MARKET ATTITUDES UNDER UNCERTAINTY: WHAT IS PRICED IN THE CRUDE OIL VOLATILITY RISK PREMIUM?

A Thesis

Presented to the Faculty of the Graduate School

of Cornell University

in Partial Fulfillment of the Requirements for the Degree of

Master of Science

by

Qixiang Gao

August 2021

ABSTRACT

Qixiang Gao

This paper studies the predictability of volatility risk premia in WTI crude oil futures markets under an uncertain environment. I find that a nontrivial fraction of the magnitude and the direction of the volatility risk premium can be explained by the unforeseeable fluctuations in macroeconomic and financial indicators. Although the previous literature has shown that most of the risk factors (for example, book-to-market ratio and momentum) used in capital asset pricing models are not responsible for variations in the volatility risk premium, I find evidence that the effects of some of the indicators like open interest momentum and growth rate of market interest could be enhanced when taking uncertainty into consideration. The effects of market participants' behaviors and risk attitudes are strongly correlated with uncertainty, and the cost of hedging against futures price variance will increase if uncertainty in the macroeconomic environment is high.

BIOGRAPHICAL SKETCH

Qixiang Gao was born in Beijing, China. He obtained a bachelor's degree in finance before coming to Cornell to pursue a master of science degree in applied economics and management. His current research interest lies in asset pricing, behavioral finance, and financial economics. He will join the Ph.D. program in finance at the University of Rochester and plan to focus on frequency-domain asset pricing approaches and capital markets mechanism design. In his spare time, Qixiang is a keen Lego collector, a tennis and football lover, and a pianist wannabe.

ACKNOWLEDGEMENTS

To begin with, I want to express my gratitude to Professor Sumudu W Watugala, the chair of my special committee. She is erudite, industrious, and always happy to lend a hand in times of need. She generously provided me with the futures and options historical data used in this article. I would also like to thank Professor Byoung-Hyoun Hwang for joining my committee and giving valuable comments on my thesis. Moreover, I greatly appreciate the help from Professor Yongmiao Hong, whose enthusiasm towards economic research greatly propelled my decision to pursue a Ph.D.

I want to thank all the friends I made at Cornell. The camaraderie among my fellow classmates made life in Ithaca more enjoyable and truly unforgettable. Last but not least, I want to thank my family for their unwavering support and always having my back.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1

INTRODUCTION

Can implied volatility serve as an unbiased estimator for future realized volatility? Classic theory suggests the answer is yes since implied volatility should equal the expectation of the volatility for the underlying asset during the remaining life of the option contract. However, the empirical findings do not share a consistent view. On the one hand, implied volatility is considered biased and informationally inferior to historical volatility when predicting future underlying volatility (Day and Lewis, 1992; Lamoureux and Lastrapes 1993; Canina and Figlewski, 1993). On the other hand, the predictive power of implied volatility is endorsed by studies on specific markets. (Jorion, 1995; Christensen and Prabhala, 1998).

More and more recent works point out that the difference between implied volatility and realized volatility, the so-called volatility risk premium is not a zero-mean sequence. It contains valuable information for future returns of the underlying asset (Bollerslev, Tauchen, Zhou, 2009) and the risk attitudes of market participants and supply-demand relations (Fan, Imerman, and Dai, 2016). These findings lead to the question of how the volatility risk premium is priced. However, some literature suggests that most, if not all the risk factors commonly used in capital asset pricing models (for example, book-to-market ratio and momentum) are not responsible for variations in the volatility risk premium, suggesting that there exist some independent risk factors driving its dynamic (Carr and Wu, 2009).

In this paper, I address the relations between crude oil futures volatility risk premia and the attitudes of market participants when considering uncertainty in the macroeconomic and financial environment. This notion of uncertainty is proposed by Jurado, Ludvigson, Ng (2015) and Ludvigson, Ma, Ng (2015), where they discover a method to obtain the purely unforeseeable fluctuations in the macroeconomic and financial indicators. In particular, I seek answers to the following questions:

1. What is the pure influence of the economic uncertainty on volatility risk premium, and how is this influence imposed?
2. Does economic uncertainty contain valid information for predicting both the magnitude and the sign of volatility risk premium? (i.e., whether the implied volatility would be higher or lower than realized volatility in the next period)
3. Are the risk factors priced in return premium also priced in the volatility risk premium? Does the answer still hold after controlling economic uncertainty?
4. How does volatility risk premium react to market participants' increasing interest in trading? Can we observe the same reaction if hedging demands mainly drive the trading interest? Does the answer still hold after controlling economic uncertainty?
5. How does volatility risk premium react to market participants' risk attitudes

(i.e., risk aversion of the hedgers and risk tolerance of the speculators)? Is this reaction relevant to economic uncertainty?

My empirical results imply that: First, macroeconomic and financial uncertainty accounts for a considerable part of the variations in both realized and implied volatility. Although both realized and implied volatility increase along with uncertainty measures, the latter's lack of sensitivity imposes downward pressure on volatility risk premium. In addition, the predictive power of macroeconomic uncertainty to both the magnitude and the sign of volatility risk premium is more potent than that of financial uncertainty. Moreover, whether implied volatility is higher than realized volatility is mainly determined by credit risks and supply-demand shocks on the spot market instead of uncertainty.

Second, I find little evidence that risk factors like return momentum, the growth rate of open interest, and the difference between spot and futures price could explain the changes in volatility risk premium. However, both the momentum and single-period growth rate of open interest significantly diminishes volatility risk premium if considering economic uncertainty. This indicates that information about market participants' risk attitudes contained in market's interest in trading is noisy, but can be observed after controlling uncertainty. Deeper studies show a consistent result if the trading interest is mainly driven by hedging demands.

Third, risk attitudes of market participants (i.e., risk aversion level of hedgers and risk tolerance level of speculators) have homogeneous effects on both volatility risk premium and return premium. This means that hedging will be more costly if hedgers are highly risk averse and the risk tolerance level of speculators is low. Furthermore, the effects of risk attitudes are highly correlated with the uncertainty measures. An increase in macroeconomic uncertainty will propel the speculators to demand more premia for risk sharing.

My results about the predictive power of economic uncertainty on crude oil futures markets align with a wide range of findings in recent literature. For example, Killian (2008) shows that exogenous uncertainty shocks play an important role in deciding the oil price during certain historical periods. In later studies, he discovers a two-sided causality between oil price risks and the aggregating effects of macroeconomic uncertainty shocks (Killian 2009). Recent studies uncover that global real economic uncertainty tends to depress investment and production in the crude oil market and could be exacerbated by higher volatility in oil prices. (Elder and Serletis, 2010; Jo, 2014).

If implied volatility is systematically biased in predicting future realized volatility, how does this bias, AKA volatility risk premium come into being? Premia in futures returns are often explained by the renowned theory of backwardation proposed by Keynes (1923) and Hicks (1939), which indicates that hedgers who enter the market with a short position face the constraint of other market participants' (for example, the speculators) lack of interest to enter the long side and hence need to offer an additional premium for risk sharing. This effect is often exacerbated by the segmentation of commodity futures markets from the financial markets, which leads to constraints in risk sharing. Similarly, literature suggests that volatility risk premium compensates investors for taking volatility risk, and its existence indicates that market participants tend to overestimate the tail risks of a market crash. (See, for example, Xiong, Idzorek, and Ibbotson, 2014; Park, 2015; Andersen, Fusari, and Todorov, 2018). These findings, in turn, link futures volatility risk premium with the predictive power of uncertainty (Buraschi, Trojani, and Vedolin, 2013) that are discussed above.

There are quite a lot of different opinions on how volatility risk premium could be constructed. The most classic and most employed method is called the model-based approach, which demands that the implied volatility be calculated using asset pricing models like the Black-Scholes-Merton model and the realized volatility be constructed using econometric models which generate the ex-ante conditional expectation of the future volatility. The other method is called the model-free approach, which follows a data-driven pattern. For example, Bollerslev, Tauchen, and Zhou (2009) propose a model-free variation measure and construct the implied volatility using high- frequency data. Similarly, model-free realized volatility could also be computed using ultra-high-frequency transaction data and frequency domain approach. (Fan, Imerman, and Dai, 2016). This paper adopts the first method by calculating the implied volatility using the B-S formula and realized volatility using a $GARCH(1,1)$ model.

Moreover, many works have been done regarding both the predictive power and the predictability of volatility risk premium. For instance, on the one hand, Bollerslev, Tauchen, and Zhou (2009) find out that volatility risk premium can explain a nontrivial part of the decrease in stock market returns. Using a non-parametric and parsimonious approach, Prokopczuk and Simen (2013) find evidence that volatility risk premium plays a vital role in predicting future volatility. Corte, Ramadorai, and Sarno (2016) show that currency volatility risk premium could predict exchange rate returns. On the other hand, Bollerslev and Todorov (2011) discover that a considerable fraction of volatility risk premium comes from the compensation for rare events. Andreou and Ghysels (2021) show that volatility factors could account for a large part of changes in future volatility risk premium.

This paper contributes to the literature regarding the predictability of volatility risk premium in the following ways. First, partially opposed to the findings of Carr and Wu (2009), I find out that not all the risk factors priced in return premium are useless when predicting volatility risk premium. Instead, their effects are too noisy to be individually displayed but can be enhanced when controlling unforeseeable fluctuations in macroeconomic and financial indicators. Secondly, as proposed by the theory of backwardation and commodity market segmentation, the risk sharing level is low and hedging constraints occur either when hedgers' risk aversion is high or when speculators' risk tolerance is low. I also discover that the effect of risk attitude is significantly correlated with macroeconomic and financial market uncertainty.

The rest parts of this article is planned as follows: Chapter 2 introduces the data sources and variable constructions, where we will discuss volatility risk premium, uncertainty measures and market attitude proxies in detail. Chapter 3 shows the empirical results and the analysis, where I would step by step examine how the effects of pure uncertainty measures and market participants' behaviors and attitudes under uncertainty could be imposed on volatility risk premium. I conclude in Chapter 4.

CHAPTER 2

DATA AND VARIABLE DEFINITIONS

2.1 Volatility Risk Premium

I use the End-of-Day commodity derivatives data purchased from CME Group to construct the volatility risk premium. The daily End-of-Day dataset contains all the official closing information for CME Group futures and options contracts and is available in three versions, differ by their settlement time: Early (E), Preliminary (P), and Final (F). E files are the earliest available files with settlement data only. P files are the preliminary files that are sent at the end of the trade date. F files are the final files sent in the morning of the next trade date and contain the most exhaustive information. For accuracy, all the data in this paper come from the final settlement (F files).

My sample covers the daily End-of-Day final settlement data of West Texas Intermediate (WTI) crude oil futures (product code CL) and options on WTI crude oil futures (product code LO) traded at XNYM (the New York Mercantile Exchange) over the period of November 14, 1986 to April 4, 2019.

Formally, the volatility risk premium is defined as the difference between risk neutral expectation of the volatility for the underlying assets and the same expectation under physical measure:

$$VRP_t = \sqrt{\mathbb{E}_t^{\mathbb{Q}}\left[\int_t^T \sigma_t^2 du\right]} - \sqrt{\mathbb{E}_t^{\mathbb{P}}\left[\int_t^T \sigma_t^2 du\right]}$$

To construct the WTI crude oil futures volatility risk premium, we need to find representative options and futures sequences to calculate the implied and realized volatility. The methods are shown in the following steps:

(1) Construction of the Front-Month Option Contract Series

The front-month options contract is often referred to as the one closest to expire among all the option contracts traded in the market with the same underlying. Front-month options attract the most volume and contain more liquidity than their peers.

When market participants wish to maintain their positions, they roll the front-month options by closing their positions when the expiry date is around the corner and open the same amount of new positions of contracts with a subsequent expiry. Usually, since most positions are closed before actual delivery, the front-month option gradually loses liquidity when it approaches its expiry. According to XNYM, the expiration date for an option contract on WTI crude oil futures is the 7th business day before the 26th calendar day of the month prior to the contract month. Hence, to make sure that on any given trading date, the representative contract is the most active among all the existing contracts, I define the set of front-month options on a given trading day to be the ones closest to expiry among all the trading options on that day that have more than 7 business days to expire, i.e., among all the existing contracts that have more than 14 business days to the 26th calendar day of the given month.

Note that our front-month options "series" is actually an imbalanced panel data with a time length of 8143 (From November 14, 1986, to April 4, 2019) and contains all the call and put options that share the same expiry and the same underlying WTI crude oil futures contract on a given time spot.

(2) Construction of the Front-Month Future Contract Series

Since the set of front-month options on a given trading date share the same underlying WTI crude oil futures contract, I define the front month future contract on a given trading day to be the underlying of the front month options on that day and hence the front month future series, a time series with length 8143, is constructed.

(3) Construction of the Realized Volatility Series

Realized volatility is the variations in the historical returns of the futures contract. In many studies, it is calculated as a prediction from an econometric model which generates the ex-ante conditional expectation of the future variance given the current value. Adopting this idea and consider the settlement price series of the front-month futures contract series p_t, I construct a $GARCH(1,1)$ model on time series p_t, to obtain the realized volatility. GARCH model provides a parsimonious description of volatility clustering and gives closed-form forecast of future variance given historical data, making it a perfect tool to compute the realized volatility. Usually, a $GARCH(1,1)$ is defined as:

$$\begin{cases} p_t = h_t^{1/2} z_t \\ h_t = a + b h_{t-1} + c p_{t-1}^2 \\ z_t \sim IID\, N(0,1) \end{cases}$$

It can be shown that the variance series σ_t^2 of p_t is $\sigma_t^2 = b\sigma_{t-1}^2 + c p_{t-1}^2$.

I define the variable realized volatility $\boldsymbol{Real\_Vol_t} = \sqrt{252}\,\sigma_t$ to be the annualized daily standard deviation series. Then, I extract the monthly realized volatility time series by choosing the $\boldsymbol{Real\_Vol_t}$ of the last day in every month as a proxy for the monthly annualized realized volatility.

(4) Construction of the Implied Volatility Series

For each trading day, I define the at-the-money call and put option contracts as the front-month call and put options on that day with settlement price closest to their underlying futures price. Then, I calculate the Black-Scholes implied volatility for the at-the-money call and put option contracts respectively and define the implied volatility $\boldsymbol{Impl\_Vol_t}$ on a given day to be their simple average. Lastly, I extract the monthly implied volatility time series by choosing the $\boldsymbol{Impl\_Vol_t}$ of the last day in every month as a proxy for the monthly annualized implied volatility.

(5) Construction of the Volatility Rick Premium

Finally, the volatility risk premium time series is calculated as:

$$\boldsymbol{VRP_t} = Impl\_Vol_t - Real\_Vol_t$$

Looking at Figure 2.1.1, the mean of the volatility risk premium (VRP) series is very close to zero, and apart from a few peaks, it oscillates closely around zero. This implies that in most conditions, the variance risks are well-priced in the market such that the risk-neutral price is almost identical to the actual price. However, the volatility risk premium series is not white noise. It shows a clear characteristic of clustering, meaning that an observed high VRP would likely imply another high VRP during the next period. Most studies believe this is caused by the irrationality in the market, for example, during the early 90s when Iraq invades Kuwait, where the volatility risk premium witnessed its highest peak. Another thing worth noticing is that the VRP series rejects the null hypothesis of the Augmented Dickey-Fuller test, meaning that a unit root process does not exist in the VRP series, and hence the volatility risk premium should not exhibit a long-memory property.

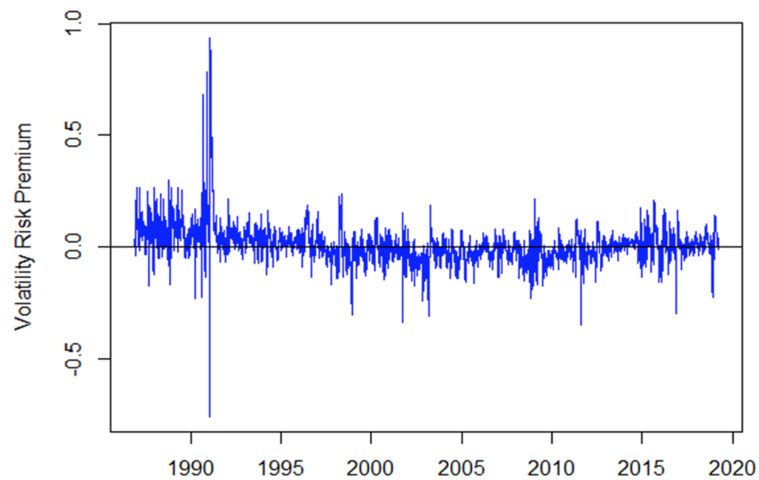

Figure 2.1.1: WTI Crude Oil Futures Volatility Risk Premium. The sample period is Nov 1986 to Apr 2019.

2.2 Uncertainty Measures

The notion of macroeconomic and financial uncertainty measures are based on the work of Jurado, Ludvigson, and Ng (2015) as well as Ludvigson, Ma, and Ng (2015). They define time-varying uncertainty as purely unpredictable fluctuations in the macroeconomic and the financial market indicators. Formally, the h-period ahead uncertainty in the variable y_j at time t is defined as:

$$u_{j,t}(h) = \sqrt{\mathbb{E}\left[(y_{j,t+h} - \mathbb{E}\left[y_{j,t+h}|I_t\right])^2|I_t\right]}$$

where the expectation $\mathbb{E}[\cdot|I_t]$ is taken with respect to information I_t available to economic agents at time t. Consider a family of economic indicators $Y_t = (y_{1,t}, y_{2,t} \ldots y_{n,t})'$, then an index or measure could be constructed by taking the weighted average of individual uncertainty at each date using aggregation weights w_j:

$$U_t(h) = p - \lim_{n\to\infty} \sum_{j=1}^{n} w_j u_{j,t}(h) = \mathbb{E}_w \left[u_{j,t}(h) \right]$$

Empirically, Jurado, Ludvigson, and Ng choose a large variety of macroeconomic and financial indicators typically used for prediction and define w_j to be either equal weighting, i.e., $w_j = 1/n$ or the eigenvector corresponding to the largest eigenvalue of the $n \times n$ covariance matrix of the individual uncertainty measure (or in other words, relates to the importance of the individual indicators in the whole set) if individual uncertainty has a factor structure. The variables $\boldsymbol{Macro\_Uncert_t}$ and $\boldsymbol{Fin\_Uncert_t}$ are hence constructed as the macroeconomic and financial uncertainty measures accordingly. Both historical data could be downloaded from the personal website of Sydney C. Ludvigson. In my analysis, I employ the one-month ahead ($h = 1$) uncertainty measures.

Finding a proxy for the purely unforeseeable (by the economic agents) parts of the macroeconomic environment and financial markets is crucial to our analysis. Usually, volatility risk premium could be seen as the "insurance premium" that the option writer charges for protecting against the expected market volatility, and it exists because tail risks are often overestimated due to risk aversion. According to this point of view, if a rational option writer decides the price of a contract based on all the available information, then the deviations of the volatility risk premium could only be explained by the unforeseeable parts in the economy.

Figure 2.2.1 shows the trend of implied volatility, realized volatility and volatility risk premium against the trend of macroeconomic and financial uncertainty measures. Although all the volatilities seem to be correlated with the uncertainty measures, the correlation between implied and realized volatility with the uncertainty measures appears to be more robust since their peaks coincide more tightly with the peaks of the uncertainty measures. On the contrary, it is counterintuitive that sometimes the volatility risk premium fluctuates calmly when the uncertainty measures reach their peaks, for example, during the 2018 financial crisis. It reminds us that something other than purely economic factors significantly affects the volatility risk premium.

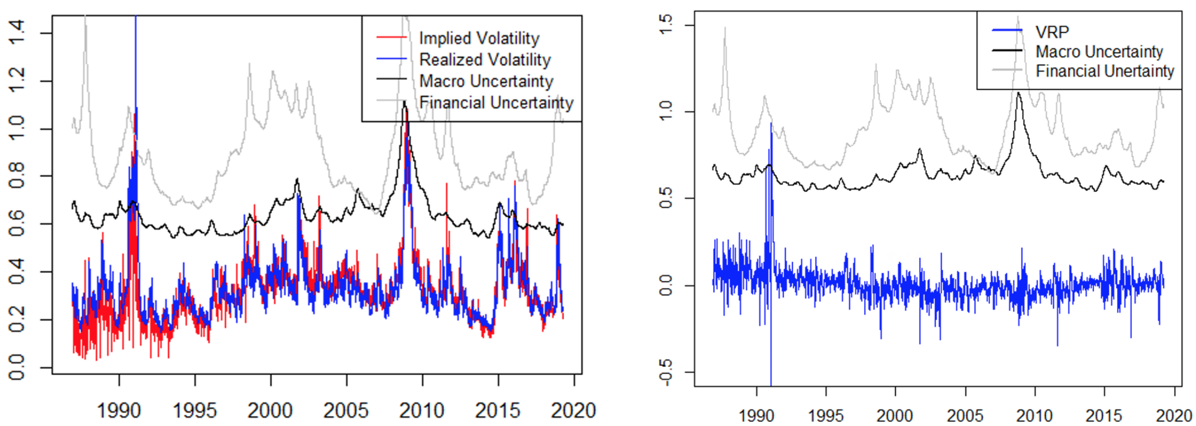

Figure 2.2.1: Co-movements of Uncertainty Measures and Volatilities. The implied volatility, realized volatility, and volatility risk premium (VRP) are shown together with macroeconomic and financial uncertainty measures, respectively. The sample period is Nov 1986 to Apr 2019.

2.3 Risk Aversion and Risk Absorption

Since volatility risk premium does not seem to follow macroeconomic and financial uncertainty measures step by step, it is natural to turn to the behaviors and characteristics of the market participants. We know that the producers' risk aversion propels them to enter the short positions of commodity futures. In addition, I follow the literature by also taking the risk absorption of their counterparts into consideration. In addition to the theory of backwardation of Keynes (1923) and Hicks (1939), recent studies show that the speculators are sometimes constrained in their ability to deploy capital in the commodity futures, in which case the commercial traders would experience limits to hedge (Acharya, Lochstoer, and Ramadorai, 2013). Following Acharya et al., I construct two variables as the proxies for the risk attitudes of producers and their counterparties.

The hedging demand, or the risk aversion of the producers is proxied by their default risks. There has been a vast range of studies supporting this choice. As is pointed out by Amihud and Lev (1981), managers tend to make more risk-averse decisions when the likelihood of default of their companies increases, which reflects in the increase of their hedging demand. They believe this is caused by the incentive incompatibility of the agency problem. Empirically, Gilson (1989), Haushalter (2001) as well as Adam, Fernanado, and Salas (2015) found evidence that the corporate governance policies tend to be more conservative if the outstanding debt or financial leverage is high, resulting in more hedging decisions to cover risk exposures.

Based on these discussions, I employ the Zmijewski (1984) score to measure default risks. The Zmijewski Score is an adjustment to the famous Altman's (1968) Z-score, a bankruptcy model used to predict a firm's bankruptcy in two years. The Zmijewski Score (or Z-score for short) is defined by:

$$\boldsymbol{Z\_Score_t} = -4.33 - 4.51 \times \frac{Net\,Income}{Total\,Assets} + 5.68 \times \frac{Total\,Liabilities}{Total\,Assets} + 0.004 \times \frac{Current\,Assets}{Current\,Liabilities}$$

I calculated the Z-Scores of all the companies under SIC code 1311 (Crude Petroleum and Gas Extraction) traded on the major exchanges around the world from 1986 to 2019. The data is downloaded from the S&P Capital IQ platform. The time series constructed from the mean of the Z-Scores is defined as the producers' risk aversion measure $\boldsymbol{Hedger\_Averse_t}$.

Acharya et al. prove that the producers' hedging demand should have a more enormous impact provided that the risk absorbing ability of the speculators is high. Therefore, following the methods of Etula (2009), I define the measure for the speculator's risk tolerance $\boldsymbol{Speculator\_Absorb_t}$ as the growth rate of the ratio of the financial intermediaries' (aggregate broker-dealer) total assets against the sum of the total assets of financial intermediaries and household (and non-profit parts) assets. The data is available through the U.S. Flow of Funds data published by the Federal Reserve System.

2.4 Commodity Futures Market Structure Risk Factors

There has also been a widespread view that the commodity market is (partially) segmented from other financial markets, resulting in insufficient risk sharing and thus exacerbates the backwardations implied by Keynes (1923) and Hicks (1939). Therefore, besides the risk aversion and risk absorbing ability of the market participants, we also need to pay attention to the endogenous structure of the commodity market.

In their work in 2012, Hong and Yogo found strong evidence that open interest, or the number of outstanding futures contracts, contains important information about future economic activity that is not fully revealed by futures prices or net supply–demand imbalances among hedgers in futures markets. So, I construct three more variables to proxy the endogenous risk factors of the commodity market.

The $\boldsymbol{Market\_Interest_t}$ is defined as the growth rate of the WTI crude oil futures market dollar open interest (spot price times the number of outstanding futures contract) and is viewed as the critical endogenous momentum of the crude oil futures market. Inspired by the theory of backwardation and the work of Hong and Yogo, I construct two more variables as the measures for crude oil futures market imbalance. The first one is the commodity market basis. On each trading day t, it is defined as:

$$\boldsymbol{Basis_t} = (F_{t,T}/S_t)^{1/(T-t)} - 1$$

Where $F_{t,T}$ is the price of a futures contract at time t that expires at T, and S_t is the spot price. According to Fama and French (1987), the deviation of futures price from the spot price can be a robust predictor for the futures return. The other one is a proxy for the imbalance of the positions of the market participants, defined as:

$$\boldsymbol{Market\_Imbalance_t} = Commercial\,Net\,Short\,Positions/All\,Commercial\,Positions$$

Where the denominator is the dollar value of short plus long positions held by commercial traders, and the numerator is the dollar value of short minus long positions held by commercial traders. It is viewed as a proxy for the supply-demand imbalance in some literature (Chang, 1985; Bessembinder, 1992), while in some works (Kang, Rouwenhorst, and Tang, 2020) it is regarded as the "Hedging Pressure" in the sense that the short positions of commercial traders tend to increase if the hedging demand is high.

The data for open interest and positions of commercial traders is available from the "Commitment of Traders" (COT) files published by the Commodity Futures Trading Commission (CFTC), where they classify the futures traders into three types: commercials, non-commercials, and non-reportables. According to CFTC, "A trader's reported futures positions in a commodity are classified as commercial if the trader uses futures contracts in that particular commodity for hedging as defined in CFTC Regulation 1.3, 17 CFR 1.3(z)."

2.5 Control Variables

Following Hong and Yogo (2012) and Watugala (2019), I identify the following control variables shown in Table 2.5.1. I divide my control variables into three parts: Finance, Macroeconomics, and Real Activities. In the Finance part, I employ $\boldsymbol{Credit\_Spread}$ and $\boldsymbol{TED\_Spread}$ to represent credit risks in the private sectors and interbank markets. The $\boldsymbol{Tspread}$ is introduced to control the term structure of the risk-free rate. Besides, $\boldsymbol{SP100VXO}$ controls the spillover effect from the financial market to the commodity market. The three very commonly used macroeconomic indicators control the changes in ambient macroeconomic environment. Additionally, I adopt two indicators to control for the effect of real economic activities. First, The $\boldsymbol{Real\_Act}$ was proposed by Killian (2009, 2019). This pro-cyclical index is reported in percentage deviations from a long memory trend. It is derived from a panel of dollar-denominated global bulk dry cargo shipping rates and may be viewed as a proxy for the volume of shipping in global industrial commodity markets, according to the Federal Reserve Bank of Dallas who updates this index monthly. Second, the Chicago Fed National Activity Index is also included to control for the domestic economic activity.

The correlation coefficients of variables of interests and the summary statistics of all variables are shown in Table 2.5.2 and Table 2.5.3, respectively. Initially speaking, the volatility risk premium is negatively correlated with both macroeconomic and financial uncertainty measures; it is positively correlated with the risk aversion level of the producers and negatively correlated with the risk absorption level of the financial intermediaries. All these above agree with our assumption and previous studies.

Table 2.5.1: Definitions and Descriptions of Control Variables

The control variables are categorized into Finance, Macroeconomics and Real Activities, each containing commonly used risk factors or indicators in its sphere.

Field	Name	Description
Financial	*Credit_Sprd*	Moody's Baa Corporate Bond Yield – Moody's Aaa Corporate Bond Yield
	Tsprd	10-Year Treasury Yield – 3-Month Treasury Yield
	TEDsprd	Spread between 3-Month LIBOR based on US dollars and 3-Month Treasury Bill
	SP100VXO	CBOE S&P 100 Volatility Index
Macroeconomy	*GDP_GR*	US Real GDP per capita growth rate
	CPI_GR	US CPI growth rate
	Unemploy	US unemployment rate
Real Activity	*Real_Act*	Killian (2009) Index of Global Real Economic Activity
	CFNAI	Chicago Fed National Activity Index

Table 2.5.2: Correlation Matrix of Variables of Interest

	VRP	*Macro_ Uncert*	*Fin_ Uncert*	*Hedger_ Averse*	*Speculator_ Absorb*	*Market_ Interest*	*Basis*	*Market_ Imbalance*
VRP	1.000							
Macro_Uncert	-0.144	1.000						
Fin_Uncert	-0.090	0.634	1.000					
Hedger_Averse	0.123	0.180	0.355	1.000				
Speculator_Absorb	-0.053	-0.282	-0.261	-0.029	1.000			
Market_Interest	-0.026	0.020	0.023	-0.009	-0.019	1.000		
Basis	-0.006	0.152	0.077	-0.087	-0.239	0.013	1.000	
Market_Imbalance	-0.119	-0.141	-0.205	-0.380	-0.011	0.027	0.003	1.000

Table 2.5.3: Summary Statistics of the Main Variables

	Mean	Median	Std Dev	Kurt.	Skew.	Min	Max	25 Pctl	75 Pctl
Dependents									
Real_Vol	0.309	0.293	0.131	3.848	1.366	0.069	1.012	1.549	0.369
Impl_Vol	0.325	0.300	0.131	11.363	2.581	0.155	1.325	0.246	0.358
VRP	0.016	0.006	0.083	26.620	3.283	-0.253	0.833	-0.029	0.047
Independents									
Macro_Uncert	0.638	0.619	0.086	10.258	2.708	0.541	1.113	0.585	0.664
Fin_Uncert	0.895	0.848	0.180	0.529	0.927	0.643	1.549	0.759	1.030
Hedger_Averse	-2.360	-2.415	0.539	-0.048	0.176	-3.396	-0.612	-2.600	-2.059
Speculator_Absorb	0.001	-0.002	0.269	7.701	-1.219	-1.796	0.935	-0.135	0.154
Market_Interest	-0.864	0.018	14.722	364.247	-18.877	-285.719	0.999	-0.053	0.077
Basis	0.000	0.000	0.003	2.243	0.303	-0.013	0.013	-0.002	0.002
Market_Imbalance	0.063	0.033	0.150	14.295	2.485	-0.455	1.000	-0.020	0.128
Controls									
Credit_Sprd	0.967	0.900	0.377	14.437	3.124	0.550	3.380	0.720	1.110
Tsprd	1.751	1.738	1.113	-1.000	-0.138	-0.697	3.679	0.864	2.643
TED_sprd	0.564	0.459	0.421	6.783	2.094	0.118	3.400	0.258	0.693
SP100VXO	20.017	17.902	8.470	5.556	1.850	8.020	65.447	13.827	24.124
GDP_GR	0.402	0.446	0.503	5.187	-1.574	-2.210	1.357	0.194	0.707
CPI_GR	0.215	0.214	0.321	5.631	-0.984	-1.915	1.222	0.057	0.413
Unemploy	5.879	5.600	1.506	0.355	0.989	3.700	10.000	4.800	6.600
Real_Act	4.281	-4.693	59.005	1.053	0.875	-158.856	191.262	-33.935	23.160
CFNAI	-0.044	0.010	0.503	6.686	-1.716	-2.880	1.440	-0.270	0.270

CHAPTER 3

EMPIRICAL RESULTS AND ANALYSIS

3.1 Direct Effects of Uncertainty

First of all, I test the pure effect of macroeconomic and financial uncertainty on volatility risk premium, realized volatility, and implied volatility in the subsequent period, respectively. Table 3.1.1 shows the regression results. Note that, I employ the Newey-West (1987) standard errors (as is shown in the parenthesis) when running the regressions. Newey-West standard errors could overcome the serial correlation and heteroskedasticity in the error terms and hence are usually larger than the original standard errors should the above problems exist. Compared with the original standard errors, Newey-West standard errors usually result in a smaller t statistic and thus less likely to reject the null hypothesis. Using the Newey-West standard errors means that my regression outcome is more conservative.

In equation (1), the first order lagged term of macroeconomic uncertainty measure enters with a negative sign and is statistically significant under the significant level of 1%. Equation (2) implies that the first order lagged term of financial uncertainty also has a negative impact on the future volatility risk premium, but it is not significant even under the 10% level. Thus, both the direct effects of macroeconomic and financial uncertainty measures imply that the volatility risk premium contains information that is not predictable and hence not considered by the market participants.

Table 3.1.1: Predictive Power of Uncertainty Measures

Volatility risk premium, realized volatility and implied volatility are regressed against macroeconomic and financial uncertainty measures respectively. All predictor variables are lagged one month. The sample period is Nov 1986 to Apr 2019 on a monthly basis. Newey-West standard errors are reported in the parenthesis.

	Dependent variable:					
	VRP_t		$Real\_Vol_t$		$Impl\_Vol_t$	
	(1)	(2)	(3)	(4)	(5)	(6)
$Macro\_Uncert_{t-1}$	-0.143^{***}		0.999^{***}		0.857^{***}	
	(0.038)		(0.117)		(0.160)	
Fin_Uncert_{t-1}		-0.038		0.375^{**}		0.337^{**}
		(0.032)		(0.174)		(0.142)
Constant	0.106^{***}	0.049^{*}	-0.327^{***}	-0.025	-0.221^{**}	0.024
	(0.023)	(0.027)	(0.075)	(0.147)	(0.099)	(0.120)
Observations	388	388	388	388	388	388
R^2	0.022	0.007	0.431	0.268	0.313	0.214
Adjusted R^2	0.019	0.004	0.430	0.266	0.311	0.212
Residual Std. Error	0.082	0.082	0.098	0.112	0.109	0.117
F Statistic	8.666^{***}	2.681	292.947^{***}	141.604^{***}	175.624^{***}	104.926^{***}

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

Equations (3) to (6) report the regression results of realized volatility and implied volatility against the two uncertainty measures. Comparing columns (3) and (4) with columns (5) and (6), the following two conclusions could be reached: First, both kinds of uncertainty measures have positive and significant impacts on realized volatility and implied volatility. Second, the magnitude and significance level of macroeconomic uncertainty are more prominent than those of financial uncertainty. The above result implies that the realized volatility is more sensitive to the unpredictable components in both the macroeconomic environment and financial markets than the implied volatility. This makes sense since implied volatility is risk neutrally priced and hence could not take the unexpected part of the economy (often referred to as the tail risks) into consideration. Nevertheless, uncertainty could be more easily reflected in realized volatility since it is priced by the supply and demand relations on the commodities market.

Another essential implication follows immediately: the negative impacts of macroeconomic and financial uncertainty measures on volatility risk premium stem from their larger magnitude of positive impact on realized volatility than on implied volatility. So, when uncertainty increases, the increment of implied volatility is smaller than that of the realized volatility, rendering their difference negative. More specifically, this variation in their difference (or fluctuations in volatility risk premium) is predominantly explained by unforeseeable parts in the macroeconomic indicators. In contrast, although financial uncertainty is also a strong predictor for both implied and realized volatility, it is too pale to account for changes in their difference.

Finally, let us focus on R^2, the coefficients of determination of all the six regression outcomes. As is reported in equation (3), macroeconomic uncertainty measure is a perfect predictor for realized volatility, explaining 43% of its variations on its own. This result agrees with the work of Bakas and Triantafyllou in 2015. In general, both kinds of uncertainty measures are robust predictors for both realized and implied volatility, with R^2 ranging from 20% to 30%. However, macroeconomic and financial uncertainty could only explain 2% and 0.7% variations in volatility risk premium.

After understanding how economic uncertainty affect volatility risk premium through implied and realized volatility, I concentrate on the direct influence channel to the volatility risk premium. In Table 3.1.2, I add control variables to the simple regressions against VRP shown in equations (1) and (2) of Table 3.1.1 to control the exogenous effects in macroeconomic environment, financial markets, and real economic activities identified in Part 2.5. As in Table 3.1.1, I report the Newey-West standard errors in parenthesis.

Equation (1) shows the aggregate effects of macroeconomic and financial uncertainty on volatility risk premium. Comparing with equations (1) and (2) in Table 3.1.1, the magnitude of the coefficient of the macroeconomic uncertainty measure increases while its significance level decreases. However, the impact of the financial uncertainty measure is still insignificant, and the adjusted R^2 is even smaller than that of equation (1) in Table 3.1.1. This outcome reinforces our previous belief that financial uncertainty measure is not a valid individual predictor for volatility risk premium. Moreover, the strong correlation between the financial and macroeconomic uncertainty measures (according to table 2.5.3) even blurred the powerful influence of the macroeconomic uncertainty measure on the volatility risk premium.

Equations (2) and (3) are augmented versions of equations (1) and (3) in Table 3.1.1 by adding macroeconomic and financial control variables to the regressions

Table 3.1.2: Predictive Power of Uncertainty Measures with Controls

Volatility risk premium, realized volatility and implied volatility are regressed against macroeconomic and financial uncertainty measures. Control variables in macroeconomics, finance, real economic activities are gradually added in the regressions. All predictor variables are lagged one month. The sample period is Nov 1986 to Apr 2019 on a monthly basis. Newey-West standard errors are reported in the parenthesis.

	Dependent variable:				
	VRP_t				
	(1)	(2)	(3)	(4)	(5)
$Macro\_Uncert_{t-1}$	-0.153^{**}	-0.235^{***}		-0.177^{*}	-0.426^{***}
	(0.068)	(0.067)		(0.096)	(0.122)
Fin_Uncert_{t-1}	0.008		-0.012	-0.015	0.050
	(0.047)		(0.056)	(0.053)	(0.058)
GDP_GR_{t-1}		-0.029			-0.021
		(0.023)			(0.021)
CPI_GR_{t-1}		0.020^{*}			0.016
		(0.011)			(0.012)
$Unemploy_{t-1}$		0.001			0.006
		(0.002)			(0.004)
$Credit\_Sprd_{t-1}$			0.003		0.040^{*}
			(0.022)		(0.021)
$Tspread_{t-1}$			0.002		-0.004
			(0.005)		(0.005)
$TEDsprd_{t-1}$			0.066^{***}		0.074^{***}
			(0.025)		(0.021)
$SP100VXO_{t-1}$			-0.002^{*}		-0.002^{**}
			(0.001)		(0.001)
$Real\_Act_{t-1}$				-0.0001^{**}	
				(0.0001)	
$CFNAI_{t-1}$				-0.022	
				(0.022)	
Constant	0.106^{***}	0.167^{***}	0.025	0.141^{***}	0.184^{***}
	(0.023)	(0.050)	(0.035)	(0.046)	(0.054)
Observations	388	388	388	388	388
R^2	0.022	0.047	0.083	0.046	0.157
Adjusted R^2	0.017	0.037	0.071	0.036	0.137
Residual Std. Error	0.082	0.081	0.080	0.081	0.077
F Statistic	4.356^{**}	4.735^{***}	6.897^{***}	4.584^{***}	7.814^{***}
Note:					*p<0.1; **p<0.05; ***p<0.01

of macroeconomic and financial uncertainty measures, respectively. As a result, both the magnitude of the coefficients of macroeconomic uncertainty measure and the adjusted R^2 in equation (2) increase after controlling changes in the macroeconomic environment. However, the impact of financial uncertainty decreases and remains insignificant after controlling the spillover effects on the financial markets, especially when controlling credit risk and the cost for debt financing (since the control variable ***TED_Spread*** enters with a positive coefficient and is significant under 1% level). This result coincides with the study of Fan, Imerman, and Dai 2016 where the effect of ***TED_Spread*** on volatility risk premium is vastly discussed.

Equations (4) and (5) expand equation (1) by testing the aggregate effect when changes in the real economy, macroeconomy, and financial markets are controlled for. As is suggested by Killian (2009), ***Real_Act*** , the Index of Global Real Economic Activity, contains information on supply and demand shocks on the crude oil market. Introducing it into the regression increases the magnitude of the effects of macroeconomic uncertainty but decreases the significance level. In equation (5), the magnitude and significance of the effects of macroeconomics uncertainty greatly increase after introducing both macroeconomic and financial control variables. The adjusted R^2 of equation (5) is 13.7%, a significant improvement from that of equation (1).

As is pointed out by Fan, Imerman, and Dai (2016), the sign of volatility risk premium contains information about the relative level of future implied and re-

Table 3.1.3: Predictive Power of Uncertainty Measures on the Sign of Volatility Risk Premium

Probit models are estimated regarding the sign of volatility risk premium where 1 stands for a positive volatility risk premium and 0 stands for a negative volatility risk premium. The regressions test for the influence factors for the probability of the sign of volatility risk premium to be positive. Macroeconomic and financial uncertainty measures are the variables of interest and control variables in macroeconomics, finance, real economic activities are gradually added in the regressions. All predictor variables are lagged one month. The sample period is Nov 1986 to Apr 2019 on a monthly basis.

	Dependent variable:				
	$Pr(VRP_t) > 0$				
	(1)	(2)	(3)	(4)	(5)
$Macro\_Uncert_{t-1}$	-4.972^{***}		-2.713^{**}	-5.906^{***}	-3.024^{*}
	(1.055)		(1.102)	(1.426)	(1.651)
Fin_Uncert_{t-1}		-1.558^{**}	-1.052^{**}	-0.653	-1.299
		(0.732)	(0.462)	(0.780)	(0.806)
GDP_GR_{t-1}	-0.265			-0.120	-0.150
	(0.164)			(0.172)	(0.192)
CPI_GR_{t-1}	0.160			0.096	0.169
	(0.219)			(0.220)	(0.221)
$Unemploy_{t-1}$	0.015			0.060	0.081
	(0.044)			(0.064)	(0.066)
$Credit\_Sprd_{t-1}$		-0.116		0.515	0.217
		(0.244)		(0.332)	(0.348)
$Tspread_{t-1}$		0.102		0.031	0.039
		(0.066)		(0.084)	(0.085)
$TEDsprd_{t-1}$		0.926^{***}		1.127^{***}	1.255^{***}
		(0.213)		(0.227)	(0.233)
$SP100VXO_{t-1}$		-0.024		-0.032^{*}	-0.030^{*}
		(0.017)		(0.018)	(0.018)
$Real\_Act_{t-1}$					-0.005^{***}
					(0.001)
$CFNAI_{t-1}$					0.130
					(0.204)
Constant	3.272^{***}	1.414^{***}	2.792^{***}	3.610^{***}	2.416^{***}
	(0.732)	(0.427)	(0.589)	(0.833)	(0.919)
Observations	388	388	388	388	388
Log Likelihood	-252.748	-244.548	-251.766	-234.520	-228.776
Akaike Inf. Crit.	515.495	501.096	509.533	489.040	481.553
Note:					*p<0.1; **p<0.05; ***p<0.01

alized volatility. Table 3.1.3 displays probit models regarding the sign of volatility risk premium against the uncertainty measures, where 1 stands for positivity and 0 stands for negativity. Equations (1) and (2) show that the increase in either macroeconomic or financial uncertainty measure would significantly reduce the probability of volatility risk premium to be greater than 0. From the magnitude of the coefficients, the impact of macroeconomic uncertainty is larger and more statistically significant than that of financial uncertainty. However, from the Akaike Information Criterion, financial uncertainty could explain a larger part of the variations in the direction of the volatility risk premium after controlling the credit risks. Equation (3) shows that the aggregate effects of both the macroeconomic and financial uncertainty measures are still significant, so uncertainty measures together are valid predictors for the sign of volatility risk premium. However, equations (4) and (5) indicate that, after controlling the spillover effects from financial markets and the supply-demand shocks in the real economy, the explanatory power of both uncertainty measures would plummet. So, the sign of volatility risk premium is dominated by the foreseeable risks on financial and commodity markets instead of their unforeseeable counterparts.

I come to the following conclusions for this section: First, although both implied volatility and realized volatility on WTI crude oil futures increase along with the unforeseeable fluctuations in macroeconomic and financial indicators, the difference in their sensitivities of response cause a negative impact on volatility risk premium. This outcome provides evidence for the risk sharing limits and the hypothesis of commodity market segmentations. Second, the macroeconomic uncertainty measure is more robust than the financial uncertainty measure when acting as an individual predictor for the magnitude and sign of the volatility risk premium. Third, the effect of macroeconomic uncertainty measure is enhanced when controlling financial market spillovers (especially credit risks) and supply-demand shocks in the crude oil markets.

3.2 Market Structure and Market Momentum

In section 3.1, we find out that macroeconomic and financial uncertainty can explain parts of the changes in the volatility risk premium; we also affirm the belief that the commodity market is (partially) segregated from the financial markets. In this part, we discuss if this effect of uncertainty is utterly exogenous to the crude oil futures market structures and test the explanatory power of risk factors in price and market interest under uncertainty.

Figure 3.2.1 displays the trend of volatility risk premium along with the returns of WTI crude oil futures and the growth rate of open interests. Since both series are noisy, I define their momentum series by taking 12-month moving averages to obtain their trend. Compared with return momentum's performance, the open interest momentum shows a more pronounced volatility clustering property. Two of its most notable spikes occur in early 1990s and 2007 – 2008 when the first gulf war and the financial crisis took place. This outcome implies that the growth rate of market interest is more sensitive to tail risks and unforeseeable extreme events.

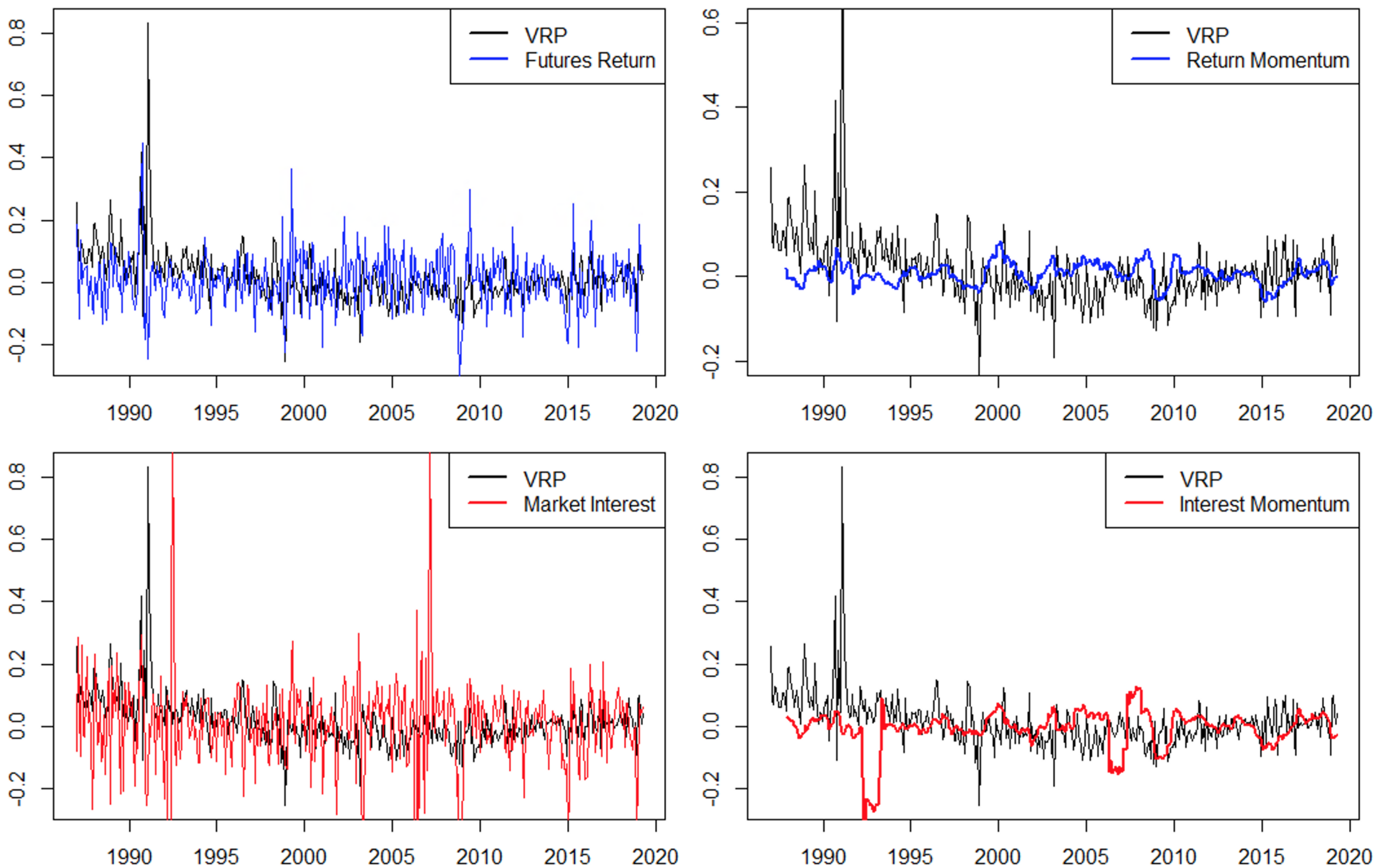

Figure 3.2.1: Co-movement between Return and Open Interest Growth with Volatility Risk Premium. Futures return, return momentum, market interest, open interest momentum shown together with volatility risk premium respectively. The sample period is Nov 1986 to Apr 2019.

Table 3.2.1: Predictive Power of Momentums Variables under Uncertainty

Volatility risk premium is regressed against the futures returns and the one month growth rate of open interest, as well as their momentums (the past 12 month moving average) with and without controlling the uncertainty in macroeconomic and financial markets. Control variables in macroeconomics, finance, real economic activities are added in all the regressions. The sample period is Nov 1986 to Apr 2019 on a monthly basis. Newey-West standard errors are reported in the parenthesis.

	Dependent variable:					
	VRP_t					
	(1)	(2)	(3)	(4)	(5)	(6)
$Macro\_Uncert_{t-1}$	−0.337**	−0.344***		−0.322**		−0.356***
	(0.140)	(0.133)		(0.132)		(0.134)
Fin_Uncert_{t-1}	0.034	0.023		0.023		0.022
	(0.063)	(0.065)		(0.059)		(0.063)
$Future\_Return_{t-1}$	−0.066					
	(0.063)					
Return Momentum		−0.157				
		(0.197)				
$Market\_Interest_{t-1}$			−0.007*	−0.008**		
			(0.004)	(0.003)		
Open Interest Momentum					−0.066	−0.102**
					(0.050)	(0.049)
Constant	0.148**	0.167***	−0.010	0.146**	−0.004	0.172***
	(0.060)	(0.059)	(0.020)	(0.061)	(0.021)	(0.060)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	388	378	388	388	378	378
R^2	0.181	0.168	0.149	0.177	0.137	0.171
Adjusted R^2	0.155	0.140	0.126	0.151	0.113	0.144
Residual Std. Error	0.076	0.077	0.077	0.076	0.078	0.076
F Statistic	6.919***	6.125***	6.602***	6.714***	5.826***	6.281***
Note:						*p<0.1; **p<0.05; ***p<0.01

In Table 3.2.1, I formally test the hypothesis that momentum in the crude oil markets have additional influences on volatility risk premium. Note that I include all the control variables identified before in every regression, so they are not reported in the results for simplicity. As before, Newey-West standard errors are shown in the parenthesis.

Columns (1) and (2) display the cumulative effects of the first order lagged term of WTI crude oil futures return and its momentum on volatility risk premium when controlling uncertainty. Both of them enter the equations with statistically insignificant coefficients, and the adjusted R^2 is of no increase comparing with equation (5) in Table 3.1.2 This result implies that past futures return and its trend do not contain information valid for predicting future volatility risk premium.

Columns (3) and (5) are baseline specifications in which the first order lagged term of market interest (i.e., the growth rate of money valued open interest of futures contracts) and open interest momentum act as sole predictors for the volatility risk premium, respectively. The market interest enters equation (3) with a coefficient of -0.007 that is statistically significant under the 10% level, while the open interest momentum enters equation (5) with an insignificant coefficient of -0.066. Equations (4) and (6) introduce macroeconomic and financial uncertainty into the regressions. As is shown in column (4), the predictive power of market interest is not driven out by the uncertainty measures. Instead it is enhanced since the magnitude of its coefficient increases, and its significance level jumps from 10% to 5%. The same evidence is found on open interest momentums. In column (6), the absolute value of the coefficient of interest momentum increases in a horse race and reaches 0.102. It becomes significant under the level of 5% comparing with its insignificant counterpart in equation (5). The adjusted R^2 of regressions (4) and (6) increase by a great deal in comparison to those of regressions (3) and (5). Overall, the negative coefficients of market interest and its momentum indicate that higher growth rate of the open interest would cause a lower volatility risk premium. Another thing worth noticing is that both the significance level and magnitude of the coefficient of macroeconomic uncertainty measure in equation (6) is greater than that of equation (4).

The findings in Table 3.2.1 conclude as follows. Though the futures return and its momentum have no predictive power for the volatility risk premium, the market interest (growth rate of open interest) does contain such information. The individual forecasting power of market interest and its momentum is weak, but it can be enhanced by controlling the uncertainty measures, especially the macroeconomic uncertainty measure. This result can be explained by Hong and Yogo (2012), who find out that past returns' predictive power on their future terms is "driven out" by the growth rate of open interest. They assert that more information about future supply and demand is contained in open interest than in price itself. Additionally, Table 3.2.1 gives evidence that information contained in open interest useful for predicting volatility risk premium can only be revealed if the unforeseeable parts in the macroeconomy are controlled. We find in Figure 3.2.1 that the momentum of open interest is sensitive to tail risks. Since tail risks are usually overpriced in the volatility risk premium and positively correlated with uncertainty, we can observe a "chemical reaction" between open interest momentum and uncertainty measures, as is shown in the regression results.

We now refocus on commodity market segmentation theory, which states that risk sharing between the financial market and commodity market is limited. In addition, the theory of backwardation implies that hedgers must pay an addi-

Table 3.2.2: Predictive Power of the Market Structure Imbalance under Uncertainty

Volatility risk premium is regressed against the measure of market imbalance (the proportion of net short positions) and the difference between futures price and spot price, with and without controlling the uncertainty in macroeconomic and financial markets. Control variables in macroeconomics, finance, real economic activities are added in all the regressions. All predictors are lagged for one month. The sample period is Nov 1986 to Apr 2019 on a monthly basis. Newey-West standard errors are reported in the parenthesis.

	Dependent variable:				
	VRP_t				
	(1)	(2)	(3)	(4)	(5)
$Macro\_Uncert_{t-1}$			-0.319^{**}		-0.223^{**}
			(0.133)		(0.087)
Fin_Uncert_{t-1}			0.027		0.030
			(0.058)		(0.049)
$Market\_Imbalance_{t-1}$	-0.085^{***}		-0.087^{**}		
	(0.029)		(0.034)		
$Basis_{t-1}$		-1.195	-0.599		
		(2.196)	(2.119)		
VRP_{t-1}				0.367^{***}	0.347^{***}
				(0.077)	(0.078)
Controls	Yes	Yes	Yes	Yes	Yes
Observations	389	386	385	388	388
R^2	0.171	0.154	0.198	0.267	0.280
Adjusted R^2	0.149	0.132	0.170	0.248	0.257
Residual Std. Error	0.077	0.078	0.075	0.072	0.071
F Statistic	7.809^{***}	6.837^{***}	7.042^{***}	13.750^{***}	12.139^{***}
Note:					$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

tional premium to incentivize speculators to trade as their counterparty. Together, the two assertations point out that when more commercial traders take conservative approaches and hedge the expected risks by shorting the futures, they will cause an imbalance of the commodity market structure by increasing the demand. The results of Table 3.2.1 tell us that the increased interest in trading would diminish the volatility risk premium. But can we observe the same result if trading interests are mainly driven by hedging demands?

As defined in Section 2.4, I identify two kinds of measures in supply-demand imbalance: The proportion of net short commercial positions (AKA the ***Market_Imbalance*** , or the hedging pressures) and the deviations in futures price relative to the spot price (AKA the ***Basis***). Their individual effects on volatility risk premium are displayed in columns (1) and (2) of Table 3.2.2, respectively. At first glance, both measures enter with a negative coefficient, but ***Market_Imbalance*** is statistically significant under the 1% level while ***Basis*** is not even significant under the 10% level. This rudimentary result answers the previous question, increasing hedging demand of commercial traders also decreases volatility risk premium.

I introduce both macroeconomic and financial uncertainty measures into equation (3). The result shows that macroeconomic uncertainty and market imbalance measure both work as robust predictors for the volatility risk premium. Comparing equations (1) and (3), it worth noticing that the magnitude and significance level of the coefficient of market imbalance measure has little change after introducing the uncertainty measure while adjusted R^2 enjoys a noticeable improvement. This result implies that market imbalance and the uncertainty measures have different influence channels to the volatility risk premium. As discussed before, uncertainty measures account for the unforeseeable part of the economic fluctuations neglected in the risk-neutral pricing. However, the market imbalance measure reflects predictable risks that propel the commercial traders to enter the short side of the futures. This action requires a higher premium paid to the speculators and hence increases the realized volatility, causing a lower volatility risk premium.

In columns (4) and (5), I test whether the uncertainty measures contain more information to forecast volatility risk premium than its past terms. In other words, I try to test if the unforeseeable parts of the macroeconomy and the financial markets are Granger causes to the volatility risk premium. Clive Granger introduced the notion of Granger Causality in 1969. By definition, a time series variable X is said to be a Granger cause of another time series variable Y if the aggregate predicting power of the past terms of X and Y on Y is stronger than when only using the past terms of Y as a predictor.

In (4), I regress volatility risk premium against its past term. We are allowed to do so because we reject the null hypothesis of the existence of unit root in volatility risk premium series. The result gives strong evidence that the volatility risk premium follows an $AR(1)$ structure, meaning that volatility risk premium robustly relies on its first order lag term. In (5), macroeconomic uncertainty enters with a statistically significant negative coefficient while the financial uncertainty measure is not significant under the 10% level. Note that the magnitude of the first-order lagged term of volatility risk premium is small compared with equation (4). This result implies that not only the macroeconomic uncertainty is a Granger cause for the volatility risk premium, but it also drives out the predictive power of volatility risk premium's past terms. I also conduct a higher-order Granger Causality test based on a VAR (vector autoregressive) model whose result is shown in the appendix.

To conclude this section, I regress volatility risk premium against some of the typical risk factors on the futures market when controlling the uncertainty measures and find out that: Firstly, some of the risk factors priced in futures return premia (for example, ***Basis*** , indicated by Fama and French in 1987) have no explanatory power for volatility risk premia. Secondly, the momentum of open interest contains more information than the momentum of futures returns. (This is consistent with the work of Hong and Yogo in 2012). But the predictive power of open interest only reveals itself when the unforeseeable fluctuations in the macroeconomic and financial indicators are controlled for. Thirdly, the growth of open interest diminishes volatility risk premium, especially when it is mainly driven by the growth of hedging demand that twists the supply-demand relations on the futures markets and increases the return premiums. This result agrees with the theory of backwardation.

3.3 Risk Sharing and Hedging Constraints

In this section, I delve deeper into the risk attitudes of different parties on the commodity futures market. In particular, we will see how the risk aversion level of the producers and the risk absorbing ability of the financial intermediaries could affect the volatility risk premium under uncertainty.

Using the proxies for commercial traders' risk aversion and speculators' risk absorption identified in section 2.3, I test their impacts on volatility risk premium and display the regression results in Table 3.3.1. A baseline specification of the pure effects of both measures and their interactions is shown in column (1). Notice that the risk aversion measure enters with a positive coefficient significant under 5% level while the risk absorption measure enters with a negative coefficient significant under 10% level. More importantly, their interaction term displays a significant negative impact. This result shows a homogeneity in the reactions of the volatility risk premium and futures return premium. The latter is documented by Etula (2009) as well as Acharya, Lochstoer, and Ramadorai (2013). Acharya et al. explain that the hedging behaviors would cause a larger increase in futures returns if the risk tolerance level of the speculators is low. Similarly, column (1) shows that an increase in risk aversion level of the commercial traders would require more risk sharing from the speculators, causing a higher insurance premium against the expected risks. If, in the meantime, speculators have higher risk absorbing abilities, the impact on volatility risk premium would be less prominent.

Table 3.3.1: Predictive Power of the Risk Attitudes under Uncertainty

Volatility risk premium is regressed against the risk attitudes of market participants (i.e., the risk aversion level of hedgers and the risk tolerance level of the speculators), with and without controlling the uncertainty in macroeconomic and financial markets. The interactions between risk aversion, risk tolerance, macroeconomic and financial uncertainty measures are also tested. Control variables in macroeconomics, finance, real economic activities are added in all the regressions. All predictors are lagged for one month. The sample period is Nov 1986 to Apr 2019 on a monthly basis.

	Dependent variable:					
	VRP_t					
	(1)	(2)	(3)	(4)	(5)	(6)
$Hedger\_Averse_{t-1}$	0.020^{**}	0.028^{***}	0.129^{*}	0.128^{***}	0.184^{***}	0.188^{***}
	(0.008)	(0.011)	(0.067)	(0.047)	(0.069)	(0.070)
$Speculator\_Absorb_{t-1}$	-0.149^{*}	-0.121	-0.205^{***}	-0.103	-0.140^{*}	-0.175
	(0.078)	(0.076)	(0.067)	(0.075)	(0.074)	(0.124)
$Macro\_Uncert_{t-1}$		-0.348^{***}	-0.678^{***}		-0.334	-0.358
		(0.095)	(0.253)		(0.321)	(0.328)
Fin_Uncert_{t-1}		0.001		-0.318^{***}	-0.332^{**}	-0.323^{**}
		(0.046)		(0.119)	(0.148)	(0.150)
$Hedger\_Averse_{t-1} \times Speculator\_Absorb_{t-1}$	-0.058^{*}	-0.044				-0.013
	(0.033)	(0.032)				(0.036)
$Macro\_Uncert_{t-1} \times Hedger\_Averse_{t-1}$			-0.168		-0.058	-0.069
			(0.105)		(0.131)	(0.135)
$Macro\_Uncert_{t-1} \times Speculator\_Absorb_{t-1}$			0.270^{***}		0.627^{***}	0.604^{***}
			(0.093)		(0.155)	(0.135)
$Fin\_Uncert_{t-1} \times Hedger\_Averse_{t-1}$				-0.115^{**}	-0.131^{**}	-0.127^{**}
				(0.049)	(0.062)	(0.063)
$Fin\_Uncert_{t-1} \times Speculator\_Absorb_{t-1}$				0.100	-0.315^{***}	-0.294^{**}
				(0.072)	(0.117)	(0.132)
Constant	0.062^{***}	0.247^{***}	0.439^{***}	0.318^{***}	0.543^{***}	0.553^{***}
	(0.019)	(0.063)	(0.158)	(0.114)	(0.161)	(0.163)
Controls	No	Yes	Yes	Yes	Yes	Yes
Observations	389	388	388	388	388	388
R^2	0.025	0.195	0.212	0.177	0.234	0.234
Adjusted R^2	0.018	0.165	0.183	0.146	0.199	0.197
Residual Std. Error	0.083	0.075	0.075	0.076	0.074	0.074
F Statistic	3.327^{**}	6.452^{***}	7.180^{***}	5.719^{***}	6.639^{***}	6.262^{***}
Note:						$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

However, after taking uncertainty into consideration, the results shown in the rest few columns tell a whole different story. As a benchmark, column (2) shows that interactions between risk aversion and risk absorption will no longer be significant after controlling the uncertainty. In addition, Columns (3) and (4) display interactions between the risk attitudes of the market participants and the macroeconomic and financial uncertainty measures, respectively. To elaborate, equation (3) shows that the risk absorption of speculators has a significant positive interaction with macroeconomic uncertainty, while equation (4) implies a strong and significant negative interaction between the risk aversion of hedgers and financial uncertainty.

The above results imply that, the speculators will require more compensation when experiencing uncertainty in the ambient macroeconomic environment if holding their risk appetite constant. However, it is counterintuitive that a rise in financial uncertainty will cause a lower volatility risk premium if the risk aversion level of speculators holds constant since more hedging behaviors would generate a higher compensation for the counterparty. One plausible explanation is that financial uncertainty is more inconspicuous, leaving part of the unforeseeable risks underpriced. This assumption is supported by the results shown in equations (5) and (6), where all the aggregate interaction effects are tested. The interaction between risk aversion and financial uncertainty also displays the same direction of effect as the interaction between risk absorption and financial uncertainty. Interestingly, neither macroeconomic uncertainty nor the risk absorption proxy is significant in equations (5) and (6), but their interaction terms are enormously significant with a positive coefficient.

In conclusion, both the effects of hedgers' risk aversion and speculators' risk tolerance on volatility risk premium are affected by uncertainty. On the one hand, when the uncertainty level in the macroeconomic environment is high, speculators will demand more premia for risk sharing, which results in a higher constraint for hedging. On the other hand, financial market uncertainty is more inconspicuous and will lead to an underpricing of the premium and loosen the hedging constraint.

CHAPTER 4

CONCLUSION

Borrowing the uncertainty measures introduced by Jurado, Ludvigson, and Ng (2015) as well as Ludvigson, Ma, and Ng (2015). I find evidence that unforeseeable fluctuations in macroeconomic and financial indicators are responsible for a considerable part of variations in both realized and implied volatility. However, the lack of sensitivity in implied volatility compared with realized volatility causes the former to be underpriced relative to the latter when uncertainty rises, resulting in a lower volatility risk premium.

Based on the theory of backwardation and market segmentation hypothesis, I tested the effects of the market participants' behaviors and attitudes when uncertainty is controlled for. The results indicate that, an increasing interest in trading, especially an increasing hedging demand could impose downward pressure on the volatility risk premium. It provides evidence that some of the risk factors priced in futures return premium could also predict volatility risk premium. Further studies show that the risk attitudes of market participants (i.e., risk aversion level of hedgers and risk tolerance level of speculators) have homogeneous impacts on both volatility risk premium and return premium. But their impacts on volatility risk premium under uncertainty is distinct from that in an uncertainty free-environment. When economic uncertainty increases, hedging will be even more costly if holding the risk appetites of market participants constant.

These aggregate effects of the behaviors and attitudes of the market participants under macroeconomic and financial uncertainty could explain the systematic bias in volatility risk premium proposed by recent literature. My work also opens a new approach to analyzing the effects of risk factors in circumstances with different levels of uncertainty.

BIBLIOGRAPHY

[1] Adam T. R., C. S. Fernando, J. M. Salas, Why do firms engage in selective hedging? Evidence from the gold mining industry, *Journal of Banking & Finance,* 109, 441–465, 1993.

[2] Acharya V., L. Lochstoer, and T. Ramadorai, Limits to arbitrage and hedging: Evidence from commodity markets, *Journal of Financial Economics,* 109, 441–465, 2013.

[3] Altman, E.I., Financial ratios, discriminant analysis and the prediction of corporate bankruptcy, *Journal of Finance,* 23, 589–609, 1968.

[4] Amihud, Y., Lev, B., Risk reduction as a managerial motive for conglomerate mergers, *Bell Journal of Economics,* 12, 605–618, 1981.

[5] Andersen T. G., N. Fusari and V. Todorov, The pricing of tail risk and the equity premium: evidence from international option markets, *Journal of Business & Economic Statistics,* 38 (3), 662-678, 2020.

[6] Andreou E. and E. Ghysels, Predicting the VIX and the volatility risk premium: The role of short-run funding spreads volatility factors, *Journal of Econometrics,* 220 (2), 366-398, 2021.

[7] Bakas D., A. Triantafyllou, Volatility forecasting in commodity markets using macro uncertainty, *Energy Economics,* 81, 79–94, 2019.

[8] Bessembinder, H., Systematic risk, hedging pressure, and risk premiums in futures markets, *Review of Financial Studies,* 5(4), 637–667, 1992.

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

[10] Bollerslev, T. and V. Todorov Tails, fears, and risk premia, *Journal of Finance,* 66 (6) 2165-2211, 2011.

[11] Buraschi A., F. Trojani, A. Vedolin, When uncertainty blows in the orchard: comovement and equilibrium volatility risk premia, *Journal of Finance,* 69 (1), 101-137, 2014

[12] Canina, L., and Figlewski, S., The informational content of implied volatility, *Review of Financial Studies,* 23, 589–609, 1993.

[13] Carr, P., and Wu, L., A tale of two indices, *Journal of Derivatives,* 13, 13–29, 2006.

[14] Chang, E.C., Returns to speculators and the theory of normal backwardation. *Journal of Finance,* 40 (1), 193–208, 1985.

[15] Christensen, B. J., and Prabhala, N. R., The relation between implied and realized volatility, *Journal of Financial Economics,* 50, 125–150, 1998.

[16] Corte P. D., T. Ramadorai, L. Sarno, Volatility risk premia and exchange rate predictability, *Journal of Financial Economics,* 120 (1), 21-40, 2016.

[17] Day, T., Lewis, C., Stock market volatility and the information content of stock index options, *Journal of Econometrics* 52, 267–287, 1992,

[18] Dickey, D. A.; Fuller, W. A., Distribution of the estimators for autoregressive time series with a unit root, *Journal of the American Statistical Association,* 74 (366), 427–431, 1979,

[19] Elder, J., Serletis, A., Oil price uncertainty, *Journal of Money Credit and Banking* 42 (6), 1137–1159, 2010.

[20] Etula E., Broker-dealer risk appetite and commodity returns. *Staff Reports 406 Federal Reserve Bank of New York* 2009.

[21] Fama, E.F. and French, K.R., Commodity futures prices: some evidence on forecast power, premiums, and the theory of storage, *Journal of Business* 60 (1), 55–73, 1987.

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

[23] Fan J., M. B. Imerman and W. Dai., What Does the Volatility Risk Premium Say About Liquidity Provision and Demand for Hedging Tail Risk?, *Journal of Business & Economic Statistics*, 34 (4), 519-535, 2016.

[24] Gilson S.C., Management turnover and financial distress, *Journal of Financial Economics*, 25, 241–262, 1989.

[25] Haushalter G.D., Why hedge? Some evidence from oil and gas producers, *Journal of Applied Corporate Finance*, 13, 87–92, 2001.

[26] Hicks J. R., Value and capital: an inquiry into some fundamental principles of economic theory, *Clarendon Press, Oxford, UK,* 1939.

[27] Hong H., and M. Yogo, What does futures market interest tell us about the macroeconomy and asset prices?, *Journal of Financial Economics* 105, 473–490, 2012.

[28] Jiang, G. J., and Y. S. Tian, The model-free implied volatility and its information content, *Review of Financial Studies*, 18 (4), 1305–1342 2005.

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

[30] Jurado, K., Ludvigson, S.C., and Ng, S., Measuring uncertainty, *American Economic Review*, 105 (3), 1177–1216, 2015.

[31] Kang W., K. G. Rouwenhorst, and K. Tang A tale of two premiums: the role of hedgers and speculators in commodity futures markets, *Journal of Finance* 75 (1), 377-417 2020.

[32] Keynes J., Some aspects of commodity markets, *Manchester Guardian Commercial*, 13, 784–786, 1923.

[33] Kilian, L., Exogenous oil supply shocks: how big are they and how much do they matter for the US economy? *Review of Economics and Statistics*, 90 (2), 216–240, 2008.

[34] Kilian, L., Not all oil price shocks are alike: disentangling demand and supply shocks in the crude oil market, *American Economic Review,* 99 (3), 1053-1069. 2009.

[35] Kilian, L., Measuring global economic activity: do recent critiques hold up to scrutiny?, *Economics Letters,* 178, 106-110, 2019.

[36] Lamoureux, C.G. and Lastrapes, W., Forecasting stock return variance: towards understanding stochastic implied volatility, *Review of Financial Studies,* 6, 293–326, 1993.

[37] Ludvigson S. C., S. Ma and S. Ng, Uncertainty and business cycles: exogenous impulse or endogenous response?, *NBER Working Papers,* 21803, 2015.

[38] Newey, W. K. and K. D. West, A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix, *Econometrica* 55 (3), 703–708, 1987.

[39] Park Y., Volatility-of-volatility and tail risk hedging returns, *Journal of Financial Markets* 26, 38-63. 2015.

[40] Prokopczuk M. and C. W. Simen, The importance of the volatility risk premium for volatility forecasting, *Journal of Banking & Finance*, 40, 303-320, 2014.

[41] Torben G. Andersen, N. Fusari, and V. Todorov, The pricing of tail risk and the equity premium: evidence from international option markets, *Journal of Business & Economic Statistics*, 38 (3), 662-678. 2020.

[42] Watugala S. W., Economic uncertainty, trading activity, and commodity futures volatility, *Journal of Futures Markets,* 39, 921–945. 2019.

[43] Xiong J. X., T. M. Idzorek and R. G. Ibbotson, Volatility versus Tail Risk:

Which One Is Compensated in Equity Funds?, *The Journal of Portfolio Management,* 40 (2), 112-121, 2014.

[44] Zmijewski M.E., Methodological issues related to the estimation of financial distress prediction models, *Journal of Accounting Research* 22, 59–82, 1984.

APPENDIX A

HIGHER-ORDER GRANGER CAUSALITY TEST: A VAR APPROACH

In this section, I would like to further discuss the question proposed in section 3.2: Are the macroeconomic and financial uncertainty measures Granger causes for the volatility risk premium? Our empirical result in section 3.2 affirms that when the lag order is 1, macroeconomics uncertainty measure is indeed a Granger cause for the volatility risk premium. In other words, macroeconomic uncertainty measure contains additional information for predicting the future trends of volatility risk premium that is not included in latter's first order lagged term. But is this answer still valid when the lag order is high? A higher order Granger causality test could provide answer for this question.

Suppose we have a d-dimensional multivariate time series, namely $\mathbf{Y}$, defined as $\mathbf{Y}_t = (Y_{1,t}, Y_{2,t}, \ldots, Y_{d,t})'$, where $Y_1, Y_2, \ldots, Y_d$ are our variables of interest; and a k-dimensional multivariate time series $\mathbf{X}_t = (X_{1,t}, X_{2,t}, \ldots, X_{k,t})'$, where $X_1, X_2, \ldots, X_k$ are control variables. A VAR (vector introgressive) model is defined as:

$$\mathbf{Y}_t = \sum_{s=1}^{L} \mathbf{A}_t \mathbf{Y}_{t-s} + \mathbf{B}_{t-1}\mathbf{X}_{t-1} + \epsilon_t$$

We say Y_i is a Granger cause of Y_j, if $A_s(j, i)$ for $s = 1 \ldots L$ is significantly different from 0. I form the test as follows, given the regression:

$$Y_t = \sum_{s=1}^{n} (\theta_s Y_{t-s} + \lambda_s Macro\_Uncert_{t-s} + \mu_s Fin\_Uncert_{t-s}) + \beta_{t-1} X_{t-1} + \epsilon_t \quad (*)$$

With $Y \in \{VRP, Real\_Vol, Impl\_Vol\}$, and X_t being control variables. Consider the F test specified below:

$$H_0 : \lambda_1 = \lambda_2 = ... = \lambda_n = 0$$

if we can reject this null hypothesis, then the macroeconomic uncertainty measure would be a Granger cause of Y at lag order n.

Similarly, consider another F test:

$$H_0 : \mu_1 = \mu_2 = ... = \mu_n = 0$$

If we can find evidence to reject this hypothesis, then financial uncertainty measure would be a Granger cause of Y at lag order n.

I choose the maximum lag order $n = 3$ by minimizing the Akaike information criterion of equation $(*)$, a relationship between the Akaike information criterion and maximum lag order n is shown in the Figure A.1.

Table A.1 displays the F-test results of the estimations of equation $(*)$ with lag order $n = 3$, the statistical significance levels of the coefficients of single variables is of no interest to us so the estimation results are not shown here, but they are available upon request. Note that, before running the regression, variables of interest are taken first-order difference to pass the Dickey-Fuller Test.

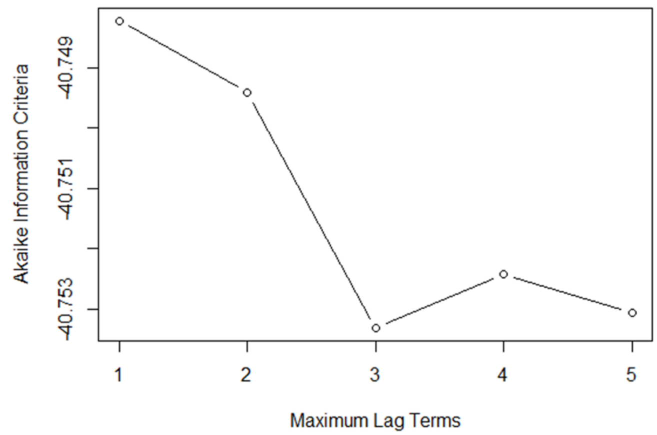

Figure A.1: The AIC Criterion. The Akaike information criterion of the regression results of equation $(*)$ are shown against the maximum lag order n taken.

Although macroeconomic uncertainty measure contains additional information valid for predicting realized volatility and implied volatility at a lag order of 3, it does not have any additional explanatory power for their difference, i.e., the volatility risk premium. This result, together with our analysis in section 3.2, may uncover the fact that volatility risk premium has a short memory, namely it only reacts to the unforeseeable fluctuations in the economy that relatively newly take place.

Table A.1: The Granger Causality Test

Dependent Variable	Predictor	F statistic	p-value	Granger Cause under significance level 5%?
VRP	*Macro_Uncert*	0.7518	0.4643	No
	Fin_Uncert	0.7518	0.5415	No
Real_Vol	*Macro_Uncert*	9.3626	<0.0001	Yes
	Fin_Uncert	0.3976	0.7548	No
Impl_Vol	*Macro_Uncert*	8.7356	<0.0001	Yes
	Fin_Uncert	1.538	0.2043	No