-0.05**	**-3.09**	
SLV						
EWMA		-7.98	8.31	5.40	-24.06	**14.05**
MFIV	5.47		**16.29**	13.39	-16.08	**22.03**
$AMFIV^h$	-2.48	**-7.94**		-2.90	**-32.36**	5.74
$AMFIV^{ar}$	-1.49	**-6.95**	0.99		**-29.46**	8.65
$AMFIV^e$	1.28	-4.19	**3.76**	**2.77**		**38.11**
$AMFIV^{ir}$	**-7.10**	**-12.57**	**-4.63**	**-5.62**	**-8.38**	
GDX						
EWMA		0.90	7.29	9.21	-24.68	14.60
MFIV	18.49		6.38	8.31	-25.58	13.69
$AMFIV^h$	3.52	**-14.96**		1.93	-31.97	7.31
$AMFIV^{ar}$	3.66	**-14.82**	0.14		-33.89	5.39
$AMFIV^e$	-6.18	-24.66	-9.70	-9.84		**39.28**
$AMFIV^{ir}$	-5.81	**-24.30**	**-9.34**	**-9.48**	**0.36**	
XLE						
EWMA		1.72	7.33	**7.48**	-18.96	**10.25**
MFIV	6.95		5.60	5.76	-20.69	**8.52**
$AMFIV^h$	**-3.05**	**-10.01**		0.16	-26.29	2.92
$AMFIV^{a}r$	**-3.09**	**-10.05**	-0.04		-26.45	2.76
$AMFIV^e$	1.37	-5.58	**4.43**	**4.47**		29.21
$AMFIV^{ir}$	**-3.29**	**-10.24**	-0.24	-0.19	**-4.66**	

Table 3.9: Difference of Forecasting Errors: Alternative Realized Volatility

Panel B: QLIKE

VARIABLES	EWMA	MFIV	$AMFIV^h$	$AMFIV^{ar}$	$AMFIV^e$	$AMFIV^{ir}$
			SPX			
EWMA		**-0.06**	**0.01**	0.01	0.00	**0.02**
MFIV	**0.10**		**0.08**	**0.07**	**0.07**	**0.08**
$AMFIV^h$	**0.00**	**-0.10**		0.00	-0.01	**0.01**
$AMFIV^{ar}$	**-0.01**	**-0.10**	0.00		-0.01	0.01
$AMFIV^e$	0.01	**-0.08**	**0.02**	**0.02**		**0.02**
$AMFIV^{ir}$	**-0.01**	**-0.11**	**-0.01**	**0.00**	**-0.02**	
			USO			
EWMA		0.00	**0.01**	0.00	0.00	**0.01**
MFIV	**0.01**		**0.01**	0.01	0.00	**0.01**
$AMFIV^h$	**0.00**	**-0.01**		0.00	**-0.01**	0.00
$AMFIV^{ar}$	0.00	**-0.01**	0.00		**-0.01**	**0.00**
$AMFIV^e$	0.00	-0.02	**-0.01**	**0.00**		**0.01**
$AMFIV^{ir}$	**-0.01**	**-0.02**	-0.01	-0.01	**0.00**	
			GLD			
EWMA		0.00	**0.01**	0.01	-0.01	**0.02**
MFIV	**0.00**		**0.01**	0.01	-0.01	**0.02**
$AMFIV^h$	**-0.02**	**-0.02**		0.00	**-0.02**	0.01
$AMFIV^{ar}$	-0.02	**-0.02**	0.00		**-0.02**	**0.01**
$AMFIV^e$	-0.01	0.00	**0.02**	**0.01**		**0.03**
$AMFIV^{ir}$	**-0.02**	**-0.02**	0.00	**0.00**	**-0.02**	
			SLV			
EWMA		0.00	0.00	0.00	-0.01	**0.01**
MFIV	0.01		0.01	0.00	-0.01	**0.01**
$AMFIV^h$	0.00	**-0.02**		0.00	**-0.02**	0.01
$AMFIV^{ar}$	-0.01	**-0.02**	0.00		**-0.01**	0.01
$AMFIV^e$	0.01	0.00	**0.01**	**0.02**		**0.02**
$AMFIV^{ir}$	0.00	**-0.02**	**0.00**	**0.00**	**-0.01**	
			GDX			
EWMA		0.00	0.00	0.00	-0.01	0.01
MFIV	0.02		0.00	0.00	0.00	0.01
$AMFIV^h$	0.02	0.00		0.00	-0.01	**0.00**
$AMFIV^{ar}$	0.01	**-0.01**	-0.01		-0.01	**0.00**
$AMFIV^e$	0.00	-0.02	-0.02	-0.01		**0.01**
$AMFIV^{ir}$	0.01	**-0.01**	**-0.01**	**0.00**	0.01	
			XLE			
EWMA		0.00	0.01	**0.01**	0.00	**0.01**
MFIV	0.01	0.01	0.00	**0.01**		
$AMFIV^h$	**0.00**	**-0.01**		0.00	-0.01	0.00
$AMFIV^{a}r$	**0.00**	**-0.01**	0.00		**-0.01**	0.00
$AMFIV^e$	0.03	0.01	**0.03**	**0.03**		**0.01**
$AMFIV^{ir}$	**0.00**	**-0.01**	0.00	0.00	**-0.03**	

Table 3.10: Univariate Regressions: Different VRP Formats

This table presents results from univariate regressions of realized volatility on competing forecasts for SPX, USO, GLD, SLV, GDX and XLE sectors and each panel corresponds to a different sector. We forecast VRP in level VRP and VRP^2 format and denote the forecast from different format with superscript *vol* and VRP^2, respectively. Each columns reports the regression results for a particular forecast in the sector. α and β denote the intercept and the slope coefficients, respectively. We present in brackets the Newey-West test statistic computed with 2 lags. Wald reports the Wald test statistics and p_wald reports the corresponding p-value of Wald test in testing the null hypothesis that α and β are jointly equal to zero and one, respectively. DW and Obs denote the Durbin-Watson test statistic and the number of observations, respectively.

Variables	EWMA	MFIV	RMFIV	$AMFIV^{vol,h}$	$AMFIV^{vol,ar}$	$AMFIV^{vol,e}$	$AMFIV^{vol,ir}$	$AMFIV^{VRP^2,h}$	$AMFIV^{VRP^2,ar}$	$AMFIV^{VRP^2,e}$	$AMFIV^{VRP^2,ir}$
						SPX					
α	3.50***	-3.21*	0.77	2.09	4.36***	4.72***	2.04***	3.34***	4.38***	4.29***	1.71**
	(3.26)	(-1.67)	(0.51)	(1.62)	(4.86)	(5.02)	(2.85)	(2.73)	(6.81)	(3.88)	(2.01)
β	0.77***	0.97***	1.06***	0.86***	0.70***	0.69***	0.84***	0.78***	0.70***	0.75***	0.83***
	(8.87)	(7.72)	(7.46)	(7.67)	(16.78)	(9.09)	(16.42)	(7.15)	(14.87)	(8.23)	(12.90)
Adj. R^2	0.59	0.61	0.61	0.60	0.52	0.61	0.75	0.58	0.51	0.60	0.74
Wald	5.88	41.95	5.29	1.60	25.01	13.25	5.04	4.68	28.35	10.28	3.71
p_wald	0.00	0.00	0.01	0.20	0.00	0.00	0.01	0.01	0.00	0.00	0.03
DW	2.17	1.42	1.37	1.41	1.74	2.24	1.41	1.36	1.57	2.18	1.28
Obs	166	166	166	166	166	166	166	166	166	166	166
						USO					
α	6.52***	-1.99	3.22*	4.97***	5.11***	9.00***	2.96**	6.73***	6.85***	8.46***	2.76*
	(3.22)	(-1.03)	(1.81)	(3.23)	(3.09)	(4.99)	(2.21)	(4.87)	(4.54)	(4.88)	(1.92)
β	0.80***	0.91***	0.96***	0.85***	0.84***	0.73***	0.90***	0.81***	0.81***	0.75***	0.89***
	(11.04)	(16.08)	(14.45)	(15.67)	(14.11)	(11.41)	(20.74)	(16.13)	(14.39)	(12.56)	(18.96)
Adj. R^2	0.62	0.74	0.73	0.75	0.72	0.65	0.77	0.76	0.73	0.66	0.77
Wald	5.34	25.05	5.09	5.28	4.87	12.91	2.72	12.53	11.16	12.39	2.88
p_wald	0.01	0.00	0.01	0.01	0.01	0.00	0.07	0.00	0.00	0.00	0.06
DW	2.14	1.62	1.57	1.71	1.55	2.42	1.58	1.83	1.63	2.39	1.47
Obs	126	126	126	126	126	126	126	126	126	126	126
						GLD					
α	8.00***	1.96	2.88	5.52***	6.88***	9.38***	3.55***	6.68***	7.14***	8.37***	3.74***
	(4.94)	(1.26)	(1.62)	(3.97)	(3.79)	(6.18)	(2.91)	(5.07)	(4.60)	(5.63)	(3.25)
β	0.47***	0.72***	0.88***	0.65***	0.56***	0.37***	0.75***	0.57***	0.54***	0.46***	0.72***
	(4.88)	(9.19)	(7.60)	(7.87)	(5.48)	(4.28)	(9.19)	(7.43)	(6.11)	(5.05)	(8.47)
Adj. R^2	0.20	0.36	0.30	0.30	0.23	0.22	0.34	0.30	0.26	0.25	0.35
Wald	16.72	38.80	3.47	9.09	10.44	27.91	4.56	15.21	13.86	17.87	5.70
p_wald	0.00	0.00	0.03	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00
DW	2.23	2.02	1.85	1.85	1.47	2.26	1.83	1.85	1.59	2.30	1.75
Obs	113	113	113	113	113	113	113	113	113	113	113

Table 3.10: Univariate Regressions: Different VRP Formats

Variables	EWMA	MFIV	RMFIV	$AMFIV^{vol,h}$	$AMFIV^{vol,ar}$	$AMFIV^{vol,e}$	$AMFIV^{vol,ir}$	$AMFIV^{VRP^2,h}$	$AMFIV^{VRP^2,ar}$	$AMFIV^{VRP^2,e}$	$AMFIV^{VRP^2,ir}$
						SLV					
α	13.77***	2.62	5.18	8.35**	11.08***	15.05***	4.73**	10.33***	11.64***	13.76***	6.49**
	(4.09)	(0.80)	(1.38)	(2.62)	(3.18)	(4.49)	(2.00)	(3.88)	(4.20)	(4.91)	(2.55)
β	0.37***	0.71***	0.84***	0.63***	0.51***	0.32**	0.77***	0.54***	0.48***	0.38***	0.66***
	(2.65)	(5.93)	(4.45)	(4.50)	(3.49)	(2.28)	(5.89)	(4.70)	(4.08)	(3.23)	(4.92)
Adj. R^2	0.11	0.31	0.24	0.26	0.21	0.12	0.37	0.27	0.24	0.16	0.36
Wald	10.46	22.11	3.03	3.54	5.65	12.81	2.16	7.90	9.49	13.64	3.26
p_wald	0.00	0.00	0.05	0.03	0.01	0.00	0.12	0.00	0.00	0.00	0.04
DW	2.13	2.11	1.87	1.95	1.38	2.19	1.71	1.93	1.55	2.28	1.56
Obs	79	79	79	79	79	79	79	79	79	79	79
						GDX					
α	9.90***	-4.62	4.86	6.15*	7.87**	14.09***	3.03	7.47**	9.14***	12.70***	2.53
	(3.50)	(-0.97)	(1.36)	(1.86)	(2.42)	(4.35)	(1.28)	(2.44)	(3.17)	(4.02)	(1.12)
β	0.73***	1.10***	0.92***	0.84***	0.79***	0.61***	0.91***	0.79***	0.75***	0.67***	0.91***
	(10.24)	(8.85)	(8.88)	(9.30)	(9.35)	(7.75)	(13.90)	(9.56)	(10.19)	(8.51)	(14.38)
Adj. R^2	0.50	0.54	0.50	0.52	0.53	0.49	0.63	0.52	0.53	0.50	0.64
Wald	7.44	0.67	1.88	1.78	3.28	12.59	0.98	3.18	5.85	9.13	1.24
p_wald	0.00	0.51	0.16	0.18	0.04	0.00	0.38	0.05	0.00	0.00	0.29
DW	2.17	1.62	1.41	1.46	1.64	2.29	1.79	1.45	1.67	2.26	1.74
Obs	79	79	79	79	79	79	79	79	79	79	79
						XLE					
α	6.88***	-3.02	0.73	2.60	3.52**	9.02***	0.74	4.43***	4.79***	8.75***	0.73
	(4.19)	(-1.23)	(0.35)	(1.54)	(2.02)	(5.64)	(0.39)	(3.05)	(3.24)	(5.69)	(0.39)
β	0.64***	0.99***	1.08***	0.89***	0.82***	0.52***	0.96***	0.79***	0.76***	0.55***	0.93***
	(6.78)	(8.06)	(7.75)	(8.27)	(7.83)	(5.73)	(8.29)	(8.36)	(8.01)	(5.99)	(8.10)
Adj. R^2	0.35	0.46	0.45	0.48	0.46	0.33	0.49	0.49	0.48	0.33	0.49
Wald	8.80	11.96	3.82	1.75	2.16	16.04	0.09	5.72	5.71	16.30	0.28
p_wald	0.00	0.00	0.03	0.18	0.12	0.00	0.91	0.00	0.00	0.00	0.76
DW	2.08	1.66	1.56	1.68	1.70	2.12	1.53	1.70	1.62	2.04	1.44
Obs	79	79	79	79	79	79	79	79	79	79	79

Table 3.11: Forecasting Errors: Different VRP Format

This table presents results of forecasting errors from competing forecasts for SPX, USO, GLD, SLV, GDX and XLE sectors and each panel corresponds to a different sector. We forecast VRP in level VRP and VRP^2 format and denote the forecast from different format with superscript *vol* and VRP^2, respectively. MSE and QLIKE denote the forecasting errors in the corresponding criterion. Obs denotes the number of observations. The forecast horizon is one month, i.e. 21 trading days in our study. We use a rolling window of 232 observations to get the out-of-sample forecasts.

Variables	EWMA	MFIV	RMFIV	$AMFIV^{vol,h}$	$AMFIV^{vol,ar}$	$AMFIV^{vol,e}$	$AMFIV^{vol,ir}$	$AMFIV^{VRP^2,h}$	$AMFIV^{VRP^2,ar}$	$AMFIV^{VRP^2,e}$	$AMFIV^{VRP^2,ir}$
							SPX				
MSE	57.50	50.69	46.34	46.31	63.53	56.50	30.37	51.85	64.66	52.22	32.85
QLIKE	3.63	3.64	3.62	3.61	3.62	3.67	3.60	3.64	3.64	3.69	3.60
Obs	166	166	166	166	166	166	166	166	166	166	166
							USO				
MSE	84.13	87.98	60.65	58.11	63.89	93.80	49.94	61.12	66.94	88.49	52.11
QLIKE	4.37	4.38	4.37	4.37	4.37	4.40	4.36	4.37	4.38	4.39	4.36
Obs	126	126	126	126	126	126	126	126	126	126	126
							GLD				
Obs	113	113	113	113	113	113	113	113	113	113	113
MSE	33.56	35.92	25.34	26.62	31.12	47.55	23.35	29.52	31.57	37.65	24.10
QLIKE	3.69	3.71	3.68	3.69	3.91	3.74	3.67	3.70	3.71	3.72	3.67
							SLV				
MSE	77.05	84.68	56.32	56.71	68.11	103.25	45.31	63.45	71.45	88.41	51.77
QLIKE	4.09	4.11	4.08	4.09	11.54	4.16	4.06	4.10	4.11	4.13	4.07
Obs	79	79	79	79	79	79	79	79	79	79	79
							GDX				
MSE	93.07	112.32	104.86	99.26	101.60	140.76	73.99	102.36	104.17	125.80	72.41
QLIKE	4.54	4.55	4.54	4.54	4.54	4.56	4.53	4.55	4.55	4.56	4.53
Obs	79	79	79	79	79	79	79	79	79	79	79
							XLE				
MSE	39.15	41.56	33.75	28.94	30.32	52.09	27.25	30.07	30.92	49.37	27.79
QLIKE	3.88	3.89	3.87	3.86	3.86	3.90	3.86	3.87	3.87	3.92	3.86
Obs	79	79	79	79	79	79	79	79	79	79	79

Table 3.12: Difference of Forecasting Errors: Level VRP Format

This table presents differences of forecasting errors from competing forecasts for SPX, USO, GLD, SLV, GDX and XLE sectors under MSE and QLIKE criterion, respectively. We forecast VRP in level VRP format. Each panel corresponds to a different loss function. We calculate the differences between the loss functions of model [name in row] and those of model [name in column]. The upper triangular matrices and lower triangular matrices report the mean and median difference of forecasting errors, respectively. For the upper triangular matrices, the values in bold indicate that the mean differences are statistically significant at the 5% level in the Diebold-Mariano (DM) test. Similarly, values in bold in lower triangular matrices indicate that the median differences are statistically significant at 5% level in the non-parametric Wilcoxon signed rank test.

Panel A: MSE

	EWMA	MFIV	RMFIV	$AMFIV^h$	$AMFIV^{ar}$	$AMFIV^e$	$AMFIV^{ir}$
				SPX			
EWMA		-6.81	4.35	4.38	-12.83	-5.80	**20.33**
MFIV	**15.53**		11.16	**11.19**	-6.02	1.00	**27.14**
RMFIV	**-4.78**	**-20.31**		0.03	-17.18	-10.15	15.98
$AMFIV^h$	**-1.82**	**-17.35**	2.96		-17.22	-10.19	15.94
$AMFIV^{ar}$	**-1.82**	**-17.35**	**2.96**	0.00		7.03	33.16
$AMFIV^e$	**6.36**	-9.17	**11.14**	**8.18**	**8.18**		**26.13**
$AMFIV^{ir}$	**-2.51**	**-18.04**	2.27	-0.68	**-0.68**	**-8.87**	
				USO			
EWMA		3.85	**27.34**	**29.87**	**24.10**	-5.82	**38.05**
MFIV	8.87		23.48	**26.02**	**20.24**	-9.67	**34.20**
RMFIV	**-18.63**	**-27.50**		2.54	-3.24	**-33.16**	10.71
$AMFIV^h$	**-14.76**	**-23.63**	3.87		-5.78	**-35.70**	8.17
$AMFIV^{ar}$	**-7.44**	**-16.31**	11.18	**7.31**		**-29.92**	**13.95**
$AMFIV^e$	5.87	-3.00	**24.49**	**20.62**	**13.31**		**43.87**
$AMFIV^{ir}$	**-17.29**	**-26.16**	1.34	-2.53	**-9.84**	**-23.15**	
				GLD			
EWMA		2.36	**10.59**	**9.30**	4.81	-11.63	**12.57**
MFIV	**4.25**		8.22	6.94	2.44	-13.99	**10.21**
RMFIV	**-5.88**	**-10.14**		-1.28	-5.78	**-22.21**	1.98
$AMFIV^h$	**-4.55**	**-8.80**	**1.33**		-4.50	**-20.93**	3.27
$AMFIV^{ar}$	**-4.96**	**-9.21**	0.93	-0.41		**-16.43**	7.76
$AMFIV^e$	-1.22	-5.48	**4.66**	**3.33**	3.73		**24.20**
$AMFIV^{ir}$	**-6.10**	**-10.35**	-0.21	**-1.54**	**-1.14**	**-4.87**	
				SLV			
EWMA		7.62	**28.35**	27.96	16.57	-18.57	39.37
MFIV	8.24		20.73	20.34	8.94	-26.20	**31.75**
RMFIV	**-7.80**	**-16.04**		-0.39	-11.79	-46.93	11.02
$AMFIV^h$	**-5.34**	**-13.58**	2.45		-11.40	-46.54	11.41
$AMFIV^{ar}$	-3.59	**-11.83**	4.20	1.75		-35.14	22.80
$AMFIV^e$	7.78	-0.47	**15.57**	**13.12**	**11.37**		57.95
$AMFIV^{ir}$	**-8.72**	**-16.96**	-0.93	-3.38	-5.13	**-16.50**	
				GDX			
EWMA		19.25	7.46	13.06	10.72	-28.44	**38.33**
MFIV	-12.05		-11.80	-6.19	-8.53	-47.69	**19.08**
RMFIV	-29.05	-17.00		5.61	3.27	-35.89	**30.87**
$AMFIV^h$	-24.95	-12.90	4.10		-2.34	-41.50	**25.27**
$AMFIV^{ar}$	-24.58	-12.53	4.47	0.36		-39.16	**27.61**
$AMFIV^e$	-13.79	-1.75	15.26	11.15	10.79		**66.77**
$AMFIV^{ir}$	**-24.25**	-12.20	4.80	**0.70**	**0.34**	**-10.45**	
				XLE			
EWMA		2.41	7.82	**12.62**	**11.24**	-10.53	**14.31**
MFIV	6.46		5.41	10.21	8.83	-12.94	**11.90**
RMFIV	**-7.80**	**-14.26**		4.80	3.43	-18.35	6.49
$AMFIV^h$	**-7.49**	**-13.95**	0.32		-1.38	**-23.15**	1.69
$AMFIV^{ar}$	**-7.36**	**-13.83**	0.44	0.12		**-21.77**	3.07
$AMFIV^e$	-0.28	-6.74	**7.53**	**7.21**	**7.09**		**24.84**
$AMFIV^{ir}$	**-8.21**	**-14.67**	-0.41	-0.73	-0.85	**-7.94**	

Table 3.12: Difference of Forecasting Errors: level VRP format

Panel B: QLIKE

	EWMA	MFIV	RMFIV	$AMFIV^h$	$AMFIV^{ar}$	$AMFIV^e$	$AMFIV^{ir}$
				SPX			
EWMA		0.00	0.02	**0.03**	0.02	**-0.03**	**0.04**
MFIV	**0.07**		0.02	**0.02**	0.02	-0.03	**0.04**
RMFIV	**-0.02**	**-0.09**		0.00	0.00	**-0.05**	**0.02**
$AMFIV^h$	**-0.01**	**-0.08**	0.01		-0.01	**-0.06**	**0.01**
$AMFIV^{ar}$	**-0.01**	**-0.08**	0.01	0.00		**-0.05**	**0.02**
$AMFIV^e$	**0.06**	-0.01	**0.09**	**0.07**	**0.07**		**0.07**
$AMFIV^{ir}$	**-0.01**	**-0.08**	0.02	0.01	**0.01**	**-0.07**	
				USO			
EWMA		0.00	0.01	0.01	0.01	**-0.02**	0.02
MFIV	0.01	0.01	0.01	**-0.03**	0.01		
RMFIV	**0.01**	**0.01**		0.00	0.00	**-0.03**	0.00
$AMFIV^h$	**-0.01**	**0.00**	-0.01		0.00	**-0.03**	0.00
$AMFIV^{ar}$	-0.01	**-0.01**	-0.02	**0.00**		**-0.03**	0.01
$AMFIV^e$	0.03	0.04	**0.03**	**0.04**	**0.04**		**0.04**
$AMFIV^{ir}$	**-0.03**	**-0.02**	-0.03	-0.02	**-0.01**	**-0.06**	
				GLD			
EWMA		0.02	**0.02**	**0.02**	-0.20	-0.04	**0.03**
MFIV	0.00		0.00	0.00	-0.22	-0.06	**0.02**
RMFIV	**-0.03**	**-0.03**		0.00	-0.22	-0.06	0.01
$AMFIV^h$	**-0.02**	**-0.02**	**0.01**		-0.22	-0.06	0.02
$AMFIV^{ar}$	**-0.02**	**-0.02**	0.01	0.00		0.16	0.24
$AMFIV^e$	0.01	0.00	**0.03**	**0.02**	0.02		0.07
$AMFIV^{ir}$	**-0.03**	**-0.03**	0.00	**-0.01**	**-0.02**	**-0.04**	
				SLV			
EWMA		0.02	**0.03**	**0.02**	-7.44	-0.05	0.04
MFIV	0.02		0.01	0.00	-7.45	-0.07	**0.03**
RMFIV	**-0.01**	**-0.04**		-0.01	-7.46	-0.07	0.02
$AMFIV^h$	**0.00**	**-0.03**	0.01		-7.46	-0.07	0.02
$AMFIV^{ar}$	-0.01	-0.04	0.00	-0.01		7.39	7.48
$AMFIV^e$	0.01	-0.01	**0.02**	**0.01**	**0.02**		0.09
$AMFIV^{ir}$	**-0.01**	**-0.04**	0.00	-0.01	0.00	**-0.02**	
				GDX			
EWMA		0.01	0.00	0.00	0.00	**-0.01**	**0.02**
MFIV	-0.01		-0.01	0.00	-0.01	-0.02	0.01
RMFIV	0.00	0.01		0.00	0.00	-0.02	**0.01**
$AMFIV^h$	0.01	0.02	0.01		0.00	**-0.02**	**0.01**
$AMFIV^{ar}$	0.00	0.01	0.00	0.00		**-0.02**	**0.02**
$AMFIV^e$	0.01	0.01	0.00	0.00	0.00		**0.03**
$AMFIV^{ir}$	**0.00**	**0.01**	**0.00**	**-0.01**	**-0.01**	**-0.01**	
				XLE			
EWMA		0.01	0.02	**0.03**	**0.03**	-0.01	**0.03**
MFIV	0.01		0.01	0.01	0.01	-0.03	**0.02**
RMFIV	**-0.01**	**-0.02**		0.01	0.01	-0.03	0.01
$AMFIV^h$	**0.00**	**-0.01**	0.01		0.00	**-0.04**	0.00
$AMFIV^{ar}$	**0.00**	**-0.01**	0.01	0.00		**-0.04**	0.00
$AMFIV^e$	0.02	0.01	**0.02**	**0.01**	**0.01**		**0.04**
$AMFIV^{ir}$	**-0.01**	**-0.02**	0.00	-0.01	-0.01	**-0.02**	

Table 3.13: Difference of Forecasting Errors: VRP^2 Format

This table presents differences of forecasting errors from competing forecasts for SPX, USO, GLD, SLV, GDX and XLE sectors under MSE and QLIKE criterion, respectively. We forecast VRP in VRP^2 format. Each panel corresponds to a different loss function. We calculate the differences between the loss functions of model [name in row] and those of model [name in column]. The upper triangular matrices and lower triangular matrices report the mean and median difference of forecasting errors, respectively. For the upper triangular matrices, the values in bold indicate that the mean differences are statistically significant at the 5% level in the Diebold-Mariano (DM) test. Similarly, values in bold in lower triangular matrices indicate that the median differences are statistically significant at 5% level in the non-parametric Wilcoxon signed rank test.

Panel A: MSE

	EWMA	MFIV	RMFIV	$AMFIV^h$	$AMFIV^{ar}$	$AMFIV^e$	$AMFIV^{ir}$
				SPX			
EWMA		-6.81	4.35	-1.16	-13.97	-1.52	17.84
MFIV	**15.53**		11.16	5.65	-7.16	5.29	24.65
RMFIV	**-4.78**	**-20.31**		-5.51	-18.32	-5.87	13.49
$AMFIV^h$	0.27	**-15.26**	**5.05**		-12.81	-0.36	19.00
$AMFIV^{ar}$	-0.82	**-16.35**	**3.96**	-1.09		12.44	31.81
$AMFIV^e$	**7.87**	-7.66	**12.65**	**7.60**	8.70		**19.37**
$AMFIV^{ir}$	**-2.29**	**-17.82**	2.49	-2.56	**-1.47**	**-10.16**	
				USO			
EWMA		3.85	**27.34**	**26.87**	21.04	-0.50	**35.87**
MFIV	8.87		23.48	**23.01**	17.19	-4.35	**32.02**
RMFIV	**-18.63**	**-27.50**		-0.47	-6.29	**-27.84**	8.53
$AMFIV^h$	**-13.29**	**-22.16**	5.34		-5.82	**-27.37**	9.00
$AMFIV^{ar}$	-3.01	**-11.88**	15.62	10.28		**-21.55**	14.83
$AMFIV^e$	6.33	-2.54	**24.95**	**19.62**	**9.34**		**36.37**
$AMFIV^{ir}$	**-14.98**	**-23.86**	3.64	-1.69	**-11.97**	**-21.31**	
				GLD			
EWMA		2.36	**10.59**	6.40	4.36	-1.72	11.83
MFIV	**4.25**		8.22	4.04	1.99	-4.08	**9.46**
RMFIV	**-5.88**	**-10.14**		-4.19	**-6.23**	**-12.31**	1.24
$AMFIV^h$	-2.41	**-6.66**	**3.47**		-2.04	-8.12	5.43
$AMFIV^{ar}$	-3.67	**-7.92**	**2.22**	-1.26		-6.08	7.47
$AMFIV^e$	-3.06	-7.31	**2.82**	-0.65	0.61		13.55
$AMFIV^{ir}$	**-5.79**	**-10.04**	0.10	-3.38	**-2.12**	**-2.72**	
				SLV			
EWMA		7.62	**28.35**	21.23	13.22	-3.73	32.91
MFIV	8.24		20.73	13.61	5.60	-11.36	**25.29**
RMFIV	**-7.80**	**-16.04**		-7.12	-15.13	**-32.09**	4.55
$AMFIV^h$	-0.07	**-8.31**	**7.73**		**-8.00**	-24.96	11.68
$AMFIV^{ar}$	1.57	-6.67	**9.37**	**1.64**		-16.96	19.68
$AMFIV^e$	12.69	4.45	**20.49**	12.76	11.12		36.64
$AMFIV^{ir}$	-5.42	**-13.67**	2.37	-5.36	-6.99	**-18.12**	
				GDX			
EWMA		19.25	7.46	9.96	8.15	-13.47	**39.91**
MFIV	-12.05		-11.80	-9.30	-11.11	-32.73	**20.66**
RMFIV	-29.05	-17.00		2.50	0.69	-20.93	32.46
$AMFIV^h$	-23.56	-11.51	5.49		-1.81	-23.43	**29.96**
$AMFIV^{ar}$	-21.35	-9.30	7.70	2.21		-21.62	**31.77**
$AMFIV^e$	-14.08	-2.04	14.97	9.47	7.26		**53.39**
$AMFIV^{ir}$	**-24.71**	-12.66	4.34	**-1.15**	**-3.36**	**-10.62**	
				XLE			
EWMA		2.41	7.82	**11.49**	10.65	-7.81	**13.77**
MFIV	6.46		5.41	9.08	8.23	-10.22	**11.36**
RMFIV	**-7.80**	**-14.26**		3.67	2.83	-15.63	5.95
$AMFIV^h$	**-6.75**	**-13.21**	1.05		-0.84	**-19.30**	2.28
$AMFIV^{ar}$	**-7.06**	**-13.52**	0.74	-0.31		**-18.46**	3.12
$AMFIV^e$	5.15	-1.31	**12.95**	**11.90**	**12.21**		**21.58**
$AMFIV^{ir}$	**-6.86**	**-13.32**	0.94	-0.11	0.20	**-12.01**	

Table 3.13: Difference of Forecasting Errors: VRP^2 Format

Panel B: QLIKE

	EWMA	MFIV	RMFIV	$AMFIV^h$	$AMFIV^{ar}$	$AMFIV^e$	$AMFIV^{ir}$
				SPX			
EWMA		0.00	0.02	0.00	0.00	**-0.06**	**0.04**
MFIV	0.02	0.00	-0.01	**-0.06**	**0.04**		
RMFIV	**-0.02**	**-0.09**		-0.02	-0.02	**-0.08**	0.02
$AMFIV^h$	0.05	**-0.02**	**0.08**		0.00	**-0.06**	**0.04**
$AMFIV^{ar}$	0.05	**-0.02**	**0.07**	-0.01		**-0.05**	**0.04**
$AMFIV^e$	**0.09**	0.02	**0.11**	**0.03**	**0.04**		**0.10**
$AMFIV^{ir}$	**0.02**	**-0.05**	0.05	**-0.03**	**-0.03**	**-0.07**	
				USO			
EWMA		0.00	0.01	0.00	0.00	-0.01	0.01
MFIV	-0.01		0.01	0.00	0.00	-0.02	0.01
RMFIV	**0.01**	**0.01**		-0.01	-0.01	**-0.02**	0.00
$AMFIV^h$	0.01	**0.01**	0.00		0.00	**-0.02**	**0.01**
$AMFIV^{ar}$	0.00	0.01	**-0.01**	-0.01		**-0.02**	**0.01**
$AMFIV^e$	0.02	0.03	**0.02**	**0.02**	**0.02**		**0.03**
$AMFIV^{ir}$	**-0.03**	**-0.02**	-0.03	-0.04	**-0.03**	**-0.05**	
				GLD			
EWMA		0.02	**0.02**	0.00	0.00	-0.02	0.04
MFIV	0.00		0.00	-0.01	-0.02	-0.03	**0.02**
RMFIV	**-0.03**	**-0.03**		-0.02	-0.02	**-0.04**	0.01
$AMFIV^h$	0.00	0.00	**0.03**		-0.01	-0.02	0.03
$AMFIV^{ar}$	-0.01	-0.01	**0.02**	-0.01		-0.01	0.04
$AMFIV^e$	0.03	0.03	**0.06**	0.03	0.04		0.05
$AMFIV^{ir}$	**-0.01**	**-0.01**	0.02	**-0.01**	**0.00**	**-0.04**	
				SLV			
EWMA		0.02	**0.03**	0.00	-0.01	-0.02	0.04
MFIV	0.02		0.01	-0.01	-0.03	-0.04	**0.02**
RMFIV	**-0.01**	**-0.04**		-0.02	-0.03	**-0.05**	0.01
$AMFIV^h$	0.01	-0.01	**0.03**		-0.01	**-0.03**	0.03
$AMFIV^{ar}$	0.01	-0.02	**0.02**	**0.00**		-0.01	0.05
$AMFIV^e$	0.03	0.01	**0.04**	**0.02**	0.02		0.06
$AMFIV^{ir}$	**-0.01**	**-0.03**	0.01	-0.02	-0.02	**-0.04**	
				GDX			
EWMA		0.01	0.00	0.00	0.00	-0.01	**0.02**
MFIV	-0.01		-0.01	-0.01	-0.01	-0.02	0.01
RMFIV	0.00	0.01		0.00	0.00	-0.02	**0.02**
$AMFIV^h$	0.01	0.02	0.01		0.00	-0.01	**0.02**
$AMFIV^{ar}$	0.01	0.02	0.01	0.00		-0.01	**0.02**
$AMFIV^e$	0.01	0.01	0.00	0.00	0.00		**0.03**
$AMFIV^{ir}$	**0.01**	0.01	0.00	**0.00**	**0.00**	**0.00**	
				XLE			
EWMA		0.01	0.02	0.02	0.02	-0.03	**0.03**
MFIV	0.01		0.01	0.01	0.01	**-0.04**	**0.02**
RMFIV	**-0.01**	**-0.02**		0.00	0.00	**-0.05**	0.01
$AMFIV^h$	**0.00**	**-0.01**	0.01		0.00	**-0.05**	0.01
$AMFIV^{ar}$	**0.00**	**-0.01**	0.01	0.00		**-0.05**	0.01
$AMFIV^e$	0.03	0.01	**0.03**	**0.02**	**0.03**		**0.06**
$AMFIV^{ir}$	**-0.01**	**-0.02**	0.00	-0.01	-0.01	**-0.03**	

Table 3.14: Univariate Regressions: Alternative Estimation Periods

This table presents results from univariate regressions of realized volatility on competing forecasts for SPX, USO, GLD, SLV, GDX and XLE sectors and each panel corresponds to a different sector. We use a rolling window of 484 trading days to estimate the value of LVRP for next period. Each columns reports the regression results for a particular forecast in the sector. α and β denote the intercept and the slope coefficients, respectively. We present in brackets the Newey-West test statistic computed with 2 lags. Wald reports the Wald test statistics and p_wald reports the corresponding p-value of Wald test in testing the null hypothesis that α and β are jointly equal to zero and one, respectively. DW and Obs denote the Durbin-Watson test statistic and the number of observations, respectively.

Variables	EWMA	MFIV	$AMFIV^h$	$AMFIV^{ar}$	$AMFIV^e$	$AMFIV^{ir}$	VARIABLES	EWMA	MFIV	$AMFIV^h$	$AMFIV^{ar}$	$AMFIV^e$	$AMFIV^{ir}$
			SPX							**USO**			
Constant	3.62***	-3.31*	0.46	1.03	5.54***	1.00	Constant	9.05***	0.79	4.30**	4.73***	11.79***	4.15**
	(3.25)	(-1.67)	(0.28)	(0.82)	(6.09)	(0.79)		(4.31)	(0.38)	(2.28)	(2.74)	(6.65)	(2.53)
erv_spx	0.77***	0.98***	1.01***	0.99***	0.61***	0.97***	erv_uso	0.68***	0.82***	0.86***	0.84***	0.58***	0.85***
	(8.76)	(7.67)	(7.24)	(8.96)	(9.37)	(9.10)		(9.27)	(12.35)	(11.82)	(12.44)	(10.25)	(14.84)
Adj. R^2	0.59	0.60	0.58	0.57	0.64	0.64	Adj. R^2	0.46	0.57	0.56	0.57	0.48	0.60
Wald	5.71	35.92	0.71	1.61	19.41	1.15	Wald	9.59	23.36	2.76	3.80	27.22	3.42
p_wald	0.00	0.00	0.49	0.20	0.00	0.32	p_wald	0.00	0.00	0.07	0.03	0.00	0.04
DW	2.16	1.41	1.29	1.43	2.26	1.42	DW	1.94	1.56	1.49	1.47	2.19	1.48
Obs	154	154	154	154	154	154	Observations	114	114	114	114	114	114
			GLD							**SLV**			
Constant	7.82***	1.90	2.33	2.41	10.08***	1.60	Constant	13.43***	1.50	2.20	1.53	15.53***	1.32
	(4.70)	(1.19)	(1.52)	(1.60)	(6.59)	(1.04)		(3.82)	(0.47)	(0.70)	(0.49)	(4.53)	(0.44)
erv_gld	0.47***	0.72***	0.87***	0.87***	0.30***	0.92***	erv_slv	0.39***	0.77***	0.95***	0.99***	0.28**	0.98***
	(4.68)	(8.74)	(9.13)	(9.45)	(3.47)	(9.16)		(2.65)	(6.51)	(6.41)	(6.23)	(2.09)	(6.58)
Adj. R^2	0.20	0.34	0.32	0.30	0.20	0.34	Adj. R^2	0.12	0.33	0.32	0.32	0.12	0.34
Wald	15.08	28.26	1.23	1.33	38.51	0.79	Wald	9.15	15.05	0.91	0.92	15.50	0.59
p_wald	0.00	0.00	0.30	0.27	0.00	0.46	p_wald	0.00	0.00	0.41	0.40	0.00	0.56
DW	2.22	2.04	2.01	1.86	2.24	1.90	DW	2.13	2.15	2.16	1.82	2.17	2.01
Obs	101	101	101	101	101	101	Observations	68	68	68	68	68	68
			GDX							**XLE**			
Constant	9.78***	-4.37	1.22	3.56	15.96***	3.05	Constant	6.89***	-3.51	-0.61	1.40	9.76***	1.36
	(3.01)	(-0.85)	(0.27)	(0.83)	(4.03)	(0.95)		(3.97)	(-1.31)	(-0.25)	(0.60)	(5.08)	(0.65)
erv_gdx	0.73***	1.10***	0.99***	0.92***	0.55***	0.96***	erv_xle	0.64***	1.03***	1.11***	0.99***	0.47***	0.98***
	(9.64)	(8.47)	(8.55)	(8.71)	(6.11)	(11.13)		(6.61)	(7.69)	(7.52)	(7.37)	(4.65)	(7.99)
Adj. R^2	0.51	0.54	0.53	0.55	0.48	0.57	Adj. R^2	0.35	0.47	0.44	0.41	0.31	0.45
Wald	6.24	0.38	0.17	0.36	14.44	0.81	Wald	7.94	8.09	1.26	1.15	14.03	0.94
p_wald	0.00	0.68	0.85	0.70	0.00	0.45	p_wald	0.00	0.00	0.29	0.32	0.00	0.40
DW	2.14	1.60	1.49	1.62	2.25	1.55	DW	2.05	1.68	1.53	1.64	2.02	1.58
Obs	68	68	68	68	68	68	Observations	68	68	68	68	68	68

Table 3.15: Forecasting Errors: Alternative Estimation Periods

This table presents results of forecasting errors from competing forecasts for SPX, USO, GLD, SLV, GDX and XLE sectors and each panel corresponds to a different sector. We use a rolling window of 484 trading days to estimate the value of LVRP for next period. MSE and QLIKE denote the forecasting errors in the corresponding criterion. Obs denotes the number of observations. The forecast horizon is one month, i.e. 21 trading days in our study.

Variables	EWMA	MFIV	$AMFTV^h$	$AMFTV^{ar}$	$AMFTV^e$	$AMFTV^{ir}$
			SPX			
MSE	60.72	53.85	49.47	50.60	73.25	42.93
QLIKE	3.66	3.66	3.64	3.64	3.67	3.63
Obs	154	154	154	154	154	154
			USO			
MSE	83.43	77.03	54.89	54.65	93.08	50.50
QLIKE	4.31	4.31	4.30	4.30	4.32	4.29
Obs	114	114	114	114	114	114
			GLD			
MSE	33.91	37.84	24.44	25.28	69.31	23.59
QLIKE	3.67	3.69	3.66	3.66	3.71	3.65
Obs	101	101	101	101	101	101
			SLV			
MSE	75.71	94.10	53.62	53.80	133.98	51.56
QLIKE	4.08	4.10	4.06	4.06	4.12	4.06
Obs	68	68	68	68	68	68
			GDX			
MSE	101.44	122.31	103.79	100.23	184.31	96.35
QLIKE	4.56	4.57	4.56	4.56	4.58	4.56
Obs	68	68	68	68	68	68
			XLE			
MSE	39.31	46.05	35.55	36.67	65.97	34.02
QLIKE	3.88	3.90	3.87	3.87	3.90	3.87
Obs	68	68	68	68	68	68

Table 3.16: Difference Forecasting Errors: Alternative Estimation Periods

This table presents differences of forecasting errors from competing forecasts for SPX, USO, GLD, SLV, GDX and XLE sectors under MSE and QLIKE criterion, respectively. We use a rolling window of 484 trading days to estimate the value of LVRP for next period. Each panel corresponds to a different loss function. We calculate the differences between the loss functions of model [name in row] and those of model [name in column]. The upper triangular matrices and lower triangular matrices report the mean and median difference of forecasting errors, respectively. For the upper triangular matrices, the values in bold indicate that the mean differences are statistically significant at the 5% level in the Diebold-Mariano (DM) test. Similarly, values in bold in lower triangular matrices indicate that the median differences are statistically significant at 5% level in the non-parametric Wilcoxon signed rank test.

Panel A: MSE

	EWMA	MFIV	$AMFIV^h$	$AMFIV^{ar}$	$AMFIV^e$	$AMFIV^{ir}$
			SPX			
EWMA		-6.87	4.39	3.25	-19.40	10.92
MFIV	**19.44**		11.26	10.12	-12.53	**17.79**
$AMFIV^h$	**-2.04**	**-21.48**		-1.14	-23.79	6.53
$AMFIV^{ar}$	**-2.48**	**-21.92**	-0.43		-22.65	7.67
$AMFIV^e$	4.24	**-15.20**	**6.28**	**6.72**		30.32
$AMFIV^{ir}$	**-3.18**	**-22.62**	-1.13	-0.70	**-7.42**	
			USO			
EWMA		-6.39	**22.14**	**22.39**	-16.05	**26.53**
MFIV	**12.07**		**28.54**	**28.78**	-9.65	**32.92**
$AMFIV^h$	**-12.74**	**-24.81**		0.25	**-38.19**	4.39
$AMFIV^{ar}$	**-14.38**	**-26.45**	-1.64		**-38.44**	4.14
$AMFIV^e$	2.02	-10.04	**14.76**	**16.41**		**42.58**
$AMFIV^{ir}$	**-13.53**	**-25.60**	-0.79	0.85	**-15.56**	
			GLD			
EWMA		3.93	**13.40**	**12.56**	-31.46	**14.25**
MFIV	2.72		**9.47**	**8.63**	-35.40	**10.32**
$AMFIV^h$	**-6.11**	**-8.83**		-0.84	-44.87	0.85
$AMFIV^{ar}$	**-6.03**	**-8.75**	0.08		-44.03	1.69
$AMFIV^e$	-2.15	-4.87	**3.96**	**3.88**		45.72
$AMFIV^{ir}$	**-6.53**	**-9.25**	-0.42	**-0.50**	**-4.38**	
			SLV			
EWMA		18.39	**40.48**	**40.30**	-39.89	**42.54**
MFIV	2.87		**22.09**	**21.91**	-58.28	**24.15**
$AMFIV^h$	**-13.01**	**-15.88**		-0.18	-80.37	2.06
$AMFIV^{ar}$	**-12.92**	**-15.78**	0.09		-80.18	2.24
$AMFIV^e$	7.39	4.52	**20.40**	**20.31**		82.42
$AMFIV^{ir}$	**-11.16**	**-14.03**	1.85	1.75	**-18.55**	
			GDX			
EWMA		20.87	18.53	**22.08**	-62.00	**25.96**
MFIV	-7.15		-2.35	1.21	-82.87	5.09
$AMFIV^h$	-8.46	-1.31		3.56	-80.53	7.43
$AMFIV^{ar}$	-14.50	-7.35	-6.04		-84.08	3.88
$AMFIV^e$	-14.34	-7.19	-5.88	0.16		87.96
$AMFIV^{ir}$	**-28.88**	-21.73	-20.42	-14.38	**-14.54**	
			XLE			
EWMA		6.74	10.49	9.37	-19.92	**12.03**
MFIV	3.49		3.76	2.64	-26.66	5.29
$AMFIV^h$	**-9.56**	**-13.05**		-1.12	-30.42	1.53
$AMFIV^{ar}$	**-9.02**	**-12.51**	0.54		-29.30	**2.65**
$AMFIV^e$	-1.23	-4.72	**8.33**	**7.79**		31.95
$AMFIV^{ir}$	**-11.03**	**-14.52**	-1.47	**-2.01**	**-9.80**	

Table 3.16: Difference Forecasting Errors: Alternative Estimation Periods

Panel B: QLIKE

	EWMA	MFIV	$AMFIV^h$	$AMFIV^{ar}$	$AMFIV^e$	$AMFIV^{ir}$
			SPX			
EWMA		0.00	**0.03**	0.02	-0.01	**0.03**
MFIV	**0.06**		0.02	0.02	-0.01	**0.02**
$AMFIV^h$	**0.00**	**-0.06**		0.00	**-0.03**	0.00
$AMFIV^{ar}$	**0.00**	**-0.07**	-0.01		**-0.03**	0.01
$AMFIV^e$	0.03	-0.04	**0.02**	**0.03**		**0.03**
$AMFIV^{ir}$	**0.00**	**-0.07**	-0.01	0.00	**-0.03**	
			USO			
EWMA		0.00	**0.01**	**0.01**	-0.01	**0.02**
MFIV	0.00		0.01	0.01	-0.01	**0.01**
$AMFIV^h$	**-0.01**	**-0.01**		0.00	**-0.02**	**0.00**
$AMFIV^{ar}$	**-0.02**	**-0.02**	0.00		**-0.02**	0.00
$AMFIV^e$	0.01	0.01	**0.02**	**0.02**		**0.03**
$AMFIV^{ir}$	**-0.02**	**-0.02**	0.00	0.00	**-0.03**	
			GLD			
EWMA		0.02	**0.03**	**0.03**	-0.02	**0.04**
MFIV	0.00		0.01	0.01	-0.04	**0.02**
$AMFIV^h$	**-0.01**	**-0.01**		0.00	-0.05	0.00
$AMFIV^{ar}$	**-0.01**	**-0.01**	0.00		-0.05	**0.00**
$AMFIV^e$	0.00	0.00	**0.01**	**0.01**		0.05
$AMFIV^{ir}$	**-0.01**	**-0.01**	**0.00**	**0.00**	**-0.01**	
			SLV			
EWMA		0.03	**0.04**	**0.04**	-0.02	**0.04**
MFIV	0.00		0.01	0.01	-0.05	0.02
$AMFIV^h$	**-0.03**	**-0.03**		0.00	-0.06	0.00
$AMFIV^{ar}$	**-0.03**	**-0.03**	0.00		-0.06	0.00
$AMFIV^e$	-0.01	-0.01	**0.02**	**0.02**		0.06
$AMFIV^{ir}$	**-0.04**	**-0.03**	-0.01	-0.01	**-0.03**	
			GDX			
EWMA		0.01	0.00	0.00	-0.01	0.01
MFIV	-0.01		0.00	0.00	-0.02	0.00
$AMFIV^h$	-0.01	0.00		0.00	-0.02	0.00
$AMFIV^{ar}$	-0.01	0.00	0.00		**-0.02**	0.00
$AMFIV^e$	-0.01	0.01	0.01	0.01		**0.02**
$AMFIV^{ir}$	-0.02	-0.01	-0.01	-0.01	-0.01	
			XLE			
EWMA		0.02	**0.03**	**0.02**	0.00	**0.03**
MFIV	-0.01		0.01	0.00	-0.02	0.01
$AMFIV^h$	**-0.03**	**-0.02**		0.00	**-0.03**	0.00
$AMFIV^{ar}$	**-0.03**	**-0.02**	0.00		-0.03	**0.00**
$AMFIV^e$	0.00	0.01	**0.03**	**0.03**		**0.03**
$AMFIV^{ir}$	**-0.04**	**-0.03**	-0.01	-0.01	**-0.04**	

Table 3.17: Alternative benchmark: HAR model

The table reports results of forecasts by HAR model for SPX, USO, GLD, SLV, GDX and XLE sectors. Panel A presents results from univariate regressions of realized volatility by HAR model. α and β denote the intercept and the slope coefficients, respectively. We present in brackets the Newey-West test statistic computed with 2 lags. Wald reports the Wald test statistics and p_wald reports the corresponding p-value of Wald test in testing the null hypothesis that α and β are jointly equal to zero and one, respectively. DW and Obs denote the Durbin-Watson test statistic and the number of observations, respectively. Panel B presents results of forecasting errors from HAR forecast. MSE and QLIKE denote the forecasting loss functions. The forecast horizon is one month, 21 trading days in our study. We use a rolling window of 232 observations to get the out-of-sample forecasts.

	SPX	USO	GLD	SLV	GDX	XLE
Panel A: Univariate Regression for Realized Volatility						
α	4.63	5.36	7.29	15.73	5.82	4.91
	4.26	2.44	2.88	4.86	1.72	1.74
β	0.70	0.79	0.49	0.27	0.82	0.71
	13.16	10.97	3.41	2.29	9.55	5.13
Adj. R^2	0.42	0.56	0.08	0.03	0.43	0.26
Wald	16.21	4.09	9.04	21.94	2.14	2.66
p_Wald	0.00	0.02	0.00	0.00	0.12	0.08
DW	1.60	1.56	1.43	1.20	1.42	1.39
Obs	166	126	113	79	79	79
Panel B: Forecasting Errors						
MSE	73.71	106.33	35.94	89.87	117.22	42.71
Qlike	3.64	4.36	3.68	4.08	4.54	3.89

Chapter 4

Implied Variance Term Structure and Monetary Policy

4.1 Introduction

A large literature, e.g. Bernanke and Kuttner (2005) and Lucca and Moench (2015), studies the response of the equity index market to monetary policy news. While the literature has documented several interesting findings about the impact of federal fund rate announcements on the equity risk premium, we know surprising very little about how interest rate news affects the market price of variance risk. Given that the monetary policy is a key factor for pricing assets and interest rate announcements significantly affect equity prices (e.g. Thorbecke (1997) and Kaminska and Roberts-Sklar (2018)), we are interested in the effect of monetary policy on variance swaps. Chuliá et al. (2010) study the influence of interest rate news on S&P100 stock volatility. Bekaert et al. (2013) and Fernandez-Perez et al. (2017) analyze the effect of monetary policy on VIX which represents implied volatility of S&P500 index. Since variance swap reflects the difference between realized variance and implied variance, we investigate how monetary policy affects the difference which is the variance risk premium in our study. Does interest rate news affect the variance risk premium? If so, what is the sign of the announcement response? How does the strength of the announcement response evolve with the maturity? What is the channel through which the announcement effect arises? These are some of the questions that we set out to answer.

Using a large dataset of S&P 500 index options and spot data, we compute the term-structure of the variance risk premium. Equipped with this term-structure, we set out to study the impact of interest rate news. We document several findings. First, the dynamics of the variance risk premium observed on announcement days are significantly different from those observed on other days. This result suggests that FOMC days are special for the pricing of the variance risk premium.

Second, interest rate announcement surprises have a significantly positive impact on the variance risk premium. Economically, the positive announcement effect suggests that investors dislike positive interest rate shocks and require a higher variance risk premium. Interestingly, the announcement effect is strongest at the short-end of the term-structure and decreases with the maturity of the variance risk premium.

Third, we decompose the term-structure of the variance risk premium into the term-structures of the (i) implied and (ii) realized variance, respectively. Our analysis reveals that both term-structures react positively to positive interest rate surprises. This finding reveals that positive interest rate shocks herald risky times. Comparing the announcement responses of the two term-structures, we find that the short-maturity implied variance generally reacts more strongly than the realized variance of equivalent maturity. Analyzing longer maturities, we find very little to distinguish between the two variance series. This set of results helps understand the declining pattern of announcement responses along the term-structure of the variance risk premium.

Fourth, we dissect the variance risk premium into good and bad variance risk premia. Intuitively, the good variance risk premium captures the compensation for the variance of positive returns. Conversely, the bad variance risk premium reflects the compensation for the variance of the negative returns. By comparing the response of these two components, we are able to shed light on the determinants of the announcement effect. We establish that most of the announcement effect arises from the response of the bad variance risk premium. The results of the 7-day variance risk premium perfectly illustrate this result. A unit shock to the interest rate announcement surprise moves the 7-day variance risk premium by 1.45% (t-stat=2.04). The response of the bad variance risk premium (1.29%, t-stat=2.26) completely dwarfs that of the good variance risk premium (0.15%, t-stat=0.92).

We conduct several additional tests. To begin with, we explore whether the reactions to the announcement surprise is state dependent. We find that contractionary policy has no significant impact on the term-structure of the variance risk premium while expansionary policy has a significantly negative impact on it. It strongly suggests that the decrease of target federal fund target rate narrows the changes in market price of variance risk. Then, we investigate whether positive and negative announcement surprises have a differential impact on the term-structure of the variance risk premium. We find that positive announcement surprises have a small and insignificant impact on the variance risk premium. In contrast, negative announcement surprises significantly move the market price of variance risk. Furthermore, we analyze the impact of timing and level surprise on variance risk premium. We find that timing surprise has a significantly positive effect on the variance risk premium of short maturity. Additionally, we also employ an alternative measure of implied variance and an alternative definition of variance risk premium to check our main results and find that they are generally robust to different measure of implied variance and variance risk premium. Moreover, we use the averages of professional forecasters to measure the interest shocks and analyze the reactions of variance risk premium to them. Again, our main findings are robust to the measurement of shocks.

The remainder of this capter proceeds as follows: Section 4.2 describes some related studies. Section 4.3 introduces our data and methodology. Section 4.4 reports our results and findings. Section 4.5 presents some additional analyses. Finally, Section 4.6 concludes.

4.2 Literature Review

Our work is related to the broader literature on the impact of federal fund rate news on the equity risk premium. Bernanke and Kuttner (2005), Savor and Wilson (2013), Lucca and Moench (2015), and Law et al. (2018) study the response of the S&P 500 index to interest rate news. Bernanke and Kuttner (2005) investigate the effect of the federal fund rate on the S&P 500 index and find that only the unexpected change of rate statistically significantly affects the S&P 500 index. Savor and Wilson (2013) focus on FOMC interest rate, CPI, PPI and employment data. Their results support that most of the average excess returns accrue on announcement days. Lucca and Moench (2015) focus on FOMC news and find that excess return of S&P 500 stock index on pre-FOMC day increases and becomes significant. They also present that mean of excess return on FOMC days is much larger than other days. Law et al. (2018) study the response of the S&P 500 index to interest rate news and find that the reactions of the stock market to macroeconomic announcement depends on economic conditions. More recent studies, e.g. Avino et al. (2019) use synthetic dividend strip data to analyze the term-structure of announcement response. They document that the announcement effect is strongest at the short-end of the term-structure of the dividend risk premium and declines with the maturity of the dividend asset. Inspired by them, we focus on the impact of the unexpected changes of federal fund rate and then explore whether the impact on variance risk premium is state dependent. Different from these studies, we focus on the the term-structure of the variance risk premium rather than that of the equity risk premium.

Our research is connected to studies on the term-structure of the variance risk premium. Bormetti et al. (2016) employ multi-component GARCH model to generate the realistic shape of variance risk premium from very short to long maturity. They document a valley-shaped variance risk premium which decreases sharply with short maturity and then increases slowly with increasing maturity. Exploiting the information embedded in the term structure of variance swaps, Egloff et al. (2010) study the problem of asset allocation and optimal investments in variance-related securities. Konstantinidi and Skiadopoulos (2016) find that trading activity variables can provide best forecasting performance among all alternative predictive models for variance risk premium with different investment horizon. Aït-Sahalia et al. (2020) propose an elaborated model to capture the dynamics of the equity and variance risk premia and they find that variance risk premium with different maturity have difference reactions to various economic indicators. We complement these studies by studying the impact of interest rate news on the term-structure of variance risk premia. To the best of our knowledge, we are the first to undertake this analysis.

We also relates to the literature on the impact of interest rate news on the implied and/or realized variance. Chuliá et al. (2010) support that surprise of federal fund rate is highly significant for stock returns while the expected interest rate changes are insignificant. They document the impact of FOMC announcement surprises on the volatility of individual stock returns and find different reactions of them to positive and negative surprises. Gospodinov and Jamali (2012) study the effect of federal fund rate news on the changes of the realized and implied volatility of the S&P 500 index returns and confirm that only surprise change has an significant impact. Similar to us, they document a significant positive relation between interest rate announcement surprises and changes in the realized and implied volatility. Bekaert et al. (2013) use a structural vector-autoregressive method to analyze the relation between monetary policy and the VIX and its components. Fernandez-Perez et al. (2017) focus on the reactions of VIX to monetary policy in intraday level. Our work improves on these studies along several dimensions. To begin with, our main focus is on the variance risk premium rather than its components, i.e. implied and/or realized variance. Furthermore, we analyze the term-structure dimension. By doing so, we can shed light on which maturity responds the most to interest rate shocks.

We contribute to the growing literature on good and bad variance and the associated risk premia. Barndorff-Nielsen et al. (2008) formally show how to decompose the realized variance into good and bad semi-variance. Segal et al. (2015) show that good variance is associated with a booming economy while bad variance predicts low economic growth. They also study how the good and bad variance affects the market price of risk. Bekaert and Engstrom (2017) consider the positive and negative Gamma shocks to extend the model of Campbell and Cochrane model (2000) and find that the adjusted model can match several empirical asset pricing puzzles. Feunou et al. (2018) and Kilic and Shaliastovich (2019) compute the good and bad variance risk premia and analyze their relationship with the equity risk premium. Consistently, they find that bad variance risk premium is the main component and the good and bad component of variance risk premium play an asymmetric role in price of risk. We leverage their methodology to study how the good and bad components of the variables react to FOMC surprises.

4.3 Data and Methodology

We begin this section by introducing the data used for our main analysis. Next, we present our main research methodology.

4.3.1 Data

Options Data We obtain the data related to the S&P 500 equity index option market between January 01, 1996 and March 11, 2019 from IvyDB OptionMetrics. We supplement this dataset with the Zero Coupon Yield Curve, which we use to proxy for the term-structure of interest rates.

The option dataset contains information related to the trading date, the expiration date of each option, the daily best bid and offer prices, the open interest, the option dividends, and the Black and Scholes (1973) implied volatility. We keep all the available options with all the maturities on each specific day. Our data cleaning steps follow Oikonomou et al. (2019). Specifically, we remove observations with zero bid or ask prices. Additionally, we discard observations with missing Black and Scholes (1973) implied volatility. We also expunge observations that violate standard no-arbitrage conditions. We discard all the data for the period that precedes March 5, 2008. Prior to that date, OptionMetrics reports the option prices recorded at 16:15 Chicago Time (CT), whereas the latest index spot price is recorded at 16:00 CT. Clearly, this difference in observation times introduces an error in any analysis that requires synchronous observations of both the option and spot index prices. Since March 5, 2008, OptionMetrics records the spot and option prices at 16:00 CT, making the data well-suited for our analysis.

Return Data We obtain the time-series of the daily underlying index price as well as the corresponding dividends from the Center for Research in Security Prices (CRSP). In order to compute the realized variance and semi-variance series, we use regularly-sampled data observed at the 5-minute frequency. This data comes from the Oxford-Man Institute Realized Library of the University of Oxford.[1]

Federal Fund Rate Announcements We collect all the data related to the scheduled Federal Open Market Committee (FOMC) interest rate announcements from Bloomberg. There are usually eight meetings per year, each of which is associated with an announcement of the target federal fund rate. The dataset includes the announcement date, the announced interest rate, as well as the expectations of professional forecasters. Given our data requirements for the computation of the variance risk premium, our sample includes 85 monetary policy announcements. Every FOMC meeting is an event in our study. The prices of 30-day federal fund futures contracts are all from Bloomberg.

Following Kuttner (2001), we compute the interest rate announcement surprise

[1] The data is available at the following address: `https://realized.oxford-man.ox.ac.uk/data/download`.

as:[2]

$$\Delta i_t^u = \frac{D}{D-d}(f_t - f_{t-1}) \qquad (4.3.1)$$

where Δi_t^u denotes the time-t surprise of the federal fund rate. D is the number of calendar days in the announcement month. d is the number of days already elapsed during that month. f_t is the federal fund rate on day t implied from the 30-day federal fund futures price.[3] As is standard in the literature, we standardize the interest rate announcement surprise using the full sample standard deviation.[4]

4.3.2 Methodology

Excess Return We compute the annualized excess return on the stock index as follows:[5]

$$er_t = 252 \times \left(\frac{S_t - S_{t-1} + D_t}{S_{t-1}}\right) - rf_t 52 \qquad (4.3.2)$$

[2]An alternative approach consists in taking the difference between the announced interest rate figure and the mean estimate of professional forecasters. Similar to the extant literature, e.g. Bernanke and Kuttner (2005) and Avino et al. (2019), we prefer to implement the methodology of Kuttner (2001) to estimate the interest rate shock. In so doing, we ensure that our results are more comparable with those of the literature. As a further analysis, we consider the surprise after the current FOMC meeting which implies the near-term path of monetary policy. Following Gürkaynak et al. (2007) we decompose the surprise into timing and level component, we discuss these results in Section 4.5.3. Another popular measure of announcement surprise is the methodology of Balduzzi et al. (2001), which is based on professional forecasters. We employ this method and discuss these findings in Section 4.5.6.

[3]Following Kurov (2010), if the announcement occurs during the last 7 days of the month, the change of the federal rate is unscaled and we use the difference between next month's futures rate and the current month rate. If the change happens in the first day of the month, the change of rate is proxied by $f_t - f_D^{-1}$, where f_D^{-1} is the future rate of the last day in the previous month.

[4]Note that the standardization does not affect the statistical significance of our results.

[5]Throughout this paper, we annualize the excess return, the variance risk premium and the related quantities. By taking this step, we make our analysis comparable to that of existing studies, e.g. Bollerslev et al. (2009).

where er_t denotes the annualized excess return of the S&P 500 index on day t. S_t and S_{t-1} denote the price of the S&P 500 index on days t and $t-1$, respectively. D_t is the daily dividends paid by the S&P 500 index firms on day t. rf_t is the annualized 1-month Treasury bill rate observed on day t. The riskless rate data come from Kenneth French's website.[6] Part A of Table 4.1 shows the descriptive statistics of the excess return of S&P 500 index.

Variance Risk Premium Bollerslev et al. (2009) define the variance risk premium as follows:

$$VRP_{t,t+\tau} = \mathbb{E}_t^Q(V_{t,t+\tau}) - \mathbb{E}_t^P(V_{t,t+\tau}) \tag{4.3.3}$$

where $VRP_{t,t+\tau}$ indicates the variance risk premium between t and $t+\tau$. $\mathbb{E}_t^Q(V_{t,t+\tau})$ denotes the time-t expectation of variance under the risk-neutral (Q) measure. $\mathbb{E}_t^P(V_{t,t+\tau})$ is the time-t expectation of variance under the physical measure.

Carr and Wu (2009) propose to use the model-free implied variance to estimate the risk-neutral expectation of the variance. Furthermore, the authors use the ex-post realized variance to proxy for the physical expectation of the realized variance, thus leading to the following result:[7]

$$VRP_{t,t+\tau} = IV_{t,t+\tau} - RV_{t,t+\tau} \tag{4.3.4}$$

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

[7] Bollerslev et al. (2009) assume that the realized variance has a unit autocorrelation and use $\mathbb{E}_t^P(V_{t,t+\tau}) = RV_{t-\tau,t}$. We repeat our analysis by this measurement of variance risk premium and discuss the results in Section 4.5.5.

where $IV_{t,t+\tau}$ and $RV_{t,t+\tau}$ are the model-free implied variance and realized variance at time t over horizons of τ days, respectively.

Andersen et al. (2007) and Lee and Mykland (2008) show that the S&P 500 index jumps around macroeconomic announcements. Following Oikonomou et al. (2019), we use the Bakshi et al. (2003) estimator, which is argued to be robust to jumps, to compute the model-free implied variance:[8]

$$IV_{t,t+\tau} = \frac{360}{\tau}\left[\int_0^{S_t} \frac{2(1+\ln\frac{S_t}{K})}{K^2} P_t(\tau,K)dK + \int_{S_t}^{\infty} \frac{2(1-\ln\frac{K}{S_t})}{K^2} C_t(\tau,K)dK\right] \tag{4.3.5}$$

$\frac{360}{\tau}$ serves to annualize the implied variance estimate. $P_t(\tau,K)$ and $C_t(\tau,K)$ indicate the time-t out-of-the-money (OTM) put and call option prices with maturity τ and strike price K, respectively.

Our implementation broadly follows that of Chang et al. (2012). To fix ideas, we define the moneyness as the ratio of the strike price (K) over the spot price (S). For each maturity date observed on a given day, we require at least two OTM call and put options. Consequently, we discard days when these requirements are not met. Next, we employ the cubic spline to interpolate the implied volatility across the moneyness levels available in the market. For the moneyness levels greater or lower than the available moneyness levels in the market, we use the implied volatility corresponding to available maximum or minimum money-

[8] The estimator of Britten-Jones and Neuberger (2000) is also a widely-used estimator of implied variance, we replace implied variance with this estimator as a further analysis. We discuss these results in Section 4.5.4.

ness levels, respectively. By implementing the above interpolation-extrapolation method, we obtain a fine grid of 1,000 implied volatilities between a moneyness level of 1% and 300%. Next, we use the Black and Scholes (1973) formula to map the implied volatilities into the corresponding OTM option prices. Finally, we use the trapezoidal rule to numerically estimate the integrals. We repeat these steps for each maturity observed on that day, thus obtaining the term structure of implied variance. From this term structure, we linearly interpolate the implied variance of constant maturity of interest. In our empirical estimation, we separately estimate the (annualized) implied variance of maturity 7, 30, 60, 90, 180, 270, and 360 days.

The risk free rate used in our application of the Black and Scholes (1973) formula is processed as follows. We employ cubic spline interpolation method to get the risk free rate with different maturity on each trading day and then match them with options with corresponding expiration days on that trading day. As for the rate that need to be extrapolated, we choose the nearest cubic spline curve parameters and extend the line to get the risk free rate with the corresponding expiration day.

Realized Variance Following Bollerslev et al. (2009) and Bekaert and Hoerova (2014), we use 5-minute data to compute the realized variance:

$$RV_{t,t+\tau} = \frac{252}{N_t^\tau} \sum_{j=1}^{N_t^\tau} \sum_{i=0}^{H} r_{t+j,i}^2 \tag{4.3.6}$$

where $RV_{t,t+\tau}$ denotes the time-t annualized realized variance over the next τ days. N_t^τ is the number of trading days between t and $t+\tau$. H indicates the number of intraday observations on a given day. $r_{t+j,i}$ is the intraday return observed at time i of day $t+j$.

4.4 Main Results

This section presents our main empirical results. We first compare the distribution of the equity and variance risk premia on announcement and non-announcement days. Then, we analyze the impact of federal fund rate announcement surprises on the risk premia. Next, we decompose the variance risk premia into good and bad variance risk premia and study their responses to interest rate announcement shocks.

Before turning to our main empirical results, it is instructive to look at the summary statistics of our main variables. In doing so, we check whether our computation of the key variable yields results that are comparable to those of the literature. Table 4.1 shows that the equity risk premium is positive on average with an annualized value of 6.74% per annum. This estimate is generally in-line with the empirical results of existing studies. Turning to the variance risk premium estimates, we observe a positive average estimate across the whole maturity spectrum. We notice that the variance risk premium with 7 days maturity is higher than that with 30 days maturity. Not surprisingly, the variance risk premium with 7 days maturity is with the highest standard deviation and kurtosis, indicating that it is much more volatile than others. In addition, its AR(1) coefficient is the lowest, suggesting low persistence. Generally, the term structure of the variance risk premium is upward sloping. This finding is consistent with that of Egloff et al. (2010) and Li and Zinna (2018). Our estimates of the average variance risk premium are generally consistent with those of the literature, e.g. Oikonomou et al. (2019). The coefficient of autoregression reveals a high persistence in the time-series of the daily variance risk premium. This is not surprising given the large overlap between two consecutive daily observations. In light of this finding, we model the change in the variance risk premium (ΔVRP) rather than the level of the variance risk premium.

4.4.1 Distribution on Announcement vs. Non-Announcement Days

The previous discussion focuses on the unconditional distribution of the variables of interest. Although interesting, that analysis does not distinguish between announcement and non-announcement days. We now present the summary statistics for each of those types of dates, separately. In doing so, we are able to shed light on whether FOMC announcement days are special in that the distribution observed on those days is different from that of non-announcement days.

Equity Risk Premium Table 4.2 reports the mean and standard deviation of the annualized *er* on FOMC days and non-FOMC days. We can see that the mean equity risk premium is significantly larger on FOMC days than on non-FOMC days (p-value=0.01). Interestingly, the difference in the standard deviation observed on announcement and non-announcement days is not significant (p-value=0.32). This result is consistent with the finding of Lucca and Moench (2015) who document that a large part of the equity risk premium is earned on FOMC announcement days. We also implement the Kolmogorov-Smirnov testing procedure to test if the distributions of the excess returns observed on announcement and non-announcement days are equal. Our null hypothesis is that the equity risk premium on FOMC announcement days and the value on other days have the same distribution. We find that we cannot statistically reject the null hypothesis (p-value=0.11) and there is no significant difference between the two distributions.

Change in the Variance Risk Premium We now focus on the distributions of the change in the variance risk premium observed on announcement and non-announcement days. Table 4.2 reveals an interesting contrast across these two days. While the ΔVRP is very negative on announcement days, it is generally positive on non-announcement days. The difference between the two mean estimates is generally statistically significant. Interestingly, the absolute values of ΔVRP on announcement days generally decreases with increases of maturity. We implement a formal test to compare the two distributions and conclude that there is a statistically significant difference for several maturities. Especially, the significant difference is for ΔVRP with 7, 30 and 60 maturity days. Collectively, these results suggest that the FOMC announcement days have a significant impact on the distribution of the ΔVRP of short maturity.

4.4.2 The Impact of FOMC Surprises on

We now explore the impact of announcement surprises on er and ΔVRP.

$$y_t = \alpha + \beta \times \Delta i_t^u + \epsilon_t \tag{4.4.1}$$

where y_t is the variable of interest on FOMC announcement day t. This variable is either er or ΔVRP. α is the intercept. β sheds light on the impact of the FOMC announcement surprise on the variable of interest y. Δi_t^u is the FOMC announcement surprise at time t. ϵ_t is the residual at time t. Throughout this paper, we use White (1980)-corrected standard errors.

The Equity Risk Premium

Table 4.3 reports the regression results linked to the equity risk premium. We first notice the low explanatory power (Adj R^2=0.7%) of the regression model. We can also see that the slope estimate (0.44) is positive but not statistically significant (t-ratio=0.96). This result echoes that of Lucca and Moench (2015) and Avino et al. (2019), who also study a recent sample. We can also see that the intercept has a value (0.89) that is very close to the mean excess return observed on FOMC days (0.90). This result suggests that the high mean *er* on announcement days is not due to the interest rate announcement surprise.

The Change in the Variance Risk Premium

Findings We now analyze the impact of the announcement surprise on ΔVRP. Several results are worth discussing. To begin with, the explanatory power of the model rises from 7.45 % at the 7-day horizon to 16.70% at the 60-day horizon. Clearly, this result suggests that FOMC announcement surprises can help explain ΔVRP better than the *er*. Furthermore, the slope estimate is positive and significant for the short-term maturities. Economically, the positive slope estimates indicate that an unexpected shock in the federal fund rate is associated with a positive ΔVRP. The magnitude of the slope estimates is revealing too. We can see a declining pattern of announcement response across the maturity spectrum. This evidence points to a declining term-structure of announcement responses: the short-term ΔVRP is more responsive to FOMC news than its long-term counterpart.

In order to better understand the pattern of announcement responses, we decompose ΔVRP into two components, namely ΔIV and ΔRV:

$$\Delta VRP_{t,t+\tau} = \Delta IV_{t,t+\tau} - \Delta RV_{t,t+\tau} \tag{4.4.2}$$

We then regress each of these two components on a constant and the announcement surprise. Table 4.3 documents that the explanatory power for ΔRV is much larger than that of ΔIV. We can see that both ΔIV and ΔRV respond positively to interest rate news. This result echoes that of Gospodinov and Jamali (2012), who document a similar pattern for the monthly maturity. The positive slope estimates of ΔIV and ΔRV both decrease across the maturity spectrum, indicating the declining responses to FOMC news. It is also worth noting that, for short maturities, ΔIV reacts more to FOMC news than ΔRV. Economically, this finding suggests that increases in interest rates make the stock market more volatile. Over long horizons, there is very little to distinguish between the two sets of estimates. Collectively, these results help explain the downward-sloping term structure of announcement responses of ΔVRP. Based on the slope estimates, we conclude that the interest rate news mostly affects ΔIV and changes of implied variance is the main channel of response of the ΔVRP to the changes of interest rates.

Digging Deeper: Good vs. Bad Variance Risk Premia Following Kilic and Shaliastovich (2019), we decompose the model-free implied variance into good and bad model-free implied variance:

$$IV_{t,t+\tau} = IV^g_{t,t+\tau} + IV^b_{t,t+\tau} \tag{4.4.3}$$

$$IV^g_{t,t+\tau} = \frac{360}{\tau}\left[\int_{S_t}^{\infty} \frac{2(1-\ln\frac{K}{S_t})}{K^2} C_t(\tau,K)dK\right] \tag{4.4.4}$$

$$IV^b_{t,t+\tau} = \frac{360}{\tau}\left[\int_{0}^{S_t} \frac{2(1+\ln\frac{S_t}{K})}{K^2} P_t(\tau,K)dK\right] \tag{4.4.5}$$

where $IV^g_{t,t+\tau}$ and $IV^b_{t,t+\tau}$ denote the good and bad implied variance for the period starting at t and ending at $t+\tau$. Intuitively, the good (bad) model-free implied variance is defined as the implied variance of positive (negative) returns.

Barndorff-Nielsen et al. (2008) also define the concept of realized semi-variances. Briefly, the good and bad realized variance capture the variation of the positive and negative returns, respectively:

$$RV_{t,t+\tau} = RV^g_{t,t+\tau} + RV^g_{t,t+\tau} \tag{4.4.6}$$

$$RV^g_{t,t+\tau} = \frac{252}{N_t^\tau}\sum_{j=1}^{N_t^\tau}\sum_{i=0}^{H} r^2_{t+j,i}\mathbb{1}(r_{t+j,i} > 0) \tag{4.4.7}$$

$$RV^b_{t,t+\tau} = \frac{252}{N_t^\tau}\sum_{j=1}^{N_t^\tau}\sum_{i=0}^{H} r^2_{t+j,i}\mathbb{1}(r_{t+j,i} \leq 0) \tag{4.4.8}$$

where $RV^g_{t,t+\tau}$ and $RV^b_{t,t+\tau}$ are the annualized good and bad realized variance at time t over horizons of τ days, respectively.

We can then calculate the good and bad variance risk premia:

$$VRP^{g}_{t,t+\tau} = IV^{g}_{t,t+\tau} - RV^{g}_{t,t+\tau} \tag{4.4.9}$$

$$VRP^{b}_{t,t+\tau} = IV^{b}_{t,t+\tau} - RV^{b}_{t,t+\tau} \tag{4.4.10}$$

where $VRP^{g}_{t,t+\tau}$ is the good variance risk premium for the period t to $t+\tau$. $VRP^{b}_{t,t+\tau}$ denotes the bad variance risk premium for the period starting at t and ending at $t+\tau$.

We study the response of the good and bad variance risk premia to monetary policy shocks. Table 4.4 presents the results. We can see that the good variance risk premium does not significantly respond to monetary policy news. In contrast, the bad variance risk premium displays a positive and strong response to interest rate announcement surprises. The strength of the announcement response declines with the horizon. This finding mirrors that of Table 4.3. Examining the magnitude of the announcement response, we can see that the slope estimates associated with the bad variance risk premia are very similar to those of the total variance risk premium. The results of the 7-day horizon perfectly illustrate this pattern. The total variance risk premium displays a slope estimate of 1.45%. This estimate is very similar to that of the bad variance risk premia 1.29%. We thus conclude that most of the announcement responses of the variance risk premium documented in Table 4.3 stems from the bad variance risk premia. Intuitively, investors are keen on positive stock returns and want to hedge against bad components. We infer that investors worry more about the variance of negative returns since investors are risk-averse.

We move to analyze the impact of announcement surprise on the good and bad component of implied variance and realized variance. We observe several findings. First, the good and bad implied variance both react more strongly than good and bad realized variance, respectively. Table 4.3 already showed that the implied variance reacts more than realized variance and this finding helps understand it. Second, the bad implied variance reacts more than the good implied variance while good realized variance reacts more than bad realized variance.

4.5 What About...

4.5.1 Contractionary vs. Expansionary Policy?

When the FOMC follows a contractionary monetary policy, the federal fund target rate will increase and the overheating economic condition is reduced. When the FOMC stimulates the economy and implements an expansionary policy, the federal fund target rate will decrease. In this analysis, we explore whether the reactions to FOMC announcement news depends the policy stance. We estimate the following regression:

$$y_t = \alpha_0 + (\alpha_1 + \beta_1 \times \Delta i_t^u) D_t^+ + (\alpha_2 + \beta_2 \times \Delta i_t^u) D_t^- + \epsilon_t \tag{4.5.1}$$

D_t^+ is the dummy variable that takes value 1 for contractionary policy on day t and dummy variable D_t^- is equal to 1 for expansionary policy on day t. α, α_1, and α_2 denote the intercept on days when the there is no announcement, increase of target rate and decrease of target rate, respectively. The coefficients β_1 and β_2 estimate the response to increase of target rate and decrease of target rate, respectively.

Table 4.5 presents the regression results. Not surprisingly, we notice that contractionary policy has no significant effect on er while it reacts significantly positively to expansionary policy. Economically, it confirms that the expansionary policy stimulate the economy and the boom of stock market is a channel. We move to the analysis on the reactions of ΔVRP. First, the presence of contractionary policy gernerally has a positive but insignificant effect on ΔVRP while the presence of expansionary policy has a negative and significantly effect. Moreover, the strength of ΔVRP reactions to the presence of expansionary policy decreases with maturity. It suggests that the reaction to the interest rate shock is state dependent and expansionary policy has a stronger impact on the market than contractionary policy. Second, the magnitude of increase of target rate generally has a positive but insignificant effect on ΔVRP. However, the magnitude of decrease of target rate has a significantly positive effect on ΔVRP with short maturities reacts and the strength of the policy stance response, proxied by the magnitude of the parameter estimates, decreases with maturity. Overall, it suggests that expansionary policy decreases the compensation for variance risk and market participants can bear more variance risk. Not surprisingly, the more decrease of the target rate, the less decrease of the change in variance compensation. It supports the declining impact of magnitude of monetary policy.

Turning to the reactions of ΔIV and ΔRV to interest rate news, we get several results. First, we can see that reactions of ΔIV dominate and ΔIV reacts more than ΔRV in both contractionary policy and expansionary policy. It is consistent with findings in Table 4.2. Moreover, the term-structure of reactions of ΔIV is almost similar with those of ΔVRP. Second, both ΔIV and ΔRV respond more strongly to expansionary policy than contractionary policy. Overall, expansionary policy diminishes the volatile in stock market and the impact of magnitude of decrease in target rate declines over the maturity.

Pursuing the analysis of the impact of announcement surprise on good and bad components, Table 4.6 presents the following findings. First, both good and bad component of ΔVRP, ΔIV and ΔRV react more to expansionary policy than contractionary policy. Second, consistent with the finding in Table 4.4, bad component of ΔVRP and ΔIV respond more strongly to both expansionary policy and contractionary policy than good component. However, expansionary policy has a stronger impact on good component of ΔIV than bad component. Third, good and bad component of ΔIV both generally react more to both expansionary policy and contractionary policy than ΔRV.

4.5.2 Positive vs. Negative Surprises?

Up to this point, we have analyzed the impact of announcement surprises on the variables of our interest. However, this analysis does not distinguish between positive and negative announcement surprises. Naturally, one may wonder whether positive and negative announcement surprises have the same impact on the variables of interest. This analysis is particularly important given the low interest rate regime that prevails over a significant part of our sample period.

To shed light on this, we estimate the following regression: the regression (4.5.1). D_t^+ is the dummy variable that takes value 1 for positive surprises of federal fund rate on day t and dummy variable D_t^- is equal to 1 for negative surprises of federal fund rate on day t. α, α_1, and α_2 denote the intercept on days when the announcement surprise is zero, positive, and negative, respectively. The coefficients β_1 and β_2 estimate the response to positive and negative surprise, respectively.

Table 4.7 presents the regression results. Starting with er, we can see that it does not react significantly to the positive or negative announcement surprises. Turning to ΔVRP, several points are worth highlighting. First, the strength of the announcement response, which we proxy by the magnitude of the parameter estimates, decreases with maturity. This is true irrespective of whether we look at positive and negative announcement surprises. Second, the positive announcement surprise has a negative, though insignificant, effect on ΔVRP while the negative surprise has a positive and often significant effect, especially for short maturities. This result is particularly striking for maturities up to 90 days. Together, these results suggest that most of our main findings (see Table 4.3) may be driven by the periods of negative interest shocks. They are intuitive too. When the central bank negatively surprises the market, markets become more volatile and investors become more risk-averse and therefore require a higher compensation for variance risk. Table 4.8 reports reactions of good and bad components to positive and negative interest rate shocks. Consistently, we notice that most of the reactions of variance risk premium to announcement is from bad components. Not surprisingly, both the good and bad components react more strongly to negative interest shocks, suggesting that investors need more compensation for the negative surprise.

4.5.3 Timing vs. Level surprise

Gürkaynak et al. (2007) decompose the federal fund rate surprise of Kuttner (2001) into two parts: timing surprise and the level surprise. The level surprise is defined as the change in interest rate which still works after the next FOMC meeting. Following Gürkaynak et al. (2007), we compute the level surprise, $\Delta i_t^{u,l}$ as follows:

$$\Delta i_t^{u,l} = \frac{D_1}{D_1 - d_1}[(f_t^1 - f_{t-1}^1) - \frac{d_1}{D_1}\Delta i_t^u] \tag{4.5.2}$$

where d_1 is the number of days of the next FOMC meeting and D_1 is the number of days in the month on which the next FOMC meeting is held, f_t is the federal fund rate from 3-month futures contract for the month containing the occurrence of the next FOMC meeting and Δi_t^u is defined as Equation (4.3.1). The timing surprise, $\Delta i_t^{u,t}$, is defined as the change of the interest rate only for the next meeting. Gürkaynak et al. (2007) estimate that $\Delta i_t^u = \Delta i_t^{u,t} + \Delta i_t^{u,t}$. Following them, we can get the $\Delta i_t^{u,t}$. Instead of Δi_t^u, we use $\Delta i_t^{u,l}$ and $\Delta i_t^{u,t}$ to augment the regression in Equation (4.4.1) and repeat our main analysis.

Table 4.9 presents the regression results. We begin with er and notice that both the timing and level surprise have no significant effect on the er. Our result is consistent with our main finding that er does not react significantly to the interest shocks, neither timing nor level surprise. Moving to ΔVRP, we find that the change in variance risk premium responds strongly to the timing surprise compared to the level surprise for maturities up to 60 days. Level surprise has an insignificant effect on the variance risk premium with maturity longer than 60 days. It is not surprise. Gürkaynak (2005) present that the impact of timing surprise on Treasury yields decreases with horizon. Since the definition of timing surprise is based on the change of the interest rate for the next FOMC meeting, timing surprise matters for the variance risk premium with short maturities. Additionally, both timing and level surprise has a decreasing effect on the variance risk premium with the increases of maturity. Table 4.10 shows the reactions of good and bad components to timing and level surprise. The finding is consistent with our main finding.

4.5.4 An Alternative Measure of Implied Variance?

In our main specification, we use the jump-robust method of Bakshi et al. (2003) to estimate the implied variance. Britten-Jones and Neuberger (2000) nonparametric approach is also popular in implied variance calculation (Carr and Wu, 2009). Du and Kapadia (2012) point that Britten-Jones and Neuberger (2000) method is not robust to the underlying asset with jumps. However, the S&P 500 index jumps around macroeconomic announcements, which is presented by Andersen et al. (2007) and Lee and Mykland (2008). In order to take the role of jumps in reactions to interest rate shocks into account, we follow Britten-Jones and Neuberger (2000) to estimate the implied variance as:

$$IV_{t,t+\tau}^{BN} = \frac{360}{\tau} \times 2 \times \left[\int_0^{S_t} \frac{P_t(\tau, K)}{K^2} dK + \int_{S_t}^{\infty} \frac{C_t(\tau, K)}{K^2} dK \right] \tag{4.5.3}$$

where all the variables are defined as before and the implied variance estimate is also annualized. We repeat our main analysis and present the results of robust test in Table 4.11-4.14. We find that these results are consistent with our benchmark.

4.5.5 An Alternative Definition of Variance Risk Premium?

The definition of variance risk premium in our previous study is the difference between the implied variance over $[t, t + \tau]$ and the ex post realized variance over

$[t, t+\tau]$. However, the variance risk premium cannot be directly observed at time t. Following Bollerslev et al. (2009), we assume that $\mathbb{E}_t^P(V_{t,t+\tau}) = RV_{t-\tau,t}$ which means that the realized variance has a unit autocorrelation. In this subsection, the definition of variance risk premium is as:

$$VRP^{ea}_{t,t+\tau} = IV_{t,t+\tau} - RV_{t-\tau,t} \tag{4.5.4}$$

where $RV_{t-\tau,t}$ is the realized variance over the $[t-\tau, t]$ time interval. Thus the realized variance is available at time t. We repeat the main analysis by $VRP^{ea}_{t,t+\tau}$ rather than $VRP_{t,t+\tau}$ and report the results in Table 4.15-4.18. Generally, our main findings are robust to the definition of variance risk premium.

4.5.6 The Reactions from Professional Forecasts?

Balduzzi et al. (2001) employ the professional forecasts of macroeconomic announcements to gauge the shocks of macroeconomic news. The professional forecaster is an alternative measure of market expectations of interest rate. Following Balduzzi et al. (2001), we compute the interest rate shocks of day t as the difference between the actual figure and the market's expectation and then standardize the surprise:

$$\Delta i_t^{u,f} = \frac{A_t - F_t}{\sigma} \tag{4.5.5}$$

where $\Delta i_t^{u,f}$ represents the standardized surprise of interest rate shock made on day t, A_t is the actual announcement of target federal fund rate released at time t, F_t denotes the expected announcement made before actual release day t and in this subsection it is proxied by the mean of all survey forecasts of federal fund rate from professional forecasters surveyed by Bloomberg. σ is the standard deviation of the interest rate shock series based on the sample of 85 FOMC meetings. We repeat the main analysis by measurement of interest rate shocks $\Delta i_t^{u,f}$ and present the results in Table 4.19-4.22. Overall, our main results are consistent with the measurement of interest shocks.

4.6 Conclusion

In this chapter, we study the impact of monetary policy news on the pricing of equity and variance risk. Consistent with recent studies, we find that the S&P 500 index does not respond to interest rate news. Interestingly, we document a positive relationship between the change in the variance risk premium and interest rate news. The magnitude of the announcement effect is strong at the short-end of the curve and gradually declines. Furthermore, we find that the shape of reactions of variance risk premium to FOMC announcements is mainly driven by the reactions of implied variance rather than realized variance.

We explore the channels through which the announcement effect arises. We report that timing surprise matters for the variance risk premium with short maturities. Considering monetary stance, we document that only expansionary policy has a significant impact on the variance risk premium, suggesting that the decrease of target rate affects more strongly. Our analysis reveals that most of the announcement effect can be traced back to the negative surprises of the federal fund rate as well as the bad variance risk premium. Collectively, this set of findings suggest that investors view negative interest rate announcement surprises as signs of bad economic times. Thus, they require a high risk premium as compensation for the increased downside risk.

4.7 Tables and Appendices

Table 4.1: Summary Statistics

This table reports summary statistics of implied variance, realized variance and variance risk premium. The definition and calculation of all the variables are presented in Section 4.3. Columns under Maturity, Number, Mean(%), Std. dev.(%), Skewness, Kurtosis report the variables with calendar days of maturity (for realized variance, it means the days of average values), number of observations, sample average in percentage, standard deviation in percentage, skewness, kurtosis respectively. AR(1) reports the values of coefficient for the first autocorrelation. Our sample period is from March 5, 2008 to March 11, 2019.

	Maturity	Number	Mean(%)	Std dev(%)	skewness	kurtosis	AR(1)
Part A: Excess Return							
S&P 500 Index		2470	6.74	19.19	-0.28	14.04	-0.07
Part B: Term-Structure of the Variance Risk Premium							
	7	2470	3.13	8.59	12.08	243.00	0.53
	30	2470	2.32	4.99	1.60	31.20	0.91
Variance	60	2470	2.60	5.13	0.06	23.11	0.97
Risk	90	2470	2.89	5.13	-0.27	18.22	0.98
Premium	180	2470	3.52	4.86	-0.06	10.39	0.99
	270	2470	4.09	4.70	0.29	7.76	0.99
	360	2470	4.64	4.46	0.68	6.79	0.99

Table 4.2: Different Dynamics on FOMC days versus on Non-FOMC days

This table provides the mean, standard deviation and distribution of the annualized er, IV, RV and VRP with different maturities on All days, FOMC days and Other (non-FOMC) days. p_T presents the p-values of t-test for the null hypothesis of mean equality, p_F presents the p-values of F-test for the null hypothesis of standard deviation equality, p_K presents the p-values of Kolmogorov Smirnov test for the null hypothesis of distribution equality. Values in bold indicate that the p-value of the test is statistically significant at 5% level.

	Mean				Standard Deviation				Dist.
Variable	All	FOMC	Other	p	All	FOMC	Other	p	p
Part A: Excess Return									
er	6.74	90.47	3.76	**0.01**	19.19	20.55	19.11	0.32	0.11
Part B: Variance Risk Premium									
ΔVRP_7	0.05	-53.10	1.95	0.33	8.33	4.95	8.43	**0.00**	**0.03**
ΔVRP_{30}	0.04	-59.60	2.16	**0.01**	2.17	2.02	2.18	0.36	**0.05**
ΔVRP_{60}	-0.03	-39.10	1.36	**0.00**	1.27	1.21	1.27	0.57	**0.04**
ΔVRP_{90}	-0.06	-28.30	0.94	**0.00**	1.06	0.89	1.06	**0.04**	0.15
ΔVRP_{180}	-0.05	-21.30	0.71	**0.01**	0.78	0.68	0.78	0.09	0.05
ΔVRP_{270}	0.36	-17.60	1.00	**0.01**	0.66	0.59	0.66	0.20	0.06
ΔVRP_{360}	0.33	-13.00	0.81	**0.02**	0.64	0.53	0.64	**0.03**	0.18
Part C: Implied Variance									
ΔIV_7	-0.18	-72.20	2.39	0.27	8.25	5.94	8.32	**0.00**	0.15
ΔIV_{30}	-0.16	-61.70	2.04	**0.01**	2.13	2.26	2.12	0.37	0.06
ΔIV_{60}	-0.16	-40.70	1.29	**0.00**	1.22	1.33	1.21	0.21	**0.04**
ΔIV_{90}	-0.15	-31.60	0.97	**0.00**	1.02	0.97	1.02	0.55	0.06
ΔIV_{180}	-0.13	-22.60	0.67	**0.01**	0.76	0.71	0.76	0.40	**0.04**
ΔIV_{270}	-0.14	-18.20	0.51	**0.01**	0.64	0.60	0.65	0.35	**0.04**
ΔIV_{360}	-0.14	-13.60	0.34	**0.05**	0.63	0.54	0.64	0.06	0.09
Part D: Realized Variance									
ΔRV_7	-0.23	-19.10	0.45	0.25	1.33	1.54	1.32	**0.03**	0.32
ΔRV_{30}	-0.20	-2.17	-0.13	0.71	0.51	0.50	0.51	0.91	0.37
ΔRV_{60}	-0.13	-1.61	-0.08	0.46	0.32	0.18	0.32	**0.00**	**0.00**
ΔRV_{90}	-0.09	-3.29	0.02	0.09	0.22	0.17	0.23	**0.00**	**0.03**
ΔRV_{180}	-0.09	-1.31	-0.04	0.19	0.13	0.08	0.13	**0.00**	0.33
ΔRV_{270}	-0.50	-0.61	-0.49	0.85	0.07	0.06	0.07	**0.01**	**0.00**
ΔRV_{360}	-0.48	-0.58	-0.47	0.84	0.05	0.05	0.05	0.87	**0.01**

Table 4.3: Surprise of Federal Fund Rate on er, ΔIV, ΔRV and ΔVRP

The table reports the regression results of Equation (4.4.1) which analyze the reactions from er (in Part A), ΔIV, ΔRV and ΔVRP (in Part B) to the FOMC surprise. It provides the intercept (α), slope (β) and adjusted R^2 and obs represents the number of observation. All standard errors are adjusted following White (1980) and robust t-statistics in parentheses. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

Part A: Excess Return

variable	obs	α	β	Adj. R^2
er	85	0.8930**	0.4419	0.00652
		(2.53)	(0.96)	

Part B: ΔVRP, ΔIV, ΔRV

		ΔVRP			ΔIV			ΔRV		
maturity	obs	α	β	Adj. R^2	α	β	Adj. R^2	α	β	Adj. R^2
7	85	-0.0057	0.0145**	0.0745	-0.0079	0.0254**	0.1730	-0.0022*	0.0109**	0.495
		(-1.10)	(2.04)		(-1.34)	(2.11)		(-1.81)	(2.19)	
30	85	-0.0062***	0.0075**	0.1270	-0.0065***	0.0107**	0.2140	-0.0003	0.0032***	0.408
		(-3.01)	(2.12)		(-2.97)	(2.42)		(-0.73)	(3.04)	
60	85	-0.0040***	0.0051**	0.1670	-0.0042***	0.0064**	0.2210	-0.0002	0.0013**	0.491
		(-3.37)	(2.13)		(-3.34)	(2.25)		(-1.38)	(2.45)	
90	85	-0.0029***	0.0021	0.0441	-0.0032***	0.0033**	0.1060	-0.0004**	0.0012**	0.493
		(-3.02)	(1.55)		(-3.23)	(2.06)		(-2.62)	(2.29)	
180	85	-0.0022***	0.0008	0.0033	-0.0023***	0.0014	0.0301	-0.0001**	0.0006**	0.503
		(-2.92)	(0.85)		(-3.05)	(1.34)		(-2.19)	(2.30)	
270	85	-0.0018***	-0.0002	-0.0110	-0.0018***	0.0002	-0.0106	-0.0001*	0.0004**	0.549
		(-2.69)	(-0.21)		(-2.78)	(0.25)		(-1.73)	(2.60)	
360	85	-0.0013**	0.0000	-0.0120	-0.0014**	0.0003	-0.0079	-0.0001*	0.0003**	0.488
		(-2.22)	(0.01)		(-2.31)	(0.48)		(-1.75)	(2.42)	

Table 4.4: Reactions of Good and Bad Components to FOMC surprise

The table reports the regression results of Equation (4.4.1) which analyze the reactions from ΔIV, ΔRV and ΔVRP to the FOMC surprise. It provides the intercept (α), slope (β) R-squared and adjusted R-squared and obs represents the number of observation. All standard errors are adjusted following White (1980) and robust t-statistics in parentheses. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

	good							bad						
	7	30	60	90	180	270	360	7	30	60	90	180	270	360
Part A: ΔVRP														
α	-0.0028*	-0.0018***	-0.0012***	-0.0008***	-0.0006***	-0.0005***	-0.0004***	-0.0029	-0.0043***	-0.0029***	-0.0020***	-0.0016***	-0.0013**	-0.0009*
	(-1.80)	(-2.99)	(-3.58)	(-3.42)	(-3.48)	(-3.59)	(-3.57)	(-0.77)	(-2.87)	(-3.21)	(-2.81)	(-2.70)	(-2.41)	(-1.87)
β	0.0015	0.0011	0.0012*	0.0007	0.0003	0.0002	0.0002	0.0129**	0.0064**	0.0039**	0.0014	0.0005	-0.0004	-0.0001
	(0.92)	(1.19)	(1.88)	(1.57)	(1.26)	(1.01)	(1.01)	(2.26)	(2.38)	(2.21)	(1.46)	(0.67)	(-0.48)	(-0.23)
obs	85	85	85	85	85	85	85	85	85	85	85	85	85	85
R^2	0.012	0.035	0.142	0.082	0.045	0.028	0.025	0.123	0.177	0.183	0.045	0.009	0.007	0.001
Adj. R^2	-0.000178	0.0236	0.131	0.0706	0.0334	0.0168	0.0132	0.112	0.168	0.173	0.0334	-0.00315	-0.00534	-0.0110
Part B: ΔIV														
α	-0.0037*	-0.0019***	-0.0013***	-0.0010***	-0.0007***	-0.0005***	-0.0004***	-0.0042	-0.0045***	-0.0030***	-0.0022***	-0.0016***	-0.0013**	-0.0010*
	(-1.99)	(-3.18)	(-3.54)	(-3.57)	(-3.63)	(-3.66)	(-3.65)	(-1.01)	(-2.84)	(-3.20)	(-2.98)	(-2.78)	(-2.47)	(-1.93)
β	0.0094**	0.0032**	0.0022**	0.0015**	0.0007*	0.0005*	0.0004*	0.0160**	0.0075**	0.0042**	0.0018*	0.0007	-0.0003	-0.0000
	(2.05)	(2.29)	(2.28)	(2.13)	(1.93)	(1.83)	(1.86)	(2.14)	(2.48)	(2.22)	(1.78)	(0.92)	(-0.32)	(-0.05)
obs	85	85	85	85	85	85	85	85	85	85	85	85	85	85
R^2	0.230	0.255	0.306	0.249	0.165	0.130	0.123	0.154	0.207	0.195	0.068	0.017	0.003	0.000
Adj. R^2	0.221	0.246	0.298	0.240	0.155	0.119	0.112	0.143	0.197	0.185	0.0569	0.00473	-0.00925	-0.0120
Part C: ΔRV														
α	-0.0009	-0.0001	-0.0001	-0.0002**	-0.0001*	-0.0000	-0.0000	-0.0013**	-0.0002	-0.0001	-0.0002***	-0.0001**	-0.0000*	-0.0000*
	(-1.29)	(-0.34)	(-0.98)	(-2.09)	(-1.83)	(-1.42)	(-1.40)	(-2.13)	(-1.05)	(-1.41)	(-2.76)	(-2.22)	(-1.74)	(-1.84)
β	0.0078**	0.0022***	0.0009**	0.0008**	0.0004**	0.0003***	0.0002**	0.0031*	0.0010***	0.0003**	0.0004**	0.0002**	0.0001**	0.0001**
	(2.45)	(3.06)	(2.62)	(2.40)	(2.42)	(2.68)	(2.52)	(1.70)	(2.87)	(2.00)	(2.07)	(2.07)	(2.43)	(2.25)
obs	85	85	85	85	85	85	85	85	85	85	85	85	85	85
R^2	0.600	0.450	0.615	0.591	0.597	0.647	0.596	0.246	0.239	0.162	0.286	0.287	0.313	0.277
Adj. R^2	0.595	0.443	0.610	0.586	0.593	0.643	0.591	0.237	0.230	0.152	0.277	0.278	0.305	0.268

Table 4.5: Surprise of Federal Fund Rate on Contractionary and Expansionary Policy

The table reports the regression results of Equation (4.5.1) which analyze the reactions from er (in Part A), ΔIV, ΔRV and ΔVRP (in Part B) depend on contractionary and expansionary policy. It provides the intercept, slope and adjusted R-squared and obs represents for the number of observation. The coefficients α, α_1 and α_2 represent the effect of no surprises days, contractionary policy presence days and expansionary policy presence days, respectively. The coefficients β_1 and β_2 estimate the response to strength of the contractionary and expansionary policy, respectively. All standard errors are adjusted following White (1980) and robust t-statistics in parentheses. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

Part A: Excess Return												
variable	Obs	α	t-stat	α_1	t-stat	β_1	t-stat	α_2	t-stat	β_2	t-stat	Adj. R^2
er	85	0.8060**	(2.35)	-1.0081	(-1.19)	-0.1945	(-1.20)	9.1528***	(3.42)	1.3809***	(3.36)	0.209

Part B: ΔVRP, ΔIV , ΔRV												
maturity	Obs	α	t-stat	α_1	t-stat	β_1	t-stat	α_2	t-stat	β_2	t-stat	Adj. R^2
						ΔVRP						
7	85	-0.0013	(-0.23)	-0.0075	(-0.98)	0.0017	(0.95)	-0.0662***	(-2.99)	0.0125***	(3.79)	0.119
30	85	-0.0041*	(-1.97)	0.0025	(0.80)	-0.0004	(-0.75)	-0.0461***	(-19.35)	0.0058***	(32.85)	0.315
60	85	-0.0024**	(-2.23)	0.0002	(0.09)	0.0003	(0.58)	-0.0360***	(-9.47)	0.0035***	(6.27)	0.477
90	85	-0.0019**	(-2.29)	0.0012	(0.90)	0.0001	(0.26)	-0.0287***	(-3.07)	0.0001	(0.05)	0.335
180	85	-0.0016**	(-2.27)	0.0009	(0.87)	0.0002	(1.13)	-0.0206***	(-2.96)	-0.0007	(-0.65)	0.248
270	85	-0.0014**	(-2.44)	0.0012	(1.66)	0.0001	(1.24)	-0.0177**	(-2.05)	-0.0018	(-1.38)	0.214
360	85	-0.0010*	(-1.80)	0.0012	(1.04)	0.0000	(0.05)	-0.0148**	(-2.52)	-0.0014	(-1.55)	0.179
						ΔIV						
7	85	-0.0017	(-0.27)	-0.0047	(-0.62)	0.0014	(1.00)	-0.0928**	(-2.17)	0.0240***	(3.66)	0.268
30	85	-0.0040*	(-1.82)	0.0027	(0.94)	0.0005	(0.97)	-0.0515***	(-8.84)	0.0087***	(10.44)	0.402
60	85	-0.0024**	(-2.12)	0.0003	(0.12)	0.0004	(0.80)	-0.0387***	(-24.61)	0.0048***	(28.14)	0.533
90	85	-0.0021**	(-2.33)	0.0012	(0.90)	0.0002	(0.70)	-0.0311***	(-4.46)	0.0014	(1.33)	0.417
180	85	-0.0016**	(-2.28)	0.0010	(0.89)	0.0002	(1.05)	-0.0217***	(-3.76)	-0.0000	(-0.04)	0.298
270	85	-0.0014**	(-2.40)	0.0012	(1.63)	0.0001	(1.31)	-0.0182**	(-2.27)	-0.0013	(-1.09)	0.228
360	85	-0.0010*	(-1.79)	0.0012	(1.04)	0.0000	(0.09)	-0.0154***	(-2.86)	-0.0010	(-1.22)	0.198
						ΔRV						
7	85	-0.0004	(-0.54)	0.0027	(1.38)	-0.0003	(-0.51)	-0.0266	(-1.27)	0.0115***	(3.54)	0.714
30	85	0.0001	(0.31)	0.0002	(0.23)	0.0009***	(9.91)	-0.0054	(-0.83)	0.0029***	(2.87)	0.377
60	85	0.0000	(0.18)	0.0001	(0.52)	0.0001***	(6.07)	-0.0027	(-1.08)	0.0013***	(3.20)	0.606
90	85	-0.0002*	(-1.75)	0.0001	(0.46)	0.0001***	(4.77)	-0.0024	(-1.00)	0.0013***	(3.61)	0.674
180	85	-0.0000	(-1.11)	0.0001	(0.55)	0.0000	(0.29)	-0.0012	(-0.98)	0.0007***	(3.66)	0.682
270	85	-0.0000	(-0.26)	0.0000	(0.17)	0.0000*	(1.80)	-0.0005	(-0.79)	0.0005***	(4.97)	0.725
360	85	-0.0000	(-0.28)	0.0000	(0.26)	0.0000	(1.37)	-0.0006	(-1.24)	0.0004***	(5.09)	0.697

Table 4.6: Reactions of Good and Bad Component to Surprise of Federal Fund Rate on Contractionary and Expansionary Policy

The table reports the regression results of Equation (4.5.1) which analyze the reactions from good and bad components of ΔVRP, ΔIV and ΔRV depend on contractionary and expansionary policy. It provides the intercept, slope and adjusted R-squared and obs represents for the number of observation. The coefficients α, α_1 and α_2 represent the effect of no surprises days, contractionary policy presence days and expansionary policy presence days, respectively. The coefficients β_1 and β_2 estimate the response to strength of the contractionary and expansionary policy, respectively. All standard errors are adjusted following White (1980) and robust t-statistics in parentheses. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

	good							bad						
	7	30	60	90	180	270	360	7	30	60	90	180	270	360
Part A: ΔVRP														
α	-0.0016	-0.0014**	-0.0008***	-0.0006***	-0.0004***	-0.0004***	-0.0003***	0.0003	-0.0028*	-0.0016*	-0.0014**	-0.0011**	-0.0011**	-0.0007
	(-0.94)	(-2.19)	(-2.68)	(-2.66)	(-2.80)	(-2.98)	(-3.02)	(0.07)	(-1.77)	(-1.99)	(-2.08)	(-2.07)	(-2.24)	(-1.50)
α_1	-0.0017	0.0013*	0.0005	0.0004*	0.0003	0.0003	0.0002	-0.0058	0.0012	-0.0003	0.0007	0.0006	0.0009	0.0010
	(-0.63)	(1.92)	(1.40)	(1.69)	(1.56)	(1.51)	(1.50)	(-1.07)	(0.47)	(-0.15)	(0.67)	(0.69)	(1.65)	(0.93)
β_1	0.0004	-0.0004***	0.0000	0.0000	0.0001**	0.0000	0.0000	0.0013	-0.0000	0.0003	0.0001	0.0002	0.0001	-0.0000
	(0.53)	(-6.75)	(0.43)	(0.02)	(2.31)	(1.56)	(1.45)	(1.19)	(-0.00)	(0.59)	(0.29)	(0.91)	(1.05)	(-0.09)
α_2	-0.0293***	-0.0148***	-0.0103***	-0.0078***	-0.0050***	-0.0039***	-0.0031***	-0.0370	-0.0314***	-0.0256***	-0.0209***	-0.0156***	-0.0137*	-0.0117**
	(-11.56)	(-4.89)	(-7.07)	(-4.76)	(-4.06)	(-4.24)	(-3.71)	(-1.57)	(-13.16)	(-10.89)	(-2.71)	(-2.73)	(-1.78)	(-2.32)
β_2	-0.0003	0.0004	0.0007***	0.0002	0.0000	-0.0001	-0.0001	0.0128***	0.0054***	0.0028***	-0.0002	-0.0007	-0.0018	-0.0013*
	(-1.01)	(0.86)	(3.37)	(0.91)	(0.26)	(-0.42)	(-0.52)	(3.56)	(19.46)	(8.16)	(-0.13)	(-0.85)	(-1.49)	(-1.72)
Adj. R^2	0.0946	0.229	0.480	0.418	0.329	0.326	0.305	0.138	0.325	0.455	0.291	0.220	0.192	0.152
Part B: ΔIV														
α	-0.0013	-0.0011**	-0.0007**	-0.0006**	-0.0004***	-0.0003***	-0.0003***	-0.0004	-0.0029*	-0.0017*	-0.0015**	-0.0012**	-0.0011**	-0.0007
	(-0.71)	(-2.02)	(-2.45)	(-2.56)	(-2.72)	(-2.81)	(-2.85)	(-0.09)	(-1.74)	(-1.97)	(-2.18)	(-2.10)	(-2.24)	(-1.51)
α_1	-0.0004	0.0009	0.0004	0.0004	0.0003	0.0002	0.0002	-0.0043	0.0018	-0.0001	0.0008	0.0007	0.0009*	0.0010
	(-0.19)	(1.44)	(1.16)	(1.32)	(1.40)	(1.32)	(1.33)	(-0.77)	(0.78)	(-0.08)	(0.75)	(0.74)	(1.67)	(0.95)
β_1	0.0003	0.0001	0.0001	0.0001	0.0001	0.0001*	0.0000	0.0012	0.0004	0.0003	0.0001	0.0002	0.0001	-0.0000
	(0.69)	(0.94)	(1.42)	(1.33)	(1.65)	(1.67)	(1.51)	(1.11)	(0.95)	(0.70)	(0.55)	(0.87)	(1.09)	(-0.08)
α_2	-0.0432***	-0.0177***	-0.0118***	-0.0091***	-0.0056***	-0.0042***	-0.0034***	-0.0496	-0.0338***	-0.0269***	-0.0220***	-0.0161***	-0.0140*	-0.0120**
	(-3.75)	(-14.98)	(-30.89)	(-32.54)	(-10.97)	(-8.14)	(-6.73)	(-1.59)	(-7.25)	(-16.78)	(-3.24)	(-3.06)	(-1.87)	(-2.45)
β_2	0.0083***	0.0025***	0.0018***	0.0011***	0.0005***	0.0003***	0.0002**	0.0157***	0.0062***	0.0030***	0.0003	-0.0005	-0.0016	-0.0012
	(4.71)	(15.66)	(44.74)	(48.27)	(6.83)	(3.49)	(2.51)	(3.28)	(9.20)	(14.46)	(0.26)	(-0.67)	(-1.40)	(-1.61)
Adj. R^2	0.195	0.348	0.465	0.326	0.238	0.192	0.156	0.421	0.526	0.662	0.605	0.493	0.454	0.449
Part C: ΔRV														
α	0.0003	0.0003	0.0001*	-0.0000	-0.0000	0.0000	0.0000	-0.0007	-0.0001	-0.0001	-0.0001*	-0.0000	-0.0000	-0.0000
	(1.15)	(0.93)	(1.69)	(-0.73)	(-0.10)	(1.23)	(1.00)	(-1.29)	(-0.56)	(-0.69)	(-1.93)	(-1.35)	(-0.82)	(-0.87)
α_1	0.0012	-0.0004	-0.0001	-0.0000	-0.0000	-0.0000	-0.0000	0.0015*	0.0006	0.0001	0.0001	0.0001	0.0000	0.0000
	(0.88)	(-1.38)	(-1.18)	(-0.84)	(-0.03)	(-0.97)	(-0.86)	(1.82)	(0.88)	(1.27)	(1.29)	(1.01)	(0.92)	(1.00)
β_1	-0.0001	0.0005***	0.0001***	0.0001***	0.0000	0.0000*	0.0000	-0.0002	0.0004***	0.0000***	0.0001***	0.0000	0.0000	0.0000
	(-0.27)	(15.26)	(5.81)	(4.19)	(0.36)	(1.92)	(1.50)	(-0.87)	(3.67)	(4.18)	(5.22)	(0.21)	(1.57)	(1.15)
α_2	-0.0140	-0.0030	-0.0015	-0.0013	-0.0006	-0.0003	-0.0003	-0.0127	-0.0025	-0.0013	-0.0011	-0.0005	-0.0002	-0.0003
	(-1.05)	(-0.74)	(-0.88)	(-0.87)	(-0.83)	(-0.67)	(-1.03)	(-1.64)	(-0.96)	(-1.47)	(-1.21)	(-1.22)	(-1.03)	(-1.64)
β_2	0.0086***	0.0021***	0.0010***	0.0009***	0.0005***	0.0003***	0.0003***	0.0029**	0.0008*	0.0002*	0.0004***	0.0002***	0.0002***	0.0001***
	(4.18)	(3.45)	(3.88)	(4.00)	(4.06)	(5.14)	(5.15)	(2.43)	(1.97)	(1.86)	(2.98)	(2.99)	(4.67)	(4.99)
Adj. R^2	0.792	0.429	0.741	0.783	0.783	0.833	0.815	0.428	0.196	0.204	0.397	0.397	0.412	0.406

Table 4.7: Asymmetric Reaction to Positive and Negative Surprise

The table reports the regression results of Equation (4.5.1) which analyze the reactions from er (in Part A), ΔIV, ΔRV and ΔVRP (in Part B) to positive and negative federal fund rate surprise. It provides the intercept, slope and adjusted R-squared and obs represents for the number of observation. The coefficients α, α_1 and α_2 represent the effect of no surprises days, positive surprise days and negative surprise days, respectively. The coefficients β_1 and β_2 estimate the response to strength of the positive and negative surprise, respectively. All standard errors are adjusted following White (1980) and robust t-statistics in parentheses. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

Part A: Excess Return

Variable	Obs	α	t-stat	α_1	t-stat	β_1	t-stat	α_2	t-stat	β_2	t-stat	Adj. R^2
er	85	0.6196	(1.07)	-0.1525	(-0.19)	1.5183	(1.07)	0.4873	(0.54)	0.1160	(0.22)	0.010

Part B: ΔVRP, ΔIV , ΔRV

Maturity	Obs	α	t-stat	α_1	t-stat	β_1	t-stat	α_2	t-stat	β_2	t-stat	Adj. R^2
						ΔVRP						
7	85	-0.0100	(-0.76)	0.0067	(0.50)	-0.0055	(-0.82)	0.0272	(1.51)	0.0275***	(12.12)	0.156
30	85	-0.0059	(-1.11)	0.0043	(0.77)	-0.0065	(-1.45)	0.0043	(0.77)	0.0135***	(8.83)	0.274
60	85	-0.0026	(-1.08)	0.0012	(0.44)	-0.0044	(-1.28)	0.0010	(0.37)	0.0092***	(6.39)	0.374
90	85	-0.0023	(-1.18)	0.0012	(0.57)	-0.0031	(-1.22)	-0.0000	(-0.00)	0.0041**	(2.31)	0.128
180	85	-0.0015	(-1.10)	0.0005	(0.32)	-0.0026	(-1.17)	-0.0003	(-0.18)	0.0021*	(1.67)	0.061
270	85	-0.0014	(-1.27)	0.0005	(0.39)	-0.0021	(-1.15)	-0.0006	(-0.35)	0.0004	(0.29)	-0.010
360	85	-0.0015	(-1.47)	0.0013	(1.01)	-0.0020	(-1.17)	0.0002	(0.12)	0.0006	(0.57)	-0.003
						ΔIV						
7	85	-0.0121	(-0.84)	0.0104	(0.71)	-0.0087	(-0.99)	0.0338*	(1.76)	0.0451***	(19.13)	0.325
30	85	-0.0067	(-1.16)	0.0056	(0.93)	-0.0055	(-1.16)	0.0059	(1.00)	0.0177***	(16.84)	0.379
60	85	-0.0029	(-1.12)	0.0017	(0.58)	-0.0045	(-1.24)	0.0018	(0.62)	0.0111***	(8.69)	0.452
90	85	-0.0026	(-1.25)	0.0016	(0.68)	-0.0033	(-1.20)	0.0006	(0.24)	0.0060***	(3.75)	0.242
180	85	-0.0016	(-1.11)	0.0006	(0.37)	-0.0027	(-1.16)	-0.0000	(-0.02)	0.0031**	(2.56)	0.123
270	85	-0.0015	(-1.27)	0.0006	(0.44)	-0.0022	(-1.15)	-0.0004	(-0.23)	0.0010	(0.78)	0.008
360	85	-0.0016	(-1.43)	0.0014	(1.00)	-0.0020	(-1.18)	0.0003	(0.20)	0.0011	(1.12)	0.019
						ΔRV						
7	85	-0.0021	(-1.50)	0.0037**	(2.29)	-0.0033	(-1.34)	0.0066***	(3.56)	0.0176***	(14.99)	0.825
30	85	-0.0007	(-1.35)	0.0013*	(1.82)	0.0009	(0.78)	0.0016**	(2.22)	0.0043***	(8.81)	0.472
60	85	-0.0003	(-1.19)	0.0005*	(1.96)	-0.0001	(-0.33)	0.0008**	(2.62)	0.0019***	(11.64)	0.712
90	85	-0.0003	(-1.56)	0.0004	(1.58)	-0.0003	(-0.96)	0.0006**	(2.40)	0.0019***	(12.03)	0.776
180	85	-0.0001	(-0.92)	0.0001	(0.91)	-0.0001	(-0.95)	0.0003**	(2.24)	0.0010***	(12.27)	0.784
270	85	-0.0001	(-0.87)	0.0001	(1.26)	-0.0000	(-0.64)	0.0002**	(2.44)	0.0006***	(13.69)	0.792
360	85	-0.0000	(-0.20)	0.0000	(0.37)	-0.0001	(-1.13)	0.0001	(1.66)	0.0005***	(18.04)	0.762

Table 4.8: Asymmetric Reaction of Good and Bad Components to Positive and Negative Surprise

The table reports the regression results of Equation (4.5.1) which analyze the reactions from ΔIV, ΔRV and ΔVRP to positive and negative federal fund rate surprise. It provides the intercept, slope and adjusted R-squared and obs represents for the number of observation. The coefficients α, α_1 and α_2 represent the effect of no surprises days, positive surprise days and negative surprise days, respectively. The coefficients β_1 and β_2 estimate the response to strength of the positive and negative surprise, respectively. All standard errors are adjusted following White (1980) and robust t-statistics in parentheses. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

	good							bad						
	7	30	60	90	180	270	360	7	30	60	90	180	270	360
Part A: ΔVRP														
α	-0.0038	-0.0017	-0.0008	-0.0006	-0.0005	-0.0003	-0.0003	-0.0061	-0.0042	-0.0018	-0.0017	-0.0011	-0.0011	-0.0012
	(-1.02)	(-1.26)	(-1.31)	(-1.30)	(-1.45)	(-1.41)	(-1.57)	(-0.65)	(-1.05)	(-0.98)	(-1.13)	(-0.99)	(-1.21)	(-1.40)
α_1	0.0022	0.0011	0.0004	0.0003	0.0002	0.0001	0.0001	0.0045	0.0032	0.0008	0.0009	0.0003	0.0004	0.0012
	(0.56)	(0.76)	(0.59)	(0.54)	(0.56)	(0.38)	(0.47)	(0.47)	(0.75)	(0.37)	(0.57)	(0.25)	(0.38)	(1.08)
β_1	-0.0043	-0.0027	-0.0014	-0.0011	-0.0007	-0.0006	-0.0004	-0.0011	-0.0038	-0.0030	-0.0020	-0.0019	-0.0016	-0.0016
	(-1.20)	(-1.54)	(-1.34)	(-1.30)	(-1.25)	(-1.20)	(-1.15)	(-0.31)	(-1.32)	(-1.24)	(-1.16)	(-1.14)	(-1.13)	(-1.17)
α_2	0.0064	0.0010	0.0003	0.0002	0.0001	0.0000	0.0001	0.0208	0.0034	0.0007	-0.0002	-0.0004	-0.0007	0.0001
	(1.18)	(0.64)	(0.44)	(0.33)	(0.26)	(0.16)	(0.43)	(1.61)	(0.81)	(0.33)	(-0.11)	(-0.29)	(-0.45)	(0.04)
β_2	0.0050***	0.0027***	0.0023***	0.0014***	0.0008***	0.0005**	0.0004**	0.0225***	0.0108***	0.0068***	0.0027*	0.0014	-0.0001	0.0002
	(3.61)	(3.61)	(5.24)	(3.57)	(2.92)	(2.51)	(2.23)	(13.27)	(13.65)	(6.90)	(1.95)	(1.33)	(-0.10)	(0.23)
Adj R^2	0.0596	0.148	0.350	0.242	0.169	0.137	0.104	0.192	0.305	0.366	0.0875	0.0330	-0.0205	-0.0123
Part B: ΔIV														
α	-0.0044	-0.0018	-0.0009	-0.0007	-0.0005	-0.0003	-0.0003	-0.0076	-0.0049	-0.0021	-0.0019	-0.0012	-0.0012	-0.0013
	(-1.09)	(-1.22)	(-1.28)	(-1.34)	(-1.37)	(-1.35)	(-1.42)	(-0.74)	(-1.13)	(-1.06)	(-1.21)	(-1.03)	(-1.23)	(-1.40)
α_1	0.0037	0.0015	0.0005	0.0004	0.0002	0.0001	0.0001	0.0067	0.0041	0.0012	0.0012	0.0004	0.0005	0.0013
	(0.90)	(0.96)	(0.73)	(0.67)	(0.51)	(0.41)	(0.39)	(0.63)	(0.91)	(0.53)	(0.67)	(0.33)	(0.44)	(1.10)
β_1	-0.0051	-0.0020	-0.0014	-0.0012	-0.0008	-0.0006	-0.0004	-0.0037	-0.0035	-0.0032	-0.0022	-0.0020	-0.0016	-0.0016
	(-1.22)	(-1.23)	(-1.26)	(-1.26)	(-1.22)	(-1.19)	(-1.15)	(-0.74)	(-1.12)	(-1.22)	(-1.15)	(-1.14)	(-1.14)	(-1.18)
α_2	0.0106*	0.0016	0.0007	0.0005	0.0002	0.0001	0.0002	0.0232*	0.0043	0.0011	0.0001	-0.0003	-0.0005	0.0001
	(1.88)	(1.07)	(0.93)	(0.83)	(0.59)	(0.47)	(0.64)	(1.69)	(0.96)	(0.50)	(0.06)	(-0.17)	(-0.37)	(0.10)
β_2	0.0170***	0.0055***	0.0037***	0.0026***	0.0014***	0.0009***	0.0007***	0.0281***	0.0122***	0.0073***	0.0033**	0.0017*	0.0001	0.0004
	(21.27)	(12.74)	(11.31)	(9.13)	(6.48)	(5.27)	(4.74)	(14.91)	(19.63)	(7.76)	(2.56)	(1.70)	(0.08)	(0.46)
Adj R^2	0.456	0.473	0.591	0.520	0.389	0.323	0.299	0.256	0.335	0.383	0.135	0.0549	-0.0195	-0.00711
Part C: ΔRV														
α	-0.0006*	-0.0001	-0.0000	-0.0001	0.0000	0.0000	0.0000	-0.0015	-0.0007	-0.0003	-0.0003	-0.0001	-0.0001	-0.0000
	(-1.71)	(-0.44)	(-0.13)	(-1.53)	(0.36)	(0.12)	(1.03)	(-1.36)	(-1.49)	(-1.29)	(-1.53)	(-1.23)	(-1.08)	(-0.74)
α_1	0.0016***	0.0003	0.0001*	0.0001	-0.0000	0.0000	-0.0000	0.0021*	0.0009*	0.0004*	0.0003	0.0001	0.0001	0.0000
	(3.01)	(1.05)	(1.76)	(1.58)	(-0.50)	(0.76)	(-0.66)	(1.73)	(1.88)	(1.74)	(1.43)	(1.29)	(1.32)	(0.82)
β_1	-0.0007	0.0007	0.0000	-0.0001	-0.0000	0.0000	-0.0000	-0.0025	0.0003	-0.0001	-0.0002	-0.0001	-0.0000	-0.0000
	(-1.08)	(0.97)	(0.36)	(-0.91)	(-0.52)	(0.69)	(-0.90)	(-1.36)	(0.43)	(-0.73)	(-0.97)	(-1.09)	(-1.12)	(-1.19)
α_2	0.0042***	0.0007**	0.0004***	0.0003**	0.0001**	0.0001***	0.0001	0.0024*	0.0009*	0.0004*	0.0003*	0.0002*	0.0001*	0.0001
	(3.98)	(2.11)	(3.05)	(2.62)	(2.25)	(2.75)	(1.62)	(1.91)	(1.86)	(1.77)	(1.84)	(1.86)	(1.82)	(1.40)
β_2	0.0121***	0.0029***	0.0014***	0.0012***	0.0006***	0.0004***	0.0003***	0.0056***	0.0014***	0.0005***	0.0007***	0.0003***	0.0002***	0.0002***
	(14.64)	(9.39)	(11.60)	(11.77)	(11.90)	(12.91)	(15.74)	(15.12)	(7.76)	(11.40)	(12.43)	(12.89)	(15.28)	(23.89)
Adj R^2	0.894	0.510	0.838	0.880	0.880	0.895	0.885	0.518	0.273	0.272	0.481	0.484	0.474	0.454

Table 4.9: Timing v.s. Level Surprise of Federal Fund Rate on er, ΔIV, ΔRV and ΔVRP

The table reports the regression results of Equation (4.4.1) which use $\Delta i_t^{u,t}$ and $\Delta i_t^{u,l}$ to analyze the reactions from er (in Part A), ΔIV, ΔRV and ΔVRP (in Part B) to the FOMC surprise. It provides the intercept (α), slope of timing surprise ($\Delta i_t^{u,t}$) , slope of level surprise ($\Delta i_t^{u,l}$), R^2 and adjusted R^2 and obs represents the number of observation. All standard errors are adjusted following White (1980) and robust t-statistics in parentheses. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

Part A: Excess Return						
Variables	Obs	α	Timing	Level	R^2	Adj. R^2
er	85	0.8864**	7.3812	8.2108	0.019	-0.00540
		(2.28)	(0.73)	(0.34)		

Part B: ΔVRP, ΔIV, ΔRV							
Maturity	7	30	60	90	180	270	360
				ΔVRP			
α	-0.0047	-0.0058***	-0.0039***	-0.0029***	-0.0022**	-0.0019**	-0.0013**
	(-0.91)	(-2.70)	(-2.94)	(-2.69)	(-2.62)	(-2.52)	(-2.04)
$\Delta i_t^{u,t}$	0.2084**	0.1123**	0.0786*	0.0351	0.0147	-0.0002	0.0011
	(2.30)	(2.07)	(1.93)	(1.13)	(0.65)	(-0.01)	(0.06)
$\Delta i_t^{u,l}$	0.0849	0.0691	0.0585	0.0390	0.0200	0.0131	0.0053
	(0.63)	(0.70)	(0.72)	(0.54)	(0.37)	(0.26)	(0.13)
obs	85	85	85	85	85	85	85
R^2	0.105	0.152	0.186	0.056	0.017	0.017	0.002
Adj. R^2	0.083	0.131	0.166	0.033	-0.007	-0.007	-0.022
				ΔIV			
α	-0.0061	-0.0060***	-0.0040***	-0.0032***	-0.0023***	-0.0019**	-0.0014**
	(-1.05)	(-2.68)	(-2.92)	(-2.84)	(-2.70)	(-2.57)	(-2.08)
$\Delta i_t^{u,t}$	0.3629**	0.1611**	0.0970**	0.0527	0.0236	0.0060	0.0061
	(2.56)	(2.53)	(2.16)	(1.59)	(1.01)	(0.29)	(0.36)
$\Delta i_t^{u,l}$	0.1338	0.1018	0.0673	0.0461	0.0242	0.0167	0.0078
	(0.78)	(0.94)	(0.80)	(0.62)	(0.45)	(0.33)	(0.19)
obs	85	85	85	85	85	85	85
R^2	0.228	0.245	0.246	0.118	0.042	0.011	0.004
Adj. R^2	0.209	0.226	0.227	0.097	0.018	-0.013	-0.020
				ΔRV			
α	-0.0014	-0.0002	-0.0001	-0.0003**	-0.0001*	-0.0001	-0.0000
	(-1.37)	(-0.52)	(-0.99)	(-2.35)	(-1.82)	(-1.35)	(-1.37)
$\Delta i_t^{u,t}$	0.1545***	0.0488***	0.0184***	0.0177***	0.0089***	0.0062***	0.0050***
	(2.79)	(3.20)	(3.03)	(2.91)	(2.85)	(3.17)	(3.00)
$\Delta i_t^{u,l}$	0.0489	0.0327	0.0088	0.0071	0.0042	0.0037**	0.0024*
	(1.01)	(1.18)	(1.27)	(1.37)	(1.57)	(2.54)	(1.83)
obs	85	85	85	85	85	85	85
R^2	0.646	0.447	0.587	0.612	0.600	0.618	0.579
Adj. R^2	0.637	0.433	0.577	0.602	0.590	0.609	0.568

Table 4.10: Timing v.s. Level Surprise: Reactions of Good and Bad Components

The table reports the regression results of Equation (4.4.1) which use $\Delta i_t^{u,t}$ and $\Delta i_t^{u,l}$ to analyze the reactions of good and bad components of ΔIV, ΔRV and ΔVRP to the FOMC surprise. It provides the intercept (α), slope of timing surprise ($\Delta i_t^{u,t}$) , slope of level surprise ($\Delta i_t^{u,l}$), R^2 and adjusted R^2 and obs represents the number of observation. All standard errors are adjusted following White (1980) and robust t-statistics in parentheses. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

	good							bad						
	7	30	60	90	180	270	360	7	30	60	90	180	270	360
Part A: ΔVRP														
α	-0.0025	-0.0017***	-0.0011***	-0.0008***	-0.0006***	-0.0005***	-0.0004***	-0.0022	-0.0041**	-0.0028***	-0.0021**	-0.0016**	-0.0014**	-0.0010*
	(-1.57)	(-2.67)	(-3.09)	(-2.97)	(-3.07)	(-3.16)	(-3.19)	(-0.58)	(-2.61)	(-2.83)	(-2.53)	(-2.45)	(-2.31)	(-1.74)
$\Delta i_t^{u,t}$	0.0180	0.0145	0.0186	0.0107	0.0055	0.0033	0.0025	0.1904**	0.0979**	0.0600**	0.0244	0.0092	-0.0035	-0.0014
	(0.65)	(0.88)	(1.63)	(1.25)	(1.00)	(0.77)	(0.75)	(2.62)	(2.43)	(2.03)	(1.07)	(0.53)	(-0.20)	(-0.11)
$\Delta i_t^{u,l}$	-0.0147	0.0005	0.0125	0.0095	0.0056	0.0031	0.0027	0.0997	0.0686	0.0460	0.0295	0.0144	0.0100	0.0026
	(-0.24)	(0.01)	(0.53)	(0.50)	(0.45)	(0.32)	(0.35)	(1.06)	(1.01)	(0.80)	(0.55)	(0.35)	(0.25)	(0.08)
Adj. R^2	0.004	0.030	0.132	0.060	0.022	0.005	0.001	0.120	0.169	0.171	0.023	-0.012	0.007	-0.021
Part B: ΔIV														
α	-0.0030	-0.0018***	-0.0012***	-0.0009***	-0.0006***	-0.0005***	-0.0004***	-0.0031	-0.0042**	-0.0028***	-0.0022***	-0.0017**	-0.0014**	-0.0010*
	(-1.64)	(-2.80)	(-3.07)	(-3.09)	(-3.16)	(-3.20)	(-3.20)	(-0.75)	(-2.60)	(-2.82)	(-2.65)	(-2.51)	(-2.34)	(-1.78)
$\Delta i_t^{u,t}$	0.1326**	0.0481**	0.0327**	0.0225**	0.0115*	0.0075	0.0058	0.2304**	0.1130**	0.0643**	0.0302	0.0120	-0.0014	0.0002
	(2.39)	(2.35)	(2.30)	(2.07)	(1.76)	(1.58)	(1.55)	(2.59)	(2.61)	(2.08)	(1.29)	(0.69)	(-0.08)	(0.01)
$\Delta i_t^{u,l}$	0.0429	0.0268	0.0209	0.0156	0.0090	0.0058	0.0046	0.0909	0.0751	0.0464	0.0306	0.0152	0.0109	0.0031
	(0.56)	(0.74)	(0.84)	(0.78)	(0.69)	(0.59)	(0.57)	(0.88)	(1.04)	(0.78)	(0.56)	(0.36)	(0.27)	(0.10)
Adj. R^2	0.278	0.271	0.318	0.248	0.151	0.113	0.106	0.170	0.204	0.186	0.045	-0.006	-0.001	-0.023
Part C: ΔRV														
α	-0.0005	-0.0000	-0.0000	-0.0001*	-0.0000	-0.0000	-0.0000	-0.0009*	-0.0001	-0.0001	-0.0002**	-0.0001*	-0.0000	-0.0000
	(-0.77)	(-0.15)	(-0.53)	(-1.72)	(-1.43)	(-1.00)	(-0.95)	(-1.78)	(-0.79)	(-1.08)	(-2.51)	(-1.87)	(-1.43)	(-1.54)
$\Delta i_t^{u,t}$	0.1146***	0.0337***	0.0141***	0.0119***	0.0060***	0.0042***	0.0033***	0.0399**	0.0151***	0.0043**	0.0058***	0.0028**	0.0020***	0.0016***
	(3.03)	(3.11)	(3.14)	(2.98)	(2.94)	(3.21)	(3.08)	(2.18)	(3.27)	(2.56)	(2.73)	(2.63)	(3.03)	(2.77)
$\Delta i_t^{u,l}$	0.0577*	0.0263	0.0084*	0.0060*	0.0034*	0.0027***	0.0019**	-0.0088	0.0065	0.0004	0.0011	0.0008	0.0010*	0.0006
	(1.90)	(1.41)	(1.82)	(1.90)	(1.98)	(2.80)	(2.37)	(-0.40)	(0.66)	(0.15)	(0.48)	(0.77)	(1.68)	(0.90)
Adj. R^2	0.690	0.453	0.677	0.678	0.666	0.696	0.666	0.418	0.271	0.219	0.383	0.359	0.355	0.334

Table 4.11: Surprise of Federal Fund Rate on ΔVRP and ΔIV: BN estimator

The table reports the regression results of Equation (4.4.1) which analyze the reactions from ΔVRP (in Part A) and ΔIV (in Part B) to the FOMC surprise. It provides the intercept (α), slope (β) and adjusted R^2 and obs represents the number of observation. All standard errors are adjusted following White (1980) and robust t-statistics in parentheses. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

Maturity	7	30	60	90	180	270	360
Part A: ΔVRP							
α	-0.0056	-0.0056***	-0.0036***	-0.0027***	-0.0020***	-0.0016***	-0.0012***
	(-1.16)	(-3.02)	(-3.41)	(-3.23)	(-3.17)	(-3.06)	(-2.76)
β	0.0136**	0.0062**	0.0044**	0.0023*	0.0010	0.0003	0.0002
	(2.01)	(2.01)	(2.08)	(1.70)	(1.11)	(0.36)	(0.43)
Obs	85	85	85	85	85	85	85
Adj. R^2	0.074	0.105	0.157	0.067	0.017	-0.009	-0.008
Part B: ΔIV							
α	-0.0079	-0.0059***	-0.0038***	-0.0031***	-0.0021***	-0.0016***	-0.0013***
	(-1.40)	(-2.99)	(-3.38)	(-3.41)	(-3.29)	(-3.15)	(-2.85)
β	0.0246**	0.0094**	0.0056**	0.0035**	0.0016	0.0007	0.0006
	(2.10)	(2.38)	(2.22)	(2.06)	(1.56)	(0.93)	(0.96)
Obs	85	85	85	85	85	85	85
Adj. R^2	0.177	0.201	0.218	0.140	0.056	0.007	0.008

Table 4.12: Reactions of Good and Bad Components to FOMC surprise: BN estimator

The table reports the regression results of Equation (4.4.1) which analyze the reactions from ΔVRP (in Part A) and ΔIV (in Part B) to the FOMC surprise. It provides the intercept (α), slope (β) R-squared and adjusted R-squared and obs represents the number of observation. All standard errors are adjusted following White (1980) and robust t-statistics in parentheses. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

	good							bad						
	7	30	60	90	180	270	360	7	30	60	90	180	270	360
Part A: ΔVRP														
α	-0.0030*	-0.0020***	-0.0013***	-0.0010***	-0.0007***	-0.0005***	-0.0004***	-0.0027	-0.0036***	-0.0023***	-0.0018***	-0.0013***	-0.0010***	-0.0008**
	(-1.81)	(-3.04)	(-3.59)	(-3.45)	(-3.48)	(-3.58)	(-3.56)	(-0.79)	(-2.85)	(-3.21)	(-3.03)	(-2.95)	(-2.76)	(-2.36)
β	0.0022	0.0015	0.0016**	0.0009*	0.0005	0.0003	0.0003	0.0114**	0.0047**	0.0028**	0.0013	0.0005	-0.0001	-0.0000
	(1.16)	(1.43)	(2.03)	(1.79)	(1.52)	(1.33)	(1.38)	(2.24)	(2.25)	(2.10)	(1.60)	(0.83)	(-0.17)	(-0.06)
obs	85	85	85	85	85	85	85	85	85	85	85	85	85	85
R^2	0.022	0.058	0.180	0.119	0.072	0.054	0.052	0.119	0.138	0.152	0.058	0.014	0.001	0.000
Adj. R^2	0.0101	0.0467	0.170	0.108	0.0609	0.0430	0.0410	0.108	0.128	0.142	0.0466	0.00213	-0.0114	-0.0120
Part B: ΔIV														
α	-0.0039*	-0.0021***	-0.0014***	-0.0011***	-0.0008***	-0.0006***	-0.0005***	-0.0040	-0.0038***	-0.0024***	-0.0020***	-0.0014***	-0.0011***	-0.0008**
	(-1.97)	(-3.19)	(-3.53)	(-3.57)	(-3.60)	(-3.63)	(-3.61)	(-1.06)	(-2.83)	(-3.21)	(-3.22)	(-3.05)	(-2.82)	(-2.43)
β	0.0101**	0.0037**	0.0025**	0.0017**	0.0009**	0.0006*	0.0005*	0.0145**	0.0057**	0.0031**	0.0017*	0.0007	0.0001	0.0001
	(2.07)	(2.34)	(2.33)	(2.21)	(2.01)	(1.92)	(1.96)	(2.12)	(2.41)	(2.12)	(1.85)	(1.11)	(0.11)	(0.23)
obs	85	85	85	85	85	85	85	85	85	85	85	85	85	85
R^2	0.238	0.274	0.327	0.270	0.183	0.150	0.144	0.153	0.175	0.168	0.088	0.027	0.000	0.001
Adj. R^2	0.229	0.266	0.319	0.261	0.173	0.139	0.134	0.143	0.165	0.157	0.0772	0.0148	-0.0118	-0.0111

Table 4.13: Surprise of Federal Fund Rate on Contractionary and Expansionary Policy: BN estimator

The table reports the regression results of Equation (4.5.1) which analyze the reactions from ΔVRP (in Part A) and ΔIV (in Part B) depend on contractionary and expansionary policy. It provides the intercept, slope and adjusted R-squared and obs represents for the number of observation. The coefficients α, α_1 and α_2 represent the effect of no surprises days, contractionary policy presence days and expansionary policy presence days, respectively. The coefficients β_1 and β_2 estimate the response to strength of the contractionary and expansionary policy, respectively. All standard errors are adjusted following White (1980) and robust t-statistics in parentheses. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

Maturity	7	30	60	90	180	270	360
Part A: ΔVRP							
α	-0.0013	-0.0038**	-0.0022**	-0.0018**	-0.0014**	-0.0012**	-0.0009**
	(-0.25)	(-2.01)	(-2.33)	(-2.39)	(-2.47)	(-2.58)	(-2.22)
α_1	-0.0072	0.0023	0.0006	0.0010	0.0008	0.0008	0.0007
	(-1.00)	(0.81)	(0.34)	(0.86)	(0.85)	(1.12)	(0.95)
β_1	0.0016	-0.0005	0.0002	0.0001	0.0002	0.0001	0.0001
	(0.94)	(-0.97)	(0.56)	(0.32)	(1.28)	(1.19)	(0.62)
α_2	-0.0682***	-0.0434***	-0.0328***	-0.0259***	-0.0181***	-0.0148***	-0.0124***
	(-3.56)	(-12.37)	(-8.56)	(-3.96)	(-3.41)	(-2.75)	(-3.10)
β_2	0.0113***	0.0044***	0.0028***	0.0007	-0.0003	-0.0010	-0.0008
	(3.96)	(9.63)	(4.94)	(0.65)	(-0.35)	(-1.18)	(-1.34)
Obs	85	85	85	85	85	85	85
Adj. R^2	0.129	0.302	0.479	0.376	0.291	0.251	0.238
Part B: ΔIV							
α	-0.0017	-0.0037*	-0.0022**	-0.0020**	-0.0015**	-0.0012**	-0.0009**
	(-0.29)	(-1.85)	(-2.20)	(-2.43)	(-2.47)	(-2.53)	(-2.18)
α_1	-0.0045	0.0025	0.0006	0.0011	0.0008	0.0008	0.0007
	(-0.62)	(0.97)	(0.37)	(0.85)	(0.88)	(1.10)	(0.94)
β_1	0.0014	0.0004	0.0003	0.0002	0.0002	0.0002	0.0001
	(0.99)	(0.88)	(0.85)	(0.80)	(1.16)	(1.25)	(0.67)
α_2	-0.0948**	-0.0488***	-0.0356***	-0.0283***	-0.0193***	-0.0153***	-0.0130***
	(-2.39)	(-11.88)	(-23.05)	(-6.78)	(-4.64)	(-3.23)	(-3.70)
β_2	0.0227***	0.0073***	0.0041***	0.0020***	0.0004	-0.0005	-0.0004
	(3.74)	(13.14)	(22.53)	(3.15)	(0.60)	(-0.67)	(-0.81)
Obs	85	85	85	85	85	85	85
Adj. R^2	0.285	0.401	0.542	0.464	0.352	0.282	0.272

Table 4.14: Asymmetric Reaction to Positive and Negative Surprise: BN estimator

The table reports the regression results of Equation (4.5.1) which analyze the reactions from ΔVRP (in Part A) and ΔIV (in Part B) to positive and negative federal fund rate surprise. It provides the intercept, slope and adjusted R-squared and obs represents for the number of observation. The coefficients α, α_1 and α_2 represent the effect of no surprises days, positive surprise days and negative surprise days, respectively. The coefficients β_1 and β_2 estimate the response to strength of the positive and negative surprise, respectively. All standard errors are adjusted following White (1980) and robust t-statistics in parentheses. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

Maturity	7	30	60	90	180	270	360
Part A: ΔVRP							
α	-0.0094	-0.0053	-0.0024	-0.0020	-0.0014	-0.0012	-0.0011
	(-0.76)	(-1.10)	(-1.11)	(-1.20)	(-1.18)	(-1.28)	(-1.34)
α_1	0.0062	0.0037	0.0011	0.0009	0.0004	0.0003	0.0006
	(0.50)	(0.74)	(0.46)	(0.50)	(0.31)	(0.30)	(0.56)
β_1	-0.0059	-0.0062	-0.0041	-0.0031	-0.0024	-0.0019	-0.0016
	(-0.85)	(-1.47)	(-1.28)	(-1.25)	(-1.18)	(-1.15)	(-1.13)
α_2	0.0253	0.0035	0.0007	0.0002	-0.0002	-0.0003	0.0001
	(1.49)	(0.69)	(0.29)	(0.08)	(-0.12)	(-0.20)	(0.05)
β_2	0.0261***	0.0114***	0.0079***	0.0044***	0.0023**	0.0010	0.0009
	(11.61)	(7.09)	(5.91)	(3.15)	(2.16)	(1.08)	(1.20)
Obs	85	85	85	85	85	85	85
Adj. R^2	0.159	0.247	0.363	0.196	0.103	0.0297	0.0266
Part B: ΔIV							
maturity	7	30	60	90	180	270	360
α	-0.0115	-0.0060	-0.0027	-0.0023	-0.0015	-0.0012	-0.0011
	(-0.85)	(-1.15)	(-1.15)	(-1.27)	(-1.19)	(-1.28)	(-1.30)
α_1	0.0099	0.0050	0.0016	0.0013	0.0005	0.0004	0.0006
	(0.72)	(0.92)	(0.63)	(0.63)	(0.37)	(0.37)	(0.57)
β_1	-0.0092	-0.0053	-0.0042	-0.0034	-0.0025	-0.0019	-0.0016
	(-1.01)	(-1.17)	(-1.23)	(-1.23)	(-1.17)	(-1.16)	(-1.14)
α_2	0.0319*	0.0051	0.0015	0.0008	0.0001	-0.0001	0.0002
	(1.76)	(0.95)	(0.58)	(0.37)	(0.07)	(-0.05)	(0.16)
β_2	0.0438***	0.0157***	0.0098***	0.0063***	0.0032***	0.0017*	0.0015*
	(20.07)	(13.80)	(8.33)	(5.10)	(3.31)	(1.82)	(1.96)
Obs	85	85	85	85	85	85	85
Adj. R^2	0.339	0.366	0.451	0.325	0.185	0.0760	0.0741

Table 4.15: Surprise of Federal Fund Rate on ΔIV, ΔRV and ΔVRP: ex ante RV

The table reports the regression results of Equation (4.4.1) which analyze the reactions from ΔVRP (in Part A), ΔIV (in Part B), ΔRV (in Part C) to the FOMC surprise. It provides the intercept (α), slope (β) and adjusted R^2 and obs represents the number of observation. All standard errors are adjusted following White (1980) and robust t-statistics in parentheses. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

Maturity	7	30	60	90	180	270	360
Part A: ΔVRP							
α	-0.0124*	-0.0072***	-0.0047***	-0.0036***	-0.0025***	-0.0020***	-0.0014**
	(-1.79)	(-3.01)	(-3.41)	(-3.37)	(-3.15)	(-2.94)	(-2.41)
β	0.0371**	0.0112**	0.0080**	0.0049**	0.0022*	0.0007	0.0007
	(2.18)	(2.23)	(2.21)	(2.31)	(1.74)	(0.80)	(0.95)
Obs	85	85	85	85	85	85	85
R^2	0.258	0.209	0.283	0.199	0.087	0.014	0.016
Adj. R^2	0.249	0.200	0.275	0.190	0.0762	0.00203	0.00456
Part B: ΔIV							
α	-0.0079	-0.0065***	-0.0042***	-0.0032***	-0.0023***	-0.0018***	-0.0014**
	(-1.34)	(-2.97)	(-3.34)	(-3.23)	(-3.05)	(-2.78)	(-2.31)
β	0.0254**	0.0107**	0.0064**	0.0033**	0.0014	0.0002	0.0003
	(2.11)	(2.42)	(2.25)	(2.06)	(1.34)	(0.25)	(0.48)
Obs	85	85	85	85	85	85	85
R^2	0.182	0.223	0.230	0.117	0.042	0.001	0.004
Adj. R^2	0.173	0.214	0.221	0.106	0.0301	-0.0106	-0.00785
Part C: ΔRV							
α	0.0045***	0.0007**	0.0005*	0.0004*	0.0002**	0.0001**	0.0001*
	(2.83)	(2.21)	(1.88)	(1.90)	(2.14)	(2.09)	(1.83)
β	-0.0117**	-0.0005	-0.0016*	-0.0016**	-0.0008**	-0.0005**	-0.0004**
	(-2.28)	(-0.71)	(-1.71)	(-2.16)	(-2.25)	(-2.17)	(-2.15)
Obs	85	85	85	85	85	85	85
R^2	0.400	0.031	0.323	0.448	0.460	0.454	0.444
Adj. R^2	0.393	0.0191	0.315	0.441	0.454	0.447	0.437

Table 4.16: Reactions of Good and Bad Components to FOMC surprise: ex ante RV

The table reports the regression results of Equation (4.4.1) which analyze the reactions from ΔVRP, ΔIV and ΔRV to the FOMC surprise. It provides the intercept (α), slope (β) R-squared and adjusted R-squared and obs represents the number of observation. All standard errors are adjusted following White (1980) and robust t-statistics in parentheses. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

	good							bad						
	7	30	60	90	180	270	360	7	30	60	90	180	270	360
Part A: ΔVRP														
α	-0.0069**	-0.0025***	-0.0016***	-0.0012***	-0.0008***	-0.0006***	-0.0005***	-0.0055	-0.0046***	-0.0031***	-0.0024***	-0.0017***	-0.0014**	-0.0010*
	(-2.58)	(-3.18)	(-3.46)	(-3.44)	(-3.47)	(-3.64)	(-3.61)	(-1.23)	(-2.85)	(-3.28)	(-3.14)	(-2.91)	(-2.56)	(-1.98)
β	0.0182**	0.0042**	0.0031**	0.0024**	0.0012**	0.0008*	0.0006**	0.0189**	0.0071**	0.0049**	0.0025**	0.0011	-0.0000	0.0001
	(2.27)	(2.00)	(2.16)	(2.21)	(2.04)	(1.98)	(2.01)	(2.09)	(2.39)	(2.23)	(2.21)	(1.32)	(-0.05)	(0.22)
obs	85	85	85	85	85	85	85	85	85	85	85	85	85	85
R^2	0.358	0.245	0.351	0.338	0.248	0.211	0.197	0.179	0.184	0.237	0.119	0.037	0.000	0.001
Adj. R^2	0.351	0.236	0.343	0.330	0.239	0.201	0.188	0.169	0.175	0.228	0.108	0.0257	-0.0120	-0.0112
Part B: ΔIV														
α	-0.0037*	-0.0019***	-0.0013***	-0.0010***	-0.0007***	-0.0005***	-0.0004***	-0.0042	-0.0045***	-0.0030***	-0.0022***	-0.0016***	-0.0013**	-0.0010*
	(-1.99)	(-3.18)	(-3.54)	(-3.57)	(-3.63)	(-3.66)	(-3.65)	(-1.01)	(-2.84)	(-3.20)	(-2.98)	(-2.78)	(-2.47)	(-1.93)
β	0.0094**	0.0032**	0.0022**	0.0015**	0.0007*	0.0005*	0.0004*	0.0160**	0.0075**	0.0042**	0.0018*	0.0007	-0.0003	-0.0000
	(2.05)	(2.29)	(2.28)	(2.13)	(1.93)	(1.83)	(1.86)	(2.14)	(2.48)	(2.22)	(1.78)	(0.92)	(-0.32)	(-0.05)
obs	85	85	85	85	85	85	85	85	85	85	85	85	85	85
R^2	0.230	0.255	0.306	0.249	0.165	0.130	0.123	0.154	0.207	0.195	0.068	0.017	0.003	0.000
Adj. R^2	0.221	0.246	0.298	0.240	0.155	0.119	0.112	0.143	0.197	0.185	0.0569	0.00473	-0.00925	-0.0120
Part C: ΔRV														
α	0.0032***	0.0006**	0.0004**	0.0002**	0.0001**	0.0001**	0.0001**	0.0013*	0.0001	0.0001	0.0001	0.0001**	0.0000	0.0000
	(3.07)	(2.63)	(2.40)	(2.14)	(2.02)	(2.34)	(2.22)	(1.98)	(0.64)	(1.08)	(1.35)	(2.11)	(1.60)	(1.18)
β	-0.0089**	-0.0009	-0.0010*	-0.0009**	-0.0004**	-0.0003**	-0.0002**	-0.0028*	0.0004***	-0.0007	-0.0007**	-0.0004**	-0.0002**	-0.0002**
	(-2.50)	(-1.29)	(-1.79)	(-2.22)	(-2.08)	(-2.03)	(-2.03)	(-1.75)	(2.64)	(-1.57)	(-2.06)	(-2.49)	(-2.33)	(-2.31)
obs	85	85	85	85	85	85	85	85	85	85	85	85	85	85
R^2	0.472	0.160	0.349	0.430	0.408	0.424	0.415	0.184	0.077	0.240	0.396	0.483	0.452	0.438
Adj. R^2	0.465	0.150	0.341	0.423	0.400	0.417	0.408	0.175	0.0657	0.231	0.389	0.477	0.446	0.432

Table 4.17: Surprise of Federal Fund Rate on Contractionary and Expansionary Policy: ex ante RV

The table reports the regression results of Equation (4.5.1) which analyze the reactions from ΔVRP (in Part A) and ΔRV (in Part B) depend on contractionary and expansionary policy. It provides the intercept, slope and adjusted R-squared and obs represents for the number of observation. The coefficients α, α_1 and α_2 represent the effect of no surprises days, contractionary policy presence days and expansionary policy presence days, respectively. The coefficients β_1 and β_2 estimate the response to strength of the contractionary and expansionary policy, respectively. All standard errors are adjusted following White (1980) and robust t-statistics in parentheses. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

Maturity	7	30	60	90	180	270	360
Part A: ΔVRP							
α	-0.0043	-0.0045*	-0.0027**	-0.0022**	-0.0016**	-0.0014**	-0.0010*
	(-0.62)	(-1.89)	(-2.16)	(-2.27)	(-2.23)	(-2.39)	(-1.77)
α_1	-0.0057	0.0023	0.0001	0.0010	0.0008	0.0011	0.0011
	(-0.61)	(0.74)	(0.06)	(0.69)	(0.72)	(1.50)	(0.98)
β_1	0.0015	0.0005	0.0004	0.0003	0.0002	0.0002	0.0000
	(0.66)	(0.74)	(0.68)	(0.73)	(0.98)	(1.21)	(0.12)
α_2	-0.1045	-0.0525***	-0.0390***	-0.0337***	-0.0237***	-0.0192***	-0.0162***
	(-1.59)	(-5.23)	(-8.08)	(-9.63)	(-5.22)	(-2.73)	(-3.42)
β_2	0.0384***	0.0096***	0.0070***	0.0032***	0.0008	-0.0008	-0.0006
	(3.79)	(6.36)	(9.65)	(6.08)	(1.22)	(-0.73)	(-0.84)
Obs	85	85	85	85	85	85	85
Adj. R^2	0.363	0.375	0.559	0.507	0.371	0.266	0.228
Part B: ΔRV							
α	0.0026*	0.0006*	0.0003	0.0001	0.0000	0.0000	0.0000
	(1.96)	(1.75)	(1.58)	(0.59)	(0.46)	(0.66)	(0.25)
α_1	0.0010	0.0004	0.0001	0.0002	0.0002	0.0001	0.0001
	(0.29)	(0.50)	(0.33)	(0.73)	(1.01)	(0.76)	(0.91)
β_1	-0.0000	-0.0000	-0.0000	-0.0001	-0.0000	-0.0000	-0.0000
	(-0.03)	(-0.07)	(-0.01)	(-0.66)	(-0.39)	(-0.53)	(-0.35)
α_2	0.0116	0.0009	0.0003	0.0026	0.0020	0.0010	0.0008
	(0.51)	(0.21)	(0.06)	(0.74)	(1.63)	(1.08)	(1.17)
β_2	-0.0144***	-0.0008	-0.0022**	-0.0018***	-0.0009***	-0.0006***	-0.0004***
	(-4.03)	(-1.26)	(-2.45)	(-3.20)	(-4.58)	(-3.72)	(-3.92)
Obs	85	85	85	85	85	85	85
Adj. R^2	0.525	0.0344	0.424	0.582	0.689	0.644	0.647

Table 4.18: Asymmetric Reaction to Positive and Negative Surprise: ex ante RV

The table reports the regression results of Equation (4.5.1) which analyze the reactions from ΔVRP (in Part A), ΔIV (in Part B) and ΔRV (in Part C) to positive and negative federal fund rate surprise. It provides the intercept, slope and adjusted R-squared and obs represents for the number of observation. The coefficients α, α_1 and α_2 represent the effect of no surprises days, positive surprise days and negative surprise days, respectively. The coefficients β_1 and β_2 estimate the response to strength of the positive and negative surprise, respectively. All standard errors are adjusted following White (1980) and robust t-statistics in parentheses. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

maturity	Obs	α	t-stat	α_1	t-stat	β_1	t-stat	α_2	t-stat	β_2	t-stat	Adj. R^2
Part A: ΔVRP												
7	85	-0.0164	(-0.97)	0.0131	(0.77)	-0.0100	(-1.08)	0.0412*	(1.98)	0.0634***	(19.52)	0.438
30	85	-0.0075	(-1.19)	0.0059	(0.90)	-0.0066	(-1.21)	0.0074	(1.15)	0.0192***	(27.24)	0.374
60	85	-0.0034	(-1.16)	0.0020	(0.61)	-0.0049	(-1.26)	0.0032	(1.04)	0.0138***	(18.40)	0.540
90	85	-0.0029	(-1.25)	0.0019	(0.74)	-0.0036	(-1.20)	0.0016	(0.58)	0.0085***	(6.34)	0.383
180	85	-0.0018	(-1.13)	0.0008	(0.43)	-0.0030	(-1.18)	0.0005	(0.24)	0.0044***	(3.83)	0.218
270	85	-0.0016	(-1.27)	0.0007	(0.46)	-0.0023	(-1.16)	-0.0001	(-0.03)	0.0018	(1.46)	0.050
360	85	-0.0016	(-1.40)	0.0014	(0.99)	-0.0021	(-1.18)	0.0005	(0.35)	0.0017*	(1.79)	0.056
Part B: ΔIV												
7	85	-0.0121	(-0.84)	0.0104	(0.71)	-0.0087	(-0.99)	0.0338*	(1.76)	0.0451***	(19.13)	0.325
30	85	-0.0067	(-1.16)	0.0056	(0.93)	-0.0055	(-1.16)	0.0059	(1.00)	0.0177***	(16.84)	0.379
60	85	-0.0029	(-1.12)	0.0017	(0.58)	-0.0045	(-1.24)	0.0018	(0.62)	0.0111***	(8.69)	0.452
90	85	-0.0026	(-1.25)	0.0016	(0.68)	-0.0033	(-1.20)	0.0006	(0.24)	0.0060***	(3.75)	0.242
180	85	-0.0016	(-1.11)	0.0006	(0.37)	-0.0027	(-1.16)	-0.0000	(-0.02)	0.0031**	(2.56)	0.123
270	85	-0.0015	(-1.27)	0.0006	(0.44)	-0.0022	(-1.15)	-0.0004	(-0.23)	0.0010	(0.78)	0.008
360	85	-0.0016	(-1.43)	0.0014	(1.00)	-0.0020	(-1.18)	0.0003	(0.20)	0.0011	(1.12)	0.019
Part C: ΔRV												
7	85	0.0044	(1.50)	-0.0027	(-0.87)	0.0013	(0.69)	-0.0074**	(-2.12)	-0.0183***	(-9.88)	0.592
30	85	0.0008	(1.31)	-0.0004	(-0.51)	0.0010	(1.27)	-0.0015**	(-2.01)	-0.0014***	(-3.94)	0.142
60	85	0.0005	(1.26)	-0.0003	(-0.69)	0.0004	(1.12)	-0.0014**	(-2.34)	-0.0028***	(-5.20)	0.535
90	85	0.0003	(1.09)	-0.0003	(-0.95)	0.0002	(0.77)	-0.0009**	(-2.52)	-0.0025***	(-9.55)	0.689
180	85	0.0001	(1.16)	-0.0002	(-1.00)	0.0002	(1.26)	-0.0005***	(-3.31)	-0.0013***	(-23.64)	0.769
270	85	0.0001	(1.04)	-0.0001	(-0.62)	0.0001	(1.02)	-0.0003***	(-3.08)	-0.0008***	(-13.82)	0.746
360	85	0.0000	(0.57)	-0.0000	(-0.29)	0.0001	(1.17)	-0.0002***	(-2.67)	-0.0006***	(-14.99)	0.743

Table 4.19: Surprise of Federal Fund Rate on er, ΔIV, ΔRV and ΔVRP: Professional Forecasts

The table reports the regression results of Equation (4.4.1) which analyze the reactions from er (in Part A), ΔIV, ΔRV and ΔVRP (in Part B) to the FOMC surprise. The interest shocks is calculated by professional forecasts rather than the 30-day federal fund futures contracts. It provides the intercept (α), slope (β) and adjusted R^2 and obs represents the number of observation. All standard errors are adjusted following White (1980) and robust t-statistics in parentheses. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

Part A: Excess Return

Variable	obs	α	β	Adj. R^2
er	85	0.8678**	-0.7116	0.0361
		(2.52)	(-1.02)	

Part B: ΔIV, ΔRV, ΔVRP

		ΔIV			drv			ΔVRP		
Maturity	obs	α	β	Adj. R^2	α	β	Adj. R^2	α	β	Adj. R^2
7	85	-0.0045	0.0150	0.081	-0.0062	0.0207	0.110	-0.0016	0.0057	0.125
		(-0.88)	(1.53)		(-1.05)	(1.36)		(-1.22)	(0.96)	
30	85	-0.0055***	0.0083***	0.160	-0.0057**	0.0098**	0.176	-0.0001	0.0014	0.072
		(-2.78)	(3.14)		(-2.63)	(2.37)		(-0.30)	(0.79)	
60	85	-0.0036***	0.0065***	0.284	-0.0037***	0.0071***	0.282	-0.0001	0.0006	0.102
		(-3.23)	(3.94)		(-3.10)	(3.25)		(-0.82)	(0.87)	
90	85	-0.0026***	0.0050***	0.308	-0.0029***	0.0055***	0.315	-0.0003*	0.0005	0.077
		(-3.14)	(4.45)		(-3.24)	(5.07)		(-1.95)	(0.79)	
180	85	-0.0020***	0.0033***	0.226	-0.0021***	0.0036***	0.245	-0.0001	0.0003	0.088
		(-3.01)	(3.64)		(-3.09)	(4.69)		(-1.56)	(0.82)	
270	85	-0.0016***	0.0027**	0.203	-0.0017***	0.0029***	0.228	-0.0001	0.0002	0.098
		(-2.89)	(2.18)		(-2.96)	(2.70)		(-1.05)	(0.88)	
360	85	-0.0012**	0.0022**	0.153	-0.0012**	0.0023***	0.174	-0.0000	0.0002	0.107
		(-2.24)	(2.47)		(-2.31)	(3.07)		(-1.14)	(0.99)	

Table 4.20: Reactions of Good and Bad Components to FOMC surprise: Professional Forecast

The table reports the regression results of Equation (4.4.1) which analyzes the reactions from ΔVRP (in Part A), ΔIV (in Part B), and ΔRV (in Part C) to positive and negative federal fund rate surprise. The interest shocks is calculated by professional forecasts rather than the 30-day federal fund futures contracts. It provides the intercept (α), slope (β) R-squared and adjusted R-squared and obs represents the number of observation. All standard errors are adjusted following White (1980) and robust t-statistics in parentheses. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

	good							bad						
	7	30	60	90	180	270	360	7	30	60	90	180	270	360
Part A: ΔVRP														
α	-0.0025	-0.0017***	-0.0011***	-0.0008***	-0.0005***	-0.0004***	-0.0003***	-0.0020	-0.0038**	-0.0025***	-0.0018***	-0.0014***	-0.0012**	-0.0008*
	(-1.66)	(-2.86)	(-3.51)	(-3.49)	(-3.53)	(-3.68)	(-3.68)	(-0.53)	(-2.58)	(-3.03)	(-2.91)	(-2.78)	(-2.59)	(-1.86)
β	0.0045***	0.0021***	0.0017***	0.0013***	0.0008***	0.0006***	0.0005***	0.0105	0.0062**	0.0048***	0.0037***	0.0025***	0.0022*	0.0017**
	(2.93)	(2.87)	(3.97)	(4.72)	(3.83)	(3.64)	(3.59)	(1.19)	(2.57)	(3.79)	(4.15)	(3.44)	(1.90)	(2.21)
obs	85	85	85	85	85	85	85	85	85	85	85	85	85	85
R^2	0.101	0.139	0.284	0.297	0.238	0.224	0.229	0.081	0.165	0.283	0.307	0.225	0.197	0.141
Adj. R^2	0.0899	0.129	0.276	0.289	0.229	0.215	0.220	0.0695	0.155	0.274	0.299	0.216	0.187	0.131
Part B: ΔIV														
α	-0.0030	-0.0017***	-0.0011***	-0.0009***	-0.0006***	-0.0004***	-0.0004***	-0.0031	-0.0040**	-0.0026***	-0.0020***	-0.0015***	-0.0012***	-0.0009*
	(-1.65)	(-2.84)	(-3.20)	(-3.33)	(-3.49)	(-3.58)	(-3.61)	(-0.75)	(-2.51)	(-2.99)	(-3.04)	(-2.84)	(-2.64)	(-1.91)
β	0.0086*	0.0032***	0.0022***	0.0016***	0.0010***	0.0007***	0.0006***	0.0121	0.0066**	0.0050***	0.0039***	0.0026***	0.0022**	0.0018**
	(1.76)	(2.65)	(2.76)	(3.07)	(3.60)	(3.99)	(4.21)	(1.16)	(2.24)	(3.50)	(4.75)	(3.94)	(2.06)	(2.42)
obs	85	85	85	85	85	85	85	85	85	85	85	85	85	85
R^2	0.195	0.243	0.308	0.300	0.272	0.267	0.280	0.087	0.161	0.274	0.305	0.230	0.205	0.148
Adj. R^2	0.186	0.234	0.300	0.291	0.263	0.259	0.271	0.0760	0.151	0.265	0.297	0.221	0.196	0.138
Part C: ΔRV														
α	-0.0005	0.0000	-0.0000	-0.0001	-0.0000	-0.0000	-0.0000	-0.0011*	-0.0002	-0.0001	-0.0002**	-0.0001*	-0.0000	-0.0000
	(-0.62)	(0.07)	(-0.34)	(-1.34)	(-1.11)	(-0.66)	(-0.71)	(-1.80)	(-0.75)	(-1.18)	(-2.36)	(-1.86)	(-1.34)	(-1.45)
β	0.0041	0.0010	0.0004	0.0003	0.0002	0.0001	0.0001	0.0016	0.0004	0.0002	0.0002	0.0001	0.0001	0.0001
	(0.98)	(0.84)	(0.87)	(0.80)	(0.82)	(0.87)	(0.96)	(0.88)	(0.69)	(0.86)	(0.76)	(0.81)	(0.88)	(1.04)
obs	85	85	85	85	85	85	85	85	85	85	85	85	85	85
R^2	0.164	0.102	0.134	0.105	0.114	0.126	0.135	0.065	0.036	0.041	0.050	0.057	0.062	0.072
Adj. R^2	0.154	0.0910	0.124	0.0943	0.104	0.115	0.125	0.0537	0.0248	0.0296	0.0387	0.0457	0.0503	0.0608

Table 4.21: Surprise of Federal Fund Rate on Contractionary and Expansionary Policy: Professional Forecast

The table reports the regression results of Equation (4.5.1) which analyze the reactions from er (in Part A), ΔIV, ΔRV and ΔVRP (in Part B) depend on contractionary and expansionary policy. The interest shocks is calculated by professional forecasts rather than the 30-day federal fund futures contracts. It provides the intercept, slope and adjusted R-squared and obs represents for the number of observation. The coefficients α, α_1 and α_2 represent the effect of no surprises days, contractionary policy presence days and expansionary policy presence days, respectively. The coefficients β_1 and β_2 estimate the response to strength of the contractionary and expansionary policy, respectively. All standard errors are adjusted following White (1980) and robust t-statistics in parentheses. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

Part A: Excess Return												
Variables	Obs	α	t-stat	α_1	t-stat	β_1	t-stat	α_2	t-stat	β_2	t-stat	Adj. R^2
er	85	0.8060**	(2.35)	-1.0081	(-1.19)	-0.1945	(-1.20)	9.1528***	(3.42)	1.3809***	(3.36)	0.209

Part B: ΔVRP, ΔIV , ΔRV												
Maturity	Obs	α	t-stat	α_1	t-stat	β_1	t-stat	α_2	t-stat	β_2	t-stat	Adj. R^2
						ΔVRP						
7	85	-0.0013	(-0.23)	-0.0075	(-0.98)	0.0017	(0.95)	-0.0662***	(-2.99)	0.0125***	(3.79)	0.119
30	85	-0.0041*	(-1.97)	0.0025	(0.80)	-0.0004	(-0.75)	-0.0461***	(-19.35)	0.0058***	(32.85)	0.315
60	85	-0.0024**	(-2.23)	0.0002	(0.09)	0.0003	(0.58)	-0.0360***	(-9.47)	0.0035***	(6.27)	0.477
90	85	-0.0019**	(-2.29)	0.0012	(0.90)	0.0001	(0.26)	-0.0287***	(-3.07)	0.0001	(0.05)	0.335
180	85	-0.0016**	(-2.27)	0.0009	(0.87)	0.0002	(1.13)	-0.0206***	(-2.96)	-0.0007	(-0.65)	0.248
270	85	-0.0014**	(-2.44)	0.0012	(1.66)	0.0001	(1.24)	-0.0177**	(-2.05)	-0.0018	(-1.38)	0.214
360	85	-0.0010*	(-1.80)	0.0012	(1.04)	0.0000	(0.05)	-0.0148**	(-2.52)	-0.0014	(-1.55)	0.179
						ΔIV						
7	85	-0.0017	(-0.27)	-0.0047	(-0.62)	0.0014	(1.00)	-0.0928**	(-2.17)	0.0240***	(3.66)	0.268
30	85	-0.0040*	(-1.82)	0.0027	(0.94)	0.0005	(0.97)	-0.0515***	(-8.84)	0.0087***	(10.44)	0.402
60	85	-0.0024**	(-2.12)	0.0003	(0.12)	0.0004	(0.80)	-0.0387***	(-24.61)	0.0048***	(28.14)	0.533
90	85	-0.0021**	(-2.33)	0.0012	(0.90)	0.0002	(0.70)	-0.0311***	(-4.46)	0.0014	(1.33)	0.417
180	85	-0.0016**	(-2.28)	0.0010	(0.89)	0.0002	(1.05)	-0.0217***	(-3.76)	-0.0000	(-0.04)	0.298
270	85	-0.0014**	(-2.40)	0.0012	(1.63)	0.0001	(1.31)	-0.0182**	(-2.27)	-0.0013	(-1.09)	0.228
360	85	-0.0010*	(-1.79)	0.0012	(1.04)	0.0000	(0.09)	-0.0154***	(-2.86)	-0.0010	(-1.22)	0.198
						ΔRV						
7	85	-0.0004	(-0.54)	0.0027	(1.38)	-0.0003	(-0.51)	-0.0266	(-1.27)	0.0115***	(3.54)	0.714
30	85	0.0001	(0.31)	0.0002	(0.23)	0.0009***	(9.91)	-0.0054	(-0.83)	0.0029***	(2.87)	0.377
60	85	0.0000	(0.18)	0.0001	(0.52)	0.0001***	(6.07)	-0.0027	(-1.08)	0.0013***	(3.20)	0.606
90	85	-0.0002*	(-1.75)	0.0001	(0.46)	0.0001***	(4.77)	-0.0024	(-1.00)	0.0013***	(3.61)	0.674
180	85	-0.0000	(-1.11)	0.0001	(0.55)	0.0000	(0.29)	-0.0012	(-0.98)	0.0007***	(3.66)	0.682
270	85	-0.0000	(-0.26)	0.0000	(0.17)	0.0000*	(1.80)	-0.0005	(-0.79)	0.0005***	(4.97)	0.725
360	85	-0.0000	(-0.28)	0.0000	(0.26)	0.0000	(1.37)	-0.0006	(-1.24)	0.0004***	(5.09)	0.697

Table 4.22: Asymmetric Reaction to Positive and Negative Surprise: Professional Forecast

The table reports the regression results of Equation (4.5.1) which analyzes the reactions from er (in Part A), ΔIV, ΔRV and ΔVRP (in Part B) to positive and negative federal fund rate surprise. The interest shocks is calculated by professional forecasts rather than the 30-day federal fund futures contracts. It provides the intercept, slope and adjusted R-squared and obs represents for the number of observation. The coefficients α, α_1 and α_2 represent the effect of no surprises days, positive surprise days and negative surprise days, respectively. The coefficients β_1 and β_2 estimate the response to strength of the positive and negative surprise, respectively. All standard errors are adjusted following White (1980) and robust t-statistics in parentheses. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

Part A: Excess Return

variable	Obs	α	t-stat	α_1	t-stat	β_1	t-stat	α_2	t-stat	β_2	t-stat	Adj. R^2
er	85	0.6989*	(1.84)	-1.3905	(-1.38)	3.0329***	(4.94)	-1.6467	(-1.23)	-1.4298***	(-3.37)	0.137

Part B: ΔVRP, ΔIV , ΔRV

maturity	Obs	α	t-stat	α_1	t-stat	β_1	t-stat	α_2	t-stat	β_2	t-stat	Adj. R^2
						ΔVRP						
7	85	-0.0048	(-0.92)	-0.0124	(-0.63)	0.0392	(0.82)	-0.0169	(-0.91)	0.0097	(1.28)	0.072
30	85	-0.0038*	(-1.70)	0.0014	(0.38)	-0.0063*	(-1.93)	-0.0035	(-0.46)	0.0099***	(3.22)	0.198
60	85	-0.0023*	(-1.93)	0.0001	(0.05)	-0.0035	(-1.28)	-0.0024	(-0.52)	0.0078***	(4.29)	0.358
90	85	-0.0019**	(-2.06)	0.0015	(0.74)	-0.0033	(-1.06)	0.0018	(1.13)	0.0065***	(32.73)	0.387
180	85	-0.0015**	(-2.00)	0.0009	(0.54)	-0.0022	(-0.98)	0.0014	(0.99)	0.0043***	(13.69)	0.279
270	85	-0.0014**	(-2.23)	0.0015	(1.26)	-0.0020	(-0.99)	0.0028	(1.17)	0.0038***	(4.28)	0.248
360	85	-0.0010*	(-1.67)	0.0017	(1.13)	-0.0018	(-0.97)	0.0014	(0.79)	0.0028***	(4.76)	0.175
						ΔIV						
7	85	-0.0053	(-0.92)	-0.0105	(-0.55)	0.0384	(0.81)	-0.0307	(-0.94)	0.0139	(1.01)	0.096
30	85	-0.0041*	(-1.70)	0.0028	(0.80)	-0.0042**	(-2.27)	-0.0072	(-0.64)	0.0105**	(2.22)	0.192
60	85	-0.0023*	(-1.88)	0.0004	(0.13)	-0.0032	(-1.13)	-0.0039	(-0.65)	0.0081***	(3.25)	0.345
90	85	-0.0020**	(-2.06)	0.0016	(0.78)	-0.0037	(-1.33)	0.0003	(0.12)	0.0069***	(9.44)	0.397
180	85	-0.0016**	(-2.00)	0.0009	(0.53)	-0.0023	(-1.05)	0.0008	(0.59)	0.0045***	(24.11)	0.301
270	85	-0.0014**	(-2.18)	0.0015	(1.26)	-0.0021	(-1.07)	0.0023	(1.16)	0.0039***	(5.93)	0.278
360	85	-0.0010	(-1.63)	0.0017	(1.14)	-0.0020	(-1.09)	0.0010	(0.67)	0.0030***	(7.08)	0.203
						ΔRV						
7	85	-0.0005	(-0.73)	0.0019	(0.73)	-0.0008	(-0.21)	-0.0137	(-0.95)	0.0042	(0.67)	0.144
30	85	-0.0003	(-1.02)	0.0013	(0.98)	0.0021	(0.60)	-0.0037	(-0.97)	0.0005	(0.33)	0.087
60	85	-0.0000	(-0.47)	0.0002	(1.06)	0.0002	(0.50)	-0.0016	(-0.96)	0.0004	(0.53)	0.106
90	85	-0.0001	(-1.41)	0.0001	(0.50)	-0.0005	(-1.41)	-0.0015	(-0.92)	0.0004	(0.58)	0.116
180	85	-0.0000	(-1.07)	-0.0000	(-0.17)	-0.0001	(-0.61)	-0.0006	(-0.74)	0.0002	(0.62)	0.098
270	85	0.0000	(0.18)	0.0000	(0.15)	-0.0001**	(-2.17)	-0.0005	(-0.96)	0.0001	(0.65)	0.136
360	85	0.0000	(0.33)	0.0000	(0.11)	-0.0002	(-1.40)	-0.0004	(-0.96)	0.0001	(0.81)	0.172

Chapter 5

Conclusions and Further Research

5.1 Summary of the Findings

This thesis investigates volatility and variance risk premium. In Chapter 2, we study volatility-managed strategies in commodity markets. We find that conventional volatility-managed strategies, which consist in scaling a portfolio by its volatility after its formation, cannot boost the performance of the original portfolio. We consider the strategy which scales portfolio by the volatility of each asset before its formation, and we find the strategy does not work in our study. It suggests that there is no significant difference between the two strategies. In details, these strategies fail either in recession economic condition or in expansion condition. We explore several mechanisms that may explain our results. We consider different potential reasons and find that, alone, economic conditions, alternative volatility, forecasting models, and alternative methods to compute the portfolio cannot explain the performance of the volatility timing strategies.

Chapter 3 focuses on the role of the volatility risk premium estimator for volatility forecasting when using the option implied volatility. We compare raw model-free implied volatility (MFIV), estimator directly from EWMA by historical realized volatility and several adjusted MFIV. We find that the ranking of performance in ascending orders is rough: adjusted MFIV, MFIV and EWMA. Comparing the adjusted MFIV, we find that there is no significant differences among volatility risk premium estimators based on the historical average, AR(1), and a combination of realized volatility and MFIV. Among them, estimators from the combination perform best in volatility forecasting inconsistently. Collectively, our results confirm that adjustment for MFIV improves the prediction of volatility and the choice of volatility risk premium plays a vital role.

Chapter 4 analyzes the impact of monetary policy news on the pricing of equity and variance risk. We document that interest rate shocks have no impact on S&P 500 index while the change in the variance risk premium responds positively to interest rate news. In detail, the response to interest rate news decreases along with the term structure curve. By dissecting the variance risk premium, we find that implied variance reacts more than realized variance at the short-end of the curve. Moreover, most reactions are from bad variance risk premium, and variance risk premium reacts stronger to negative interest rate shocks than positive ones. These findings confirm that investors need more compensation for risk premium for the increased downside risk.

5.2 Suggestions for Future Research

In the following, we discuss further researches that is based on our findings and previous literature.

Volatility-managed Strategy Chapter 2 concludes that scaling the original portfolio before or after its formation by volatility-managed strategies cannot consistently and significantly improve the performance. One may compare these two strategies in other asset classes and apply them to more trading strategies. Another interesting question is why these strategies fail and how to remediate these issues. The volatility-managed strategy is based on the negative relation between return and volatility. The failure of strategy suggests that the relationship does not hold in the commodity market. Cederburg et al. (2020) point that in the equity market, when the volatility of the portfolio is in an extreme state, the relation between future return and volatility is more likely to be negative, and the volatility autocorrelation is higher. We analyze the performance of strategies in different economic conditions. One may explore the strategies that perform in different volatility states. In that way, one could understand more the relation between return and volatility and the pricing of the commodity.

Variance risk premium Chapter 3 focus on the prediction of volatility risk premium, which is close to variance risk premium. Chapter 4 investigates the impact of monetary policy news on variance risk premium. It would be natural to extend the analysis to other macroeconomic news. Bollerslev et al. (2011) view the variance risk premium as a measure of investor's risk aversion and test the explanatory power of 29 macro-finance indicators. They show that realized volatility, AAA bond spread, housing starts, P/E ratio, industrial production, producer price index (PPI) and payroll employment jointly explain the variance risk premium. Thus one may analyze the impact of this macro news on the price of the variance risk. Another extension is focusing on the term-structure of variance risk premium. In our study, we notice that the term-structure of variance risk premium is a humped shape. It is worth testing the Expectation Hypothesis in the variance risk premium and trying to compute the forward variance risk premium. So far, there is a lack of research on forwarding variance risk premium.

References

Agnolucci, P., 2009. Volatility in crude oil futures: a comparison of the predictive ability of garch and implied volatility models. Energy Economics 31, 316–321.

Aït-Sahalia, Y., Karaman, M., Mancini, L., 2020. The term structure of equity and variance risk premia. Journal of Econometrics .

Andersen, T. G., Bollerslev, T., 1998. Answering the skeptics: Yes, standard volatility models do provide accurate forecasts. International Economic Review pp. 885–905.

Andersen, T. G., Bollerslev, T., Diebold, F. X., 2007. Roughing it up: Including jump components in the measurement, modeling, and forecasting of return volatility. Review of Economics and Statistics 89, 701–720.

Avino, D. E., Stancu, A., Wese Simen, C., 2019. Dissecting macroeconomic news. Journal of Money, Credit and Banking .

Bakshi, G., Gao, X., Rossi, A. G., 2019. Understanding the sources of risk underlying the cross section of commodity returns. Management Science 65, 619–641.

Bakshi, G., Kapadia, N., Madan, D., 2003. Stock return characteristics, skew laws, and the differential pricing of individual equity options. Review of Financial Studies 16, 101–143.

Balduzzi, P., Elton, E. J., Green, T. C., 2001. Economic news and bond prices: Evidence from the us treasury market. Journal of Financial and Quantitative Analysis 36, 523–543.

Barndorff-Nielsen, O. E., Kinnebrock, S., Shephard, N., 2008. Measuring downside risk-realised semivariance. CREATES Research Paper .

Barndorff-Nielsen, O. E., Shephard, N., 2002. Econometric analysis of realized volatility and its use in estimating stochastic volatility models. Journal of the Royal Statistical Society: Series B (Statistical Methodology) 64, 253–280.

Barroso, P., Maio, P. F., 2019. The risk-return tradeoff among equity factors. Working Paper .

Barroso, P., Santa-Clara, P., 2015. Momentum has its moments. Journal of Financial Economics 116, 111–120.

Bekaert, G., Engstrom, E., 2017. Asset return dynamics under habits and bad environment–good environment fundamentals. Journal of Political Economy 125, 713–760.

Bekaert, G., Hoerova, M., 2014. The vix, the variance premium and stock market volatility. Journal of Econometrics 183, 181–192.

Bekaert, G., Hoerova, M., Duca, M. L., 2013. Risk, uncertainty and monetary policy. Journal of Monetary Economics 60, 771–788.

Bernanke, B. S., Kuttner, K. N., 2005. What explains the stock market's reaction to federal reserve policy? Journal of Finance 60, 1221–1257.

Black, F., Scholes, M., 1973. The pricing of options and corporate liabilities. Journal of Political Economy 81, 637–654.

Bollerslev, T., 1986. Generalized autoregressive conditional heteroskedasticity. Journal of Econometrics 31, 307–327.

Bollerslev, T., Gibson, M., Zhou, H., 2011. Dynamic estimation of volatility risk premia and investor risk aversion from option-implied and realized volatilities. Journal of Econometrics 160, 235–245.

Bollerslev, T., Hood, B., Huss, J., Pedersen, L. H., 2018. Risk everywhere: Modeling and managing volatility. Review of Financial Studies 31, 2729–2773.

Bollerslev, T., Tauchen, G., Zhou, H., 2009. Expected stock returns and variance risk premia. Review of Financial Studies 22, 4463–4492.

Bongaerts, D., Kang, X., van Dijk, M., 2020. Conditional volatility targeting. Financial Analysts Journal 76, 54–71.

Boons, M., Prado, M. P., 2019. Basis-momentum. Journal of Finance 74, 239–279.

Bormetti, G., Corsi, F., Majewski, A., 2016. Term structure of variance risk premium and returns' predictability. Working paper .

Britten-Jones, M., Neuberger, A., 2000. Option prices, implied price processes, and stochastic volatility. Journal of Finance 55, 839–866.

Campbell, J. Y., Cochrane, J. H., 2000. Explaining the poor performance of consumption-based asset pricing models. Journal of Finance 55, 2863–2878.

Canina, L., Figlewski, S., 1993. The informational content of implied volatility. Review of Financial Studies 6, 659–681.

Carr, P., Wu, L., 2008. Variance risk premiums. Review of Financial Studies 22, 1311–1341.

Carr, P., Wu, L., 2009. Variance risk premiums. Review of Financial Studies 22, 1311–1341.

Cederburg, S., O'Doherty, M. S., Wang, F., Yan, X. S., 2020. On the performance of volatility-managed portfolios. Journal of Financial Economics .

Chabi-Yo, F., 2012. Pricing kernels with stochastic skewness and volatility risk. Management Science 58, 624–640.

Chang, B.-Y., Christoffersen, P., Jacobs, K., Vainberg, G., 2012. Option-implied measures of equity risk. Review of Finance 16, 385–428.

Charoenwong, C., Jenwittayaroje, N., Low, B. S., 2009. Who knows more about future currency volatility? Journal of Futures Markets 29, 270–295.

Chen, Y., Shu, J., Zhang, J. E., 2016. Investor sentiment, variance risk premium and delta-hedged gains. Applied Economics 48, 2952–2964.

Chernov, M., 2007. On the role of risk premia in volatility forecasting. Journal of Business & Economic Statistics 25, 411–426.

Chiras, D. P., Manaster, S., 1978. The information content of option prices and a test of market efficiency. Journal of Financial Economics 6, 213–234.

Christensen, B. J., Prabhala, N. R., 1998. The relation between implied and realized volatility1. Journal of Financial Economics 50, 125–150.

Chuliá, H., Martens, M., van Dijk, D., 2010. Asymmetric effects of federal funds target rate changes on S&P100 stock returns, volatilities and correlations. Journal of Banking & Finance 34, 834–839.

Clements, A., Silvennoinen, A., 2013. Volatility timing: How best to forecast portfolio exposures. Journal of Empirical Finance 24, 108–115.

Corsi, F., 2009. A simple approximate long-memory model of realized volatility. Journal of Financial Econometrics 7, 174–196.

Daniel, K., Moskowitz, T. J., 2016. Momentum crashes. Journal of Financial Economics 122, 221–247.

Della Corte, P., Ramadorai, T., Sarno, L., 2016. Volatility risk premia and exchange rate predictability. Journal of Financial Economics 120, 21–40.

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

Ding, J., Meade, N., 2010. Forecasting accuracy of stochastic volatility, garch and ewma models under different volatility scenarios. Applied Financial Economics 20, 771–783.

Du, J., Kapadia, N., 2012. The tail in the volatility index. U. Massachusetts, Amherst Working paper .

Egloff, D., Leippold, M., Wu, L., 2010. The term structure of variance swap rates and optimal variance swap investments. Journal of Financial and Quantitative Analysis pp. 1279–1310.

Fan, J., Imerman, M. B., Dai, W., 2016. What does the volatility risk premium say about liquidity provision and demand for hedging tail risk? Journal of Business & Economic Statistics 34, 519–535.

Fernandez-Perez, A., Frijns, B., Tourani-Rad, A., 2017. When no news is good news–the decrease in investor fear after the fomc announcement. Journal of Empirical Finance 41, 187–199.

Feunou, B., Jahan-Parvar, M. R., Okou, C., 2018. Downside variance risk premium. Journal of Financial Econometrics 16, 341–383.

Fleming, J., 1998. The quality of market volatility forecasts implied by s&p 100 index option prices. Journal of Empirical Finance 5, 317–345.

Fleming, J., Kirby, C., Ostdiek, B., 2001. The economic value of volatility timing. Journal of Finance 56, 329–352.

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

Garg, S., Vipul, 2015. Volatility risk premium in indian options prices. Journal of Futures Markets 35, 795–812.

Garman, M. B., Klass, M. J., 1980. On the estimation of security price volatilities from historical data. Journal of Business pp. 67–78.

Glosten, L. R., Jagannathan, R., Runkle, D. E., 1993. On the relation between the expected value and the volatility of the nominal excess return on stocks. Journal of Finance 48, 1779–1801.

Gospodinov, N., Jamali, I., 2012. The effects of federal funds rate surprises on S&P 500 volatility and volatility risk premium. Journal of Empirical Finance 19, 497–510.

Grundy, B. D., Martin, J. S. M., 2001. Understanding the nature of the risks and the source of the rewards to momentum investing. The Review of Financial Studies 14, 29–78.

Gürkaynak, R. S., 2005. Using federal funds futures contracts for monetary policy analysis. FEDS Working Paper .

Gürkaynak, R. S., Sack, B. P., Swanson, E. T., 2007. Market-based measures of monetary policy expectations. Journal of Business & Economic Statistics 25, 201–212.

Han, Y., Huang, D., Zhou, G., 2021. Anomalies enhanced: A portfolio rebalancing approach. Financial Management 50, 371–424.

Harvey, C. R., Hoyle, E., Korgaonkar, R., Rattray, S., Sargaison, M., Van Hemert, O., 2018. The impact of volatility targeting. Journal of Portfolio Management 45, 14–33.

Heston, S. L., 1993. A closed-form solution for options with stochastic volatility with applications to bond and currency options. Review of Financial Studies 6, 327–343.

Hevia, C., Petrella, I., Sola, M., 2018. Risk premia and seasonality in commodity futures. Journal of Applied Econometrics 33, 853–873.

Hull, J., White, A., 1987. The pricing of options on assets with stochastic volatilities. Journal of Finance 42, 281–300.

Jegadeesh, N., Titman, S., 1993. Returns to buying winners and selling losers: Implications for stock market efficiency. Journal of Finance 48, 65–91.

Jiang, G. J., Tian, Y. S., 2005. The model-free implied volatility and its information content. Review of Financial Studies 18, 1305–1342.

Jorion, P., 1995. Predicting volatility in the foreign exchange market. Journal of Finance 50, 507–528.

Kaminska, I., Roberts-Sklar, M., 2018. Volatility in equity markets and monetary policy rate uncertainty. Journal of Empirical Finance 45, 68–83.

Kang, B. J., Kim, T. S., Yoon, S.-J., 2010. Information content of volatility spreads. Journal of Futures Markets 30, 533–558.

Kang, J., Kwon, K. Y., 2021. Volatility-managed commodity futures portfolios. Journal of Futures Markets 41, 159–178.

Kilic, M., Shaliastovich, I., 2019. Good and bad variance premia and expected returns. Management Science 65, 2522–2544.

Kim, A. Y., Tse, Y., Wald, J. K., 2016. Time series momentum and volatility scaling. Journal of Financial Markets 30, 103–124.

Konstantinidi, E., Skiadopoulos, G., 2016. How does the market variance risk premium vary over time? Evidence from S&P 500 variance swap investment returns. Journal of Banking & Finance 62, 62–75.

Kourtis, A., Markellos, R. N., Symeonidis, L., 2016. An international comparison of implied, realized, and GARCH volatility forecasts. Journal of Futures Markets 36, 1164–1193.

Kurov, A., 2010. Investor sentiment and the stock market's reaction to monetary policy. Journal of Banking & Finance 34, 139–149.

Kuttner, K. N., 2001. Monetary policy surprises and interest rates: Evidence from the fed funds futures market. Journal of Monetary Economics 47, 523–544.

Lamoureux, C. G., Lastrapes, W. D., 1993. Forecasting stock-return variance: Toward an understanding of stochastic implied volatilities. Review of Financial Studies 6, 293–326.

Latane, H. A., Rendleman Jr, R. J., 1976. Standard deviations of stock price ratios implied in option prices. Journal of Finance 31, 369–381.

Law, T. H., Song, D., Yaron, A., 2018. Fearing the fed: How wall street reads main street. Working Paper .

Lee, S. S., Mykland, P. A., 2008. Jumps in financial markets: A new nonparametric test and jump dynamics. Review of Financial Studies 21, 2535–2563.

Li, J., Zinna, G., 2018. The variance risk premium: Components, term structures, and stock return predictability. Journal of Business & Economic Statistics 36, 411–425.

Liu, F., Tang, X., Zhou, G., 2019. Volatility-managed portfolio: Does it really work? Journal of Portfolio Management 46, 38–51.

Lucca, D. O., Moench, E., 2015. The pre-fomc announcement drift. Journal of Finance 70, 329–371.

Marshall, B. R., Cahan, R. H., Cahan, J. M., 2008. Can commodity futures be profitably traded with quantitative market timing strategies? Journal of Banking & Finance 32, 1810–1819.

McAleer, M., Medeiros, M. C., 2008. Realized volatility: A review. Econometric Reviews 27, 10–45.

Miffre, J., Rallis, G., 2007. Momentum strategies in commodity futures markets. Journal of Banking & Finance 31, 1863–1886.

Mina, J., Xiao, J. Y., et al., 2001. Return to riskmetrics: the evolution of a standard. RiskMetrics Group 1, 1–11.

Moreira, A., Muir, T., 2017. Volatility-managed portfolios. Journal of Finance 72, 1611–1644.

Moskowitz, T. J., Ooi, Y. H., Pedersen, L. H., 2012. Time series momentum. Journal of Financial Economics 104, 228–250.

Nelson, D. B., 1991. Conditional heteroskedasticity in asset returns: A new approach. Econometrica pp. 347–370.

Oikonomou, I., Stancu, A., Symeonidis, L., Simen, C. W., 2019. The information content of short-term options. Journal of Financial Markets 46, 100504.

Paschke, R., Prokopczuk, M., Wese Simen, C., 2020. Curve momentum. Journal of Banking & Finance 113, 105718.

Patton, A. J., 2011a. Data-based ranking of realised volatility estimators. Journal of Econometrics 161, 284–303.

Patton, A. J., 2011b. Volatility forecast comparison using imperfect volatility proxies. Journal of Econometrics 160, 246–256.

Poteshman, A. M., 2000. Forecasting future variance from option prices. Working paper .

Prokopczuk, M., Symeonidis, L., Wese Simen, C., 2017. Variance risk in commodity markets. Journal of Banking & Finance 81, 136–149.

Prokopczuk, M., Wese Simen, C., 2014. The importance of the volatility risk premium for volatility forecasting. Journal of Banking & Finance 40, 303–320.

Riskmetrics, T., 1996. JP Morgan Technical Document.

Savor, P., Wilson, M., 2013. How much do investors care about macroeconomic risk? evidence from scheduled economic announcements. Journal of Financial and Quantitative Analysis 48, 343–375.

Segal, G., Shaliastovich, I., Yaron, A., 2015. Good and bad uncertainty: Macroeconomic and financial market implications. Journal of Financial Economics 117, 369–397.

Sørensen, C., 2002. Modeling seasonality in agricultural commodity futures. Journal of Futures Markets 22, 393–426.

Szakmary, A., Ors, E., Kim, J. K., Davidson III, W. N., 2003. The predictive power of implied volatility: Evidence from 35 futures markets. Journal of Banking & Finance 27, 2151–2175.

Szymanowska, M., De Roon, F., Nijman, T., Van Den Goorbergh, R., 2014. An anatomy of commodity futures risk premia. Journal of Finance 69, 453–482.

Taylor, S. J., Yadav, P. K., Zhang, Y., 2010. The information content of implied volatilities and model-free volatility expectations: Evidence from options written on individual stocks. Journal of Banking & Finance 34, 871–881.

Tee, C. W., Ting, C., 2017. Variance risk premiums of commodity etfs. Journal of Futures Markets 37, 452–472.

Thorbecke, W., 1997. On stock market returns and monetary policy. The Journal of Finance 52, 635–654.

Trolle, A. B., Schwartz, E. S., 2010. Variance risk premia in energy commodities. Journal of Derivatives 17, 15–32.

White, H., 1980. A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity. Econometrica pp. 817–838.

Yang, D., Zhang, Q., 2000. Drift-independent volatility estimation based on high, low, open, and close prices. Journal of Business 73, 477–492.