Bad Volatility is not always Bad: Evidence from Commodity Markets

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Abstract

Using the four commodity exchange-traded fund (ETF) options data, we systematically examine the return predictability of the variance risk premiums in commodity markets. We also analyze the predictability of upside and downside variance risk premiums by performing a conditional decomposition based on the direction in which the market moves. We find that both the total and decomposed variance risk premiums contain predicative information about commodity prices, and the decomposed variance risk premiums jointly outperform the undecomposed premium. The importance of the downside (upside) variance risk premium varies across markets; in energy commodity markets, both upside and downside variance risk premiums have significant predictive power; in precious metal commodity markets, only the upside variance risk premium is predicative.

JEL Classification: G1; C5; Q3; Q4

Keywords: Commodity markets; Upside and downside variance risk premiums; Asymmetric risk; Prediction

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1 Introduction

The commodity derivative market has been going through rapid expansion in recent years, and it has become an important part of the global derivative market. The rapid expansion of commodity markets, along with the increasing participation of investors and hedgers, has led to the rising attention to the study of commodity-related volatility and the compensation requested by market participants for volatility investing/trading (i.e., the variance risk premiums). The previous research of variance risk premiums on equity market (see, e.g., Bakshi and Kapadia (2003); Bakshi and Madan (2006); Carr and Wu (2009)) can be a reference for constructing and analyzing variance risk premiums in commodity markets. [1] Moreover, the work of Trolle and Schwartz (2009) for pricing commodity derivatives points out that commodity options contain information about stochastic volatility which is unspanned by commodity futures. Therefore, the construction of variance risk premium in commodity markets reveals the information contained by options and futures markets. Specifically, our work focuses on four commodity exchange-traded fund (ETF) option markets, namely, USO options, UNG options, GLD options and SLV options. [2]

The significant predicative information contained by variance risk premiums has been demonstrated by numerous empirical studies, starting from Bollerslev et al. (2009) in the equity market to the research on other major assets such as bond and currencies (e.g., Londono and Zhou (2017); Mueller et al. (2011)). More importantly, recent studies such as Chevallier and Sévi (2013) and Kang and Pan (2015) have also found the return predictability by variance risk premiums in the crude oil market.

Another widely acknowledged fact is that financial markets react differently to positive and negative shocks. This idea is further supported by recent empirical evidence that upside

[1] According to the model-free approach proposed by Carr and Wu (2009), variance risk premium is payoff of a synthetic swap contract with the fixed leg using option data and the floating leg using futures (spot) data.

[2] USO stands for United States Oil Fund, and it is one of the largest and most liquid oil ETFs; UNG stands for United States Natural Gas Fund; GLD stands for SPDR Gold Shares; SLV stands for iShares Silver Trust.

and downside risks have different forecasting power for equity excess returns (see, e.g., Guo et al. (2014); Segal et al. (2015)). In a similar context, Feunou2015 and Shaliastovich2015 examine the information asymmetries contained by upside and downside variance risk premiums. They find that the joint model of the decomposed variance risk premiums shows stronger predictive power than that of the undecomposed ones and the downside variance risk is the main component for improved predictive power. Key insight for the improvement is that investors require different levels of risk compensation for downside and upside market movements. Regarding the case of the equity index, downside market risk provides more compensation.

We contribute to the existing literature in three key aspects. First, we systematically study the predictability of variance risk premiums in several commodity markets and find their significant predictive information, which complements the current research on variance risks in commodity markets (see, e.g. Trolle and Schwartz (2010);Prokopczuk et al. (2017)). This is the first paper that comprehensively examines the return predictability of variance risk premiums for four major commodity markets (crude oil, natural gas, gold and silver), under various forecasting horizons.

Second, by performing a conditional decomposition of variance risk premiums, we examine the predicative information content of the upside and downside variance risk premiums in the commodity markets. We find that the decomposed variance risk premiums outperform the undecomposed one. Moreover, we find the predicative information contained by upside and downside variance risk premiums is asymmetric. The asymmetries in the predicative information contained by upside and downside variance risk premiums varies across the markets whereas Feunou et al. (2015) demonstrate that in equity market, the main component of the variance risk premium is the downside component. [3] Our work enriches a few studies (Chevallier and Sévi (2013); Kang and Pan (2015)) on commodity

[3] We find that in energy commodity markets (crude oil and natural gas), both upside and downside variance risk premiums are important; however, in precious metal commodity markets (gold and silver), the upside variance risk premium is the main component in prediction. In other words, the downside variance risk premium does not always take the dominant role in commodity markets.

price predictability from the perspective of time-varying variance risk premiums. Additionally, our work can be linked to recent studies that attempted to forecast commodity prices by using macroeconomic and financial variables. (Hong and Yogo (2012); Gargano and Timmermann (2014)). We find a new strong predictor of commodity returns even controlling for the effect of other macroeconomic and financial variables.

Finally, we further analyze the impacts of asymmetric risk in commodity markets based on the return predictability test of a variable constructed by taking the difference between upside and downside variance risk premiums, in reference to Patton and Sheppard (2015). We find the evidence for predictability in the energy commodity markets, However, we do not find any evidence for the precious metal commodity markets.

This paper is organized as follows. In Section 2, we describe the data set and methodology employed. Section 3 presents the empirical analysis in commodity markets and corresponding discussion. Section 4 concludes our study.

2 Pricing formulas

In this section, we synthesize a variance swap contract to measure the variance risk premium which actually provides the expected payoff of the contact. A decomposition of the variance risk premiums into "good" and "bad" components based on market moving directions is also discussed here.[4] Furthermore, the asymmetry measured by the difference between upside and downside variance risk premiums is provided. In the following part we will construct the risk-neutral and realized variances and then decompose them into upside and downside parts, which finally leads to the construction of decomposed variance risk premiums and the corresponding asymmetry measure.

2.1 Risk-neutral variance and its decomposition

In this part, we follow the nonparametric methodology to construct the risk-neutral variance and then decompose it into upside and downside components with respect to the sign of daily returns.[5] Among the literature of model-free approaches (e.g. Bakshi et al. (2003), Carr and Wu (2009) and Kozhan et al. (2013)), we utilize the generalized methodology proposed by Kozhan et al. (2013) which can infer the any-order risk-neutral moment from the option prices. Specifically, the risk-neutral variance can be computed based upon a set of out-of-money (OTM) calls and puts

$$\begin{aligned} iv_{t,T} &= 2\int_{S_t}^{+\infty} \frac{C_{t,T}(K)}{B_{t,T}K^2} dK + 2\int_0^{S_t} \frac{P_{t,T}(K)}{B_{t,T}K^2} dK \\ &= iv_{t,T}^u + iv_{t,T}^d, \end{aligned} \tag{1}$$

where $C_{t,T}(K)$ and $P_{t,T}(K)$ denote the time-t prices of calls and puts with strike price K and maturity date T, and $B_{t,T}$ is the time-t price of unit bond with maturity date T. Considering that call (put) options contain the forward-looking upward (downward)

[4]Here "good" and "bad" indicate that the components are related with the upward and downward market movements, respectively.

[5]The daily market price changes are decomposed into positive and negative parts regarding a suitable threshold. In this work, we set the threshold value at zero.

market information, the integral related to calls in Eq.(2) is actually the decomposed upside (downside) risk-neutral variance. Therefore, we can write the upside risk-neutral variance iv^u and downside risk-neutral variance iv^d in the discretized form for the limited number of options available in the market

$$\begin{aligned} iv^u_{t,T} &= 2\sum_{S_t \le K_i} \frac{C_{t,T}(K_i)}{B_{t,T}K_i^2}\Delta I(K_i), \\ iv^d_{t,T} &= 2\sum_{K_i \le S_t} \frac{P_{t,T}(K_i)}{B_{t,T}K_i^2}\Delta I(K_i), \end{aligned} \tag{2}$$

with the weight function $\Delta I(K_i)$ defined as

$$\Delta I(K_i) = \begin{cases} \frac{K_{i+1}-K_{i-1}}{2}, 0 \le i \le N \quad (\text{with } K_{-1} = 2K_0 - K_1, K_{N+1} = 2K_N - K_{N-1}) \\ 0, \quad \text{otherwise.} \end{cases}$$

At each date t, we linearly interpolate the risk-neutral variance at two maturities to obtain the risk-neutral variance with a fixed 30-day horizon, which further leads to

$$iv_{t,T} = \frac{iv_{t,T_1}(T_2 - t) + iv_{t,T_2}(t - T_1)}{T_2 - T_1}, \tag{3}$$

where T_1 and T_2 denote the two maturity dates and T denotes the interpolated maturity date with a 30-day time to maturity such that $T - t = 30$. The same interpolation applies to iv^u_{t,T_1} (iv^d_{t,T_1}) and iv^u_{t,T_2} (iv^d_{t,T_1}) to get $iv^u_{t,T}$ ($iv^d_{t,T}$).

2.2 Realized variance and its decomposition

On a trading day t, if we denote by p_{t_j} the intraday logarithmic price at time t_j, then the log return $r_{t_j} = p_{t_j} - p_{t_{j-1}}$. Following the non-parametric method based on high-frequency data proposed by Barndorff Nielsen and Neil (2004), the realized variance on day t is

$$rv_t = \sum_{i=1}^{M_t} r^2_{t_i}, \tag{4}$$

where M_t denotes the number of intraday prices.[6]

[6]We take the intraday frequency as a 5-minute interval; we also treat the period from close of trading day t to the open of next day as the last 5-minute period.

Correspondingly, the realized variance for the period $[t, T]$ is

$$rv_{t,T} = \sum_{k=t}^{T} rv_k. \tag{5}$$

The decomposition of upside and downside realized variance from trading day t to T depends on the sign of 5-minute intraday return

$$\begin{aligned} rv_{t,T}^u &= \sum_{k=t}^{T} \sum_{i=1}^{M_k} r_{k_i}^2 \mathbf{1}_{\{r_{k,i}>0\}}, \\ rv_{t,T}^d &= \sum_{k=t}^{T} \sum_{i=1}^{M_k} r_{k_i}^2 \mathbf{1}_{\{r_{k,i}\leq 0\}}. \end{aligned} \tag{6}$$

Eq.(6) indicates that $rv_{t,T}^u$ and $rv_{t,T}^d$ capture variation caused by the positive and negative intraday returns respectively.

2.3 Upside and downside variance risk premiums

The underpinning of the model-free methodology is that the variance risk premium is the payoff of the synthetic variance swap contract, namely, the difference between the floating leg and fixed leg. It is actually the compensation for the change of variance of the underlying asset

$$vrp_{t,T} = rV_{t,T} - iv_{t,T}. \tag{7}$$

Correspondingly, the upside (downside) variance risk premium is the compensation for the change of the upward (downward) variance, which is the difference between the upside (downside) realized and upside (downside) risk-neutral variances

$$\begin{aligned} vrp_{t,T}^u &= rV_{t,T}^u - iv_{t,T}^u, \\ vrp_{t,T}^d &= rV_{t,T}^d - iv_{t,T}^d. \end{aligned} \tag{8}$$

Notably, in later part we will implement an empirical analysis of predicting future market returns using the total and decomposed variance risk premium. By following Bollerslev et al. (2009), the one-period ahead realized variance is used as a proxy for $E_t^P[Var_{t,T}]$

forecasting purposes. The same replacements will be made for $vrp_{t,T}^u$ and $vrp_{t,T}^d$ when discussing their prediction power. Another point we need to emphasize is that only variance risk premiums with 30-day time to maturity are analyzed in this work. For simplification of notation, T is dropped from all the notations mentioned above.

2.4 Signed jump risk premium

Patton and Sheppard (2015) show that the difference between upside and downside realized variances is actually the difference of the squared return caused by positive and negative jumps, called the realized signed jump risk. A similar definition also applies to the risk-neutral signed jump risk. Correspondingly, the signed jump risk premium is the difference between risk-neutral and realized signed jump risk. As positive and negative jumps have impacts on the skewness of return distribution, the signed jump risk premium is correlated with skew risk premium. Thus, the signed jump risk premium can be expressed by upside and downside variance risk premiums

$$\begin{aligned} sjrp &= E^Q[sjr] - E^P[sjr] \\ &= vrp^u - vrp^d, \end{aligned} \tag{9}$$

where sjr denotes the signed jump risk and $sjrp$ denotes the signed jump risk premium. The value of $sjrp$ is related to the asymmetric impacts caused by upside and downside jumps. In the empirical analysis part, we also analyze the financial implication of the asymmetric risk caused by jumps.

3 Data

3.1 Option data and risk-neutral variances

We compute the total and decomposed risk-neutral variances at daily frequency using the commodity ETF option data. The data sample contains options written on four sets of commodity ETFs, namely, crude oil ETF (USO), natural gas ETF (UNG), gold ETF (GLD) and silver ETF (SLV), provided by Thomas Reuters Ticker History (TRTH) of SIRCA. [7] We choose the period from January 2010 to August 2017. To avoid possible noises caused by the Global Financial Crisis and the relatively lower trading liquidity, we disregard option data before 2010. Figure 1 shows annual total trading volumes associated with commodity options. It clearly demonstrates the increasing popularity of commodity options.

[Insert Figure 1 here]

We take the average of close bid and close ask as option prices. We filter out options with incomplete or incorrect information. [8] At least two OTM calls and puts are required for computing the upside and downside risk-neutral variances. To get the one-month (30-day) risk-neutral variance at the daily frequency, we linearly interpolate across risk-neutral variances with two nearest maturities.

Figure 2 and Figure 3 plot the time series of total and decomposed risk-neutral variances, respectively. For all the four commodity options, the total, upside and downside risk-neutral variances have a similar trend. Except silver, both iv^u and iv^d are highly correlated to iv, around 95% in levels. In contrast, iv^u and iv^d are less correlated with each other for all four commodity markets, around 30% in levels for silver and 85% in levels for the

[7] http://www.sirca.org.au

[8] Specifically, we remove options meeting one of the following conditions: options with a zero close bid; options with close ask greater than close bid; options with zero trading volume; options violate the standard no-arbitrage conditions.

others. The *iv* curves in Figure 2 shows large spikes during the European debt crisis in 2011, for the crude oil, gold, and natural gas markets. Moreover, the *iv* curves also spike at the events caused by market-specific risks.

For example, the *iv* curve associated with the crude oil market displays the largest spike on February 11, 2016, when the oil market went through a crash. In contrast, the values of *iv* for other markets are below their own historical average values: *iv* for the natural gas market is 0.004, compared to its mean value of 0.012; *iv* for the gold market is 0.007, compared to its mean value of 0.003; *iv* for the silver market is 0.008, compared to its mean value of 0.009.

[Insert Figure 2 here]

Figure 3 demonstrates that upside and downside risk-neutral variances move in similar directions for all four markets. The downside risk-neutral variances exhibit larger spikes for all four commodity markets, highlighting the asymmetric distribution of asset returns and its possible impact on future markets.

[Insert Figure 3 here]

3.2 High-frequency data and realized variances

We use 5-minute intraday return data to construct the monthly realized variances. The intraday data is from TRTH.[9] Figure 4 and Figure 5 plot the time-series of total realized variances and decomposed realized variances of the four commodity markets. The figures indicate strong correlations. Compared to risk-neutral variances, the total, upside and downside realized variances are more volatile and less persistent.

[Insert Figure 4 here]

[9] In general, 5-minute frequency is the most proper choice as it achieves the optimal trade-off between the precision of estimation and the impact of microstructure noise.

[Insert Figure 5 here]

3.3 Total, upside and downside variance risk premiums

Figure 6 and Figure 7 plot the total and decomposed variance risk premiums in the four commodity markets, respectively. The figures clearly show comovements among the total, upside and downside variance risk premiums can be observed. In all four markets, vrp, vrp^u and vrp^d exhibit concentrated spikes during the period associated with the market-specific shocks. For example, the rv curve for the crude oil market exhibits concentrated spikes around year 2015, when the oil market went through a sharp drop. For the natural gas market, there are large spikes around Feb 2012, March 2014 and Feb 2016. For the gold market, spikes are also dense around June 2013.

[Insert Figure 6 here]

[Insert Figure 7 here]

Table II reports the correlation among the variance risk premiums. For all four markets, both vrp^u and vrp^d are highly correlated with vrp, around 80% in levels. In contrast, the correlation between vrp^u and vrp^d is much lower for the four markets, ranging from 16.5% to 46.4%. The statistics are consistent with the patterns exhibited in Figure 6 and Figure 7. Table I also reports the summary statistics of the key variables. For the crude oil market, the mean for vrp^u is $9.630e - 05$, positive and close to zero; in contrast, the mean for vrp^d is -0.001. It indicates that investors are willing to pay a small premium for upward changes of the variance, while they require compensation for downward changes of the variance. For the natural gas market, both the mean for vrp^u and vrp^d are positive, but with different magnitudes, which implies that investors are willing to pay premiums for both directions of changes in variance. Regarding the gold and silver markets, both the mean of vrp^u and vrp^d are negative. Contrary to the natural gas market, investors require compensation for both upward and downward changes of variance.

[Insert Table I here]

[Insert Table II here]

3.4 Other data

The risk-free rates used here are proxied by Libor rates, provided by Bloomberg. The macroeconomic variables such as Effective Federal Funds Rate, Moody's Seasoned Baa/Aaa Corporate Bond Yield, 3-Month Treasury Bill Rate, 10-Year Treasury Bond Rate are all from Federal Reserve Bank of St. Louis.[10]

[10] https://fred.stlouisfed.org

4 Empirical analysis

4.1 The predictability of variance risk premiums

In this section, we conduct an extensive empirical analysis of the return predictability of the total and decomposed variance risk premiums in the four commodity markets. There are two leading studies in this field with a focus on the equity market. According to Bollerslev et al. (2009), the total variance risk premium contains short-term predictive information in the equity market. The later research of Kilic and Shaliastovich (2015), which is also carried out in the equity market, decomposes the variance risk premium into upside and downside components and then proves that the decomponents jointly have stronger predictive power. Studies such as Chevallier and Sévi (2013) and Kang and Pan (2015) extend the analysis to the predictability of total variance risk premium in the crude oil market and conclude that the variance risk premium shows predictive power on oil market returns. It is robust to the inclusion of control variables.

Our empirical analysis mainly contributes to the current literature in two aspects. First, it enriches the research on the asset return predictability of the variance risk premium by extending to several commodity markets, namely, crude oil, natural gas, gold and silver. Second, our study also extends the research on the asset return predictability of upside and downside variance risk premiums, showing that upside and downside risks play different roles in each commodity market. In all, this work provides a more comprehensive understanding of commodity markets by incorporating the information contained in the total and the decomposed variance risk premiums.

The predictability will be examined based on two groups of regressions. The first group of regressions provides a comparison of the predictability by the total and the decomposed variance risk premiums, without a controlling group. The set of regressions are as follows

$$xm_{t,h}^{index} = \alpha_{0,h} + \alpha_{1,h} vrp_t + \epsilon_t^{\alpha}, \tag{10}$$

$$xm_{t,h}^{index} = \beta_{0,h} + \beta_{1,h} vrp_t^u + \epsilon_t^{\beta}, \tag{11}$$

$$xm_{t,h}^{index} = \gamma_{0,h} + \gamma_{1,h} vrp_t^d + \epsilon_t^{\gamma}, \tag{12}$$

$$xm_{t,h}^{index} = \delta_{0,h} + \delta_{1,h} vrp_t^u + \delta_{2,h} vrp_t^d + \epsilon_t^{\delta}. \tag{13}$$

In the above equations, $xm_{t,h}^{index}$ denotes the cumulative forward return of the index, with $index$ related to the specific commodity market and h denotes the forecasting horizon. It is computed as

$$xm_{t,h}^{index} = \sum_{i=0}^{h} r_{t+i}^{index}, \tag{14}$$

with r_{t+i}^{index} denoting the daily log return of the specific $index$.

The second group of regressions add control variables for checking out the robustness of the results associated with the first group. The set of control variables are the federal funds rate, the default spread and the term spread. These variables are known to predict future markets returns in the related literature.[11] The second group of regressions are specified as

$$xm_{t,h}^{index} = \alpha_{0,h} + \alpha_{1,h} vrp_t + \alpha_{2,h} \Delta fed_t + \alpha_{3,h} \Delta def_t + \alpha_{4,h} \Delta term_t + \epsilon_t^{\alpha}, \tag{15}$$

$$xm_{t,h}^{index} = \beta_{0,h} + \beta_{1,h} vrp_t^u + \beta_{2,h} vrp_t^d + \beta_{3,h} \Delta fed_t + \beta_{4,h} \Delta def_t + \beta_{5,h} \Delta term_t + \epsilon_t^{\beta}, \tag{16}$$

where Δfed denotes the daily change of the federal funds rate, Δdef denotes the daily change of the default spread, and $\Delta term$ denotes the daily change of the term spread.[12]

The empirical analysis across the four commodity markets demonstrates that generally upside and downside variance risk premiums jointly predict future market returns better

[11] The group of controlling variables are selected following the work of Bali and Peng (2006) and Bali and Engle (2010), which found that macroeconomic variables such as federal funds rate, default spread and term spread have predictive power for future market returns as they convey some information about the general economic situation.

[12] Default spread is the difference between he yields on BAA- and AAA-rated corporate bonds. Term spread is the difference between the yields on the 10-Year Treasury bond and the 3-Month Treasury bill

than the total variance risk premium, at a longer forecasting horizon, as indicated by the large R^2 values; the predictive information contained by variance risk premiums, whether or not they are decomposed, is not covered by those macroeconomic variables. [13] In the following four sub-sections, the empirical results for each commodity market will be discussed in detail.

4.1.1 Return prediction in the crude oil market

It is well-known that crude oil spot and futures prices are difficult to predict. Previous literature (see Chevallier and Sévi (2013) and Kang and Pan (2015)) mainly focus on the role of the total variance risk premium in predicting oil market returns. To emphasize the impacts of asymmetric risks on oil futures returns, we also analyze the predictability of upside and downside variance risk premiums. The results are given in Table III.

[Insert Table III here]

Panel 1 of Table III shows the predictability of the total variance risk premium, over the forecasting horizon from 2 weeks to 12 months. vrp is weakly significant at the 6-month horizon, with R^2 valued at 1.43%. The constant term remains highly significant from the 1-month to 9-month horizons, indicating the possible existence of other predictors. Panel 2 and 3 check the predictability of the upside and downside variance risk premiums, respectively. vrp^u significantly predicts oil market returns at the 2-month horizon, with a positive slope, while vrp^d significantly predicts the future market at the 3- and 6-month horizons, with the negative slope. Therefore, the semi variance risk premium alone, whether it is an upside or downside component, even works better in prediction than the total variance risk premium, regardless of forecasting horizons. Panel 4 shows the joint predictive model of vrp^u and vrp^d for the future oil market, which works best in prediction among the four groups. In summary, vrp^u positively predicts future oil returns, indicating that an upward increase of market variation is “good” news; vrp^d contains

[13] All the regression results actually report adjusted R^2, but we omit the term “adjusted” throughout the work.

negative predicting information of the future oil market, indicating that a downward increase of market variation is “bad” news.

Table IV reports the predictability of total and decomposed variance risk premiums with a set of macroeconomic variables. Although the control variables such as Δdef and $\Delta term$ are predictive for the oil market, the strong predictability of total and decomposed variance risk premiums still remains even after adding the macroeconomic variables.

[Insert Table IV here]

In sum, in the crude oil market, increasing downside variation is “bad” for investors and increasing upside variation is “good” for investors, which is consistent with what has been found in the equity market by Kilic and Shaliastovich (2015).

4.1.2 Return prediction in the natural gas market

Even though the natural gas market is the second largest energy commodity market, most research on the return predictability in the energy commodity market mainly focuses on crude oil. This study is the first that extends the research on predictability of variance risk premiums into the natural gas market. Table V reports the predictability by total and decomposed variance risk premiums without the inclusion of control variables. Consistent with what we find in the crude oil market, the joint model with vrp^u and vrp^d performs best among the four models. Moreover, vrp^u takes a dominant role in predicting the returns of natural gas in the short run, from 2 months to 6 months, while vrp^d plays a more important role in prediction at the longer horizons. Unlike the crude oil market, the slopes of vrp^u and vrp^d are both positive in natural gas market, indicating that when the market volatility increases with either upward or downward market movement, the natural gas price will go up in the future. Moreover, the predictability of variance risk premiums, whether or not they are decomposed, lasts longer in the natural gas market than in the crude oil market. Note that the slope of vrp^d is positive, while it is negative in the crude oil market.

[Insert Table V here]

Table VI reports the predictability of total and decomposed variance risk premiums, after adding control variables. Specifically, Δdef is significant in predicting natural gas returns from 2 to 6 months, with a negative slope. The role of Δdef in the natural gas market is consistent with that in the crude oil market, which means that an increase in the default risk negatively impacts the future market. The predictability of variance risk premiums is unaffected by adding the control variables. In contrast to the crude oil market, the slope of vrp^d is positive in the natural gas market. In other words, the increase of downward fluctuation is not perceived as "bad" news for investors in the natural gas market.

[Insert Table VI here]

4.1.3 Return prediction in the gold market

Table VII shows the predictability of total and decomposed variance risk premiums in the gold market. The total variance risk premium vrp remains predictive up to 12 months. The joint model of vrp^u and vrp^d produces a slightly higher R^2 than that of the total vrp, while vrp^u takes a dominant role. As shown by Panel 3, vrp^d remains significant from the 6- to 9- month horizons when predicting market returns alone. However, when combining vrp^d with vrp^u, exhibited by Panel 4, vrp^d is only significant at the 12-month horizon, while vrp^u significantly predicts gold returns from 1 month to 12 months. Note that both the slopes of vrp^u and vrp^d are negative, suggesting that an increase of variation in either upward or downward volatility is "bad news" for investors and causes the future gold price to drop. In other words, the negative slope of vrp^u indicates that an increase of upward variation ("good volatility") is not really good in the gold market.

[Insert Table VII here]

Table VIII reports the predictability by total and decomposed variance risk premiums, adding controlling macroeconomic variables. Similar to the crude oil and natural gas markets, the control variables have no impact on the predictability of variance risk premiums.

[Insert Table VIII here]

4.1.4 Return prediction in the silver market

The predictability of total and decomposed variance risk premiums are reported by Table IX. It shows that both vrp^u and vrp^d contain predictive information for the future silver market, at the 6-month forecasting horizon. But the predictive information in variance risk premiums are not as prominent as it is for the gold case. Panel 2 indicates that vrp^u is slightly more predictive than vrp, as the R^2 corresponding to vrp^u is 1.05% and the R^2 corresponding to vrp is 0.67%. Similarly to the gold prediction case, vrp^u takes a dominant role in the joint prediction model. Moreover, an increase of upward variation is "bad news" for the future silver market, while an increase of downward variation is "neutral news".

[Insert Table IX here]

The results for the robustness checks are given in Table X, which shows that the predictability of variance risk premiums is unaffected by the inclusion of control variables.

[Insert Table X here]

4.2 The predictability of signed jump risk premiums

We also analyze the predictability of signed jump risk premiums in each commodity market by running the following two groups of regressions, with and without control variables

$$xm_{t,h}^{index} = \alpha_{0,h} + \alpha_{1,h} sjrp_t + \epsilon_t^{\alpha}, \tag{17}$$

$$xm_{t,h}^{index} = \beta_{0,h} + \beta_{1,h} sjrp_t + \beta_{2,h} \Delta fed_t + \beta_{3,h} \Delta def_t + \beta_{4,h} \Delta term_t + \epsilon_t^{\beta}. \tag{18}$$

Table XI to XIV report the results. For the crude oil market, the signed jump risk premium contains predictive information from the 1- to 3-month horizons. The significantly positive slope of $sjrp$ indicates that it contains predicative information of the crude oil market, and the results are robust to the inclusion of control variables. Regarding the natural gas market, $sjrp$ predicts market returns at the 9- to 12-month forecasting horizons. Note that the slope of $sjrp$ is negative, suggesting that investors require compensation for the skewness risk of the natural gas market.

[Insert Table XI here]

[Insert Table XII here]

[Insert Table XIII here]

[Insert Table XIV here]

In summary, the signed jump risk premium significantly predicts the asset returns in the energy commodity market that includes the crude oil and natural gas, as presented in Table XI and XII. However, in both the gold and silver markets, the signed jump risk premiums do not contain any predictive information, as presented by Table XIII and XIV.

5 Conclusion

We analyze the upside and downside variance risk premiums across four commodity markets, namely the crude oil, natural gas, gold and silver markets, by focusing on their predictability. Our analysis concludes that generally decomposed variance risk premiums jointly predict market returns better than the total variance risk premium. Unlike the dominant role of downside variance risk premium in the equity market, in energy commodity markets, both upside and downside variance risk premiums are important for prediction; and in the precious metal commodity markets, the upside variance risk premium takes a much more important role. Moreover, we also analyze the role of the signed jump risk premium, which is highly related with the asymmetry of asset return distribution, and find that it is important in the energy commodity markets, but not the precious metal commodity markets. We provide a more comprehensive understanding of upside and downside variance risk premiums in commodity markets, complementing the previous studies on the equity market.

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A Tables

Table I: Descriptive statistics of key variables

	rv^u	rv^d	rv	iv^u	iv^d	iv	vrp^u	vrp^d	vrp
A.USO									
Mean	0.004	0.005	0.009	0.004	0.006	0.010	9.630e-05	-0.001	-0.001
Std. dev.	0.004	0.004	0.007	0.003	0.004	0.007	0.003	0.002	0.004
Skewness	2.337	2.238	2.219	1.878	1.595	1.628	1.267	-1.052	-0.001
Kurtosis	9.935	9.925	9.877	9.563	6.031	6.880	9.948	7.848	9.330
Min	0.001	0.001	0.002	0.001	0.001	0.002	-0.011	-0.017	-0.025
Max	0.024	0.025	0.047	0.027	0.027	0.051	0.016	0.009	0.022
B.UNG									
Mean	0.007	0.007	0.014	0.006	0.006	0.012	2.650e-04	0.001	0.002
Std. dev.	0.004	0.005	0.008	0.004	0.004	0.007	0.004	0.005	0.007
Skewness	1.461	1.632	1.525	0.927	1.111	0.951	0.342	0.545	1.072
Kurtosis	4.994	5.487	5.382	3.695	4.947	3.667	4.737	5.724	7.357
Min	0.001	0.002	0.003	0.000	0.000	0.000	-0.019	-0.026	-0.029
Max	0.024	0.026	0.048	0.025	0.032	0.046	0.018	0.024	0.039
C.GLD									
Mean	0.001	0.001	0.002	0.001	0.002	0.003	-1.300e-04	-3.990e-04	-0.001
Std. dev.	0.001	0.001	0.002	0.001	0.001	0.002	0.001	0.001	0.001
Skewness	2.689	3.325	2.643	2.348	2.179	2.272	0.877	1.735	1.009
Kurtosis	12.038	15.493	10.560	11.135	10.187	10.816	8.115	15.062	11.601
Min	2.900e-04	2.430e-04	0.001	4.610e-04	3.830e-04	0.001	-0.004	-0.005	-0.008
Max	0.006	0.007	0.012	0.005	0.008	0.013	0.003	0.004	0.006
D.SLV									
Mean	0.004	0.004	0.008	0.004	0.005	0.009	-2.150e-04	-0.001	-0.001
Std. dev.	0.003	0.004	0.007	0.002	0.004	0.006	0.002	0.003	0.005
Skewness	3.137	4.485	4.049	2.186	3.210	2.952	1.903	0.123	0.921
Kurtosis	16.110	28.453	24.868	10.695	18.767	16.251	17.326	18.686	22.352
Min	0.001	0.001	0.002	0.001	0.001	0.002	-0.015	-0.028	-0.038
Max	0.024	0.035	0.057	0.021	0.037	0.052	0.015	0.020	0.033

Note: Descriptive statistics for the variables: the upside and downside realized variances (rv^u and rv^d, given by Eq.(6)), the realized variance (rv, given by Eq.(5)), the upside and downside risk neutral variances (iv^u and iv^d, given by Eq.(2)), the risk neutral variance (iv, given by Eq.(1)), the upside and downside variance risk premiums (vrp^u and vrp^d, given by Eq.(8)) and the variance risk premium (vrp, given by Eq.(7)). Sample with daily frequency ranging from January, 2010 to August, 2017.

Table II: Correlations between key variables

	rv^u	rv^d	rv	iv^u	iv^d	iv	vrp^u	vrp^d	vrp
A.USO									
rv^u	1.000	0.782	0.942	0.794	0.783	0.816	-0.177	-0.289	-0.284
rv^d		1.000	0.946	0.633	0.640	0.660	-0.203	-0.200	-0.249
rv			1.000	0.754	0.753	0.781	-0.202	-0.259	-0.282
iv^u				1.000	0.859	0.950	-0.201	-0.298	-0.304
iv^d					1.000	0.976	-0.007	-0.471	-0.275
iv						1.000	-0.090	-0.414	-0.297
vrp^u							1.000	0.306	0.837
vrp^d								1.000	0.777
B.UNG									
rv^u	1.000	0.783	0.936	0.489	0.455	0.584	-0.074	0.060	-0.005
rv^d		1.000	0.952	0.549	0.464	0.625	-0.095	0.030	-0.039
rv			1.000	0.552	0.487	0.641	-0.090	0.047	-0.024
iv^u				1.000	0.303	0.786	-0.541	0.197	-0.204
iv^d					1.000	0.827	0.098	-0.500	-0.280
iv						1.000	-0.255	-0.208	-0.302
vrp^u							1.000	0.165	0.739
vrp^d								1.000	0.786
C.GLD									
rv^u	1.000	0.669	0.900	0.610	0.569	0.606	-0.075	-0.180	-0.156
rv^d		1.000	0.926	0.424	0.454	0.455	0.055	-0.105	-0.040
rv			1.000	0.558	0.555	0.575	-0.006	-0.153	-0.103
iv^u				1.000	0.874	0.959	-0.066	-0.312	-0.238
iv^d					1.000	0.976	0.044	-0.251	-0.142
iv						1.000	-0.004	-0.287	-0.190
vrp^u							1.000	0.455	0.812
vrp^d								1.000	0.889
D.SLV									
rv^u	1.000	0.760	0.921	0.607	0.562	0.604	-0.119	-0.321	-0.277
rv^d		1.000	0.954	0.481	0.455	0.485	-0.050	-0.185	-0.151
rv			1.000	0.571	0.534	0.572	-0.086	-0.260	-0.219
iv^u				1.000	0.828	0.932	-0.047	-0.234	-0.183
iv^d					1.000	0.975	0.113	-0.324	-0.169
iv						1.000	0.054	-0.302	-0.182
vrp^u							1.000	0.464	0.793
vrp^d								1.000	0.907

Note: Correlation between the variables: the upside and downside realized variances (rv^u and rv^d, given by Eq.(6)), the realized variance (rv, given by Eq.(5)), the upside and downside risk neutral variances (iv^u and iv^d, given by Eq.(2)), the risk neutral variance (iv, given by Eq.(1)), the upside and downside variance risk premiums (vrp^u and vrp^d, given by Eq.(8)) and the variance risk premium (vrp, given by Eq.(7)). Sample with daily frequency ranging from January, 2010 to August, 2017.

Table III: Predictability of variance risk premiums I: crude oil

					xm^{USO}			
		2w	1m	2m	3m	6m	9m	12m
1	Const.	-0.006*	-0.015***	-0.030***	-0.051***	-0.105***	-0.150***	-0.207***
		(-1.71)	(-2.44)	(-3.15)	(-4.08)	(-6.06)	(-6.62)	(-8.21)
	vrp	0.887	0.670	1.443	-2.264	-6.113*	-6.123	-5.113
		(0.89)	(0.50)	(0.62)	(-0.69)	(-1.89)	(-1.28)	(-0.97)
	Adj. R^2(%)	0.27%	0.02%	0.12%	0.24%	1.43%	0.75%	0.35%
2	Const.	-0.008**	-0.016***	-0.032***	-0.049***	-0.097***	-0.142***	-0.201***
		(-2.10)	(-2.59)	(-3.51)	(-4.24)	(-6.08)	(-7.20)	(-8.39)
	vrp^u	2.159	3.130	5.845**	1.362	-5.365	-7.121	-0.956
		(1.43)	(1.64)	(1.98)	(0.30)	(-1.15)	(-0.88)	(-0.12)
	Adj. R^2(%)	0.80%	0.75%	1.26%	-0.01%	0.36%	0.40%	-0.06%
3	Const.	-0.008*	-0.018***	-0.036***	-0.061***	-0.113***	-0.155***	-0.219***
		(-1.82)	(-2.61)	(-3.38)	(-4.32)	(-5.70)	(-6.36)	(-7.74)
	vrp^d	-0.178	-2.123	-3.383	-8.695*	-11.542**	-9.080	-13.834
		(-0.12)	(-0.82)	(-0.86)	(-1.85)	(-2.11)	(-1.34)	(-1.62)
	Adj. R^2(%)	-0.06%	0.22%	0.27%	1.42%	1.41%	0.55%	0.96%
4	Const.	-0.009**	-0.021***	-0.041***	-0.063***	-0.112***	-0.152***	-0.221***
		(-2.17)	(-2.82)	(-3.82)	(-4.60)	(-5.48)	(-6.27)	(-7.55)
	vrp^u	2.431	4.067*	7.454***	4.117	-2.449	-5.099	3.091
		(1.57)	(1.94)	(2.61)	(0.95)	(-0.49)	(-0.59)	(0.34)
	vrp^d	-1.031	-3.548	-6.027	-10.173**	-10.653*	-7.332	-14.890
		(-0.70)	(-1.29)	(-1.59)	(-2.31)	(-1.83)	(-1.02)	(-1.58)
	Adj. R^2(%)	0.87%	1.40%	2.15%	1.76%	1.43%	0.70%	0.95%

Note: The table shows the predictability of cumulative forward USO returns (xm^{USO}) which is defined as Eq.(14), by using the variance risk premium (vrp, given by Eq.(7)), the upside variance risk premium (vrp^u, given by Eq.(8)) and the downside variance risk premium (vrp^d, given by Eq.(8)). The forecasting horizon spans from 2 weeks (2w) to 12 months (12m). The t-statistics are computed according to Newey and West (1987). We use $*$, $**$ and $***$ to denote the significance level of 5%, 1% and 0.1% respectively. The daily observations range from January 2010 to August, 2017.

Table IV: Predictability of variance risk premiums II: crude oil

xm^{USO}

		2w	1m	2m	3m	6m	9m	12m
1	Const.	-0.006*	-0.015**	-0.030***	-0.052***	-0.105***	-0.151***	-0.208***
		(-1.73)	(-2.46)	(-3.15)	(-4.10)	(-6.09)	(-6.64)	(-8.23)
	vrp	0.757	0.482	1.267	-2.479	-6.390*	-6.441	-5.530
		(0.75)	(0.35)	(0.54)	(-0.75)	(-1.95)	(-1.34)	(-1.04)
	Δfed	-5.715	-5.123	-0.126	-18.184	-27.147	-24.736	-51.418
		(-0.82)	(-0.53)	(-0.01)	(-1.33)	(-1.46)	(-0.84)	(-1.38)
	Δdef	-2.151	-12.102	-13.354	-34.951	-45.574	-64.842*	-43.411
		(-0.21)	(-0.79)	(-0.62)	(-1.34)	(-1.37)	(-1.66)	(-0.88)
	$\Delta term$	11.035***	13.586***	12.165**	9.847	12.022	5.622	13.875
		(4.12)	(3.22)	(2.16)	(1.44)	(1.29)	(0.51)	(1.00)
	Adj. R^2(%)	0.97%	0.49%	0.19%	0.34%	1.27%	0.77%	0.31%
2	Const.	-0.009**	-0.021***	-0.041***	-0.063***	-0.112***	-0.152***	-0.221***
		(-2.19)	(-2.83)	(-3.82)	(-4.61)	(-5.49)	(-6.29)	(-7.56)
	vrp^u	2.295	3.863*	7.273**	3.836	-2.824	-5.568	2.546
		(1.49)	(1.85)	(2.54)	(0.89)	(-0.56)	(-0.65)	(0.28)
	vrp^d	-1.148	-3.703	-6.174	-10.282**	-10.795*	-7.466	-15.094
		(-0.77)	(-1.34)	(-1.62)	(-2.31)	(-1.83)	(-1.03)	(-1.58)
	Δfed	-5.262	-4.129	2.286	-15.354	-25.418	-23.781	-40.804
		(-0.77)	(-0.42)	(0.22)	(-1.18)	(-1.38)	(-0.83)	(-1.08)
	Δdef	-1.278	-10.182	-9.869	-31.298	-43.634	-64.474*	-40.626
		(-0.12)	(-0.70)	(-0.49)	(-1.28)	(-1.36)	(-1.67)	(-0.84)
	$\Delta term$	11.038***	13.593***	12.154**	9.875	12.034	5.602	13.757
		(4.12)	(3.26)	(2.17)	(1.47)	(1.30)	(0.51)	(1.00)
	Adj. R^2(%)	1.57%	1.85%	2.21%	1.81%	1.48%	0.71%	0.89%

Note: The table shows the predictability of cumulative forward USO returns (xm^{USO}) which is defined as Eq.(14), by using the variance risk premium (vrp, given by Eq.(7)) with control variables such as Δfed, Δdef and $\Delta term$. It also shows the predictability of the upside variance risk premium (vrp^u, given by Eq.(8)) and the downside variance risk premium (vrp^d, given by Eq.(8)) jointly with the same set of control variables. The forecasting horizon spans from 2 weeks (2w) to 12 months (12m). The t-statistics are computed according to Newey and West (1987). We use $*$, $**$ and $***$ to denote the significance level of 5%, 1% and 0.1% respectively. The daily observations range from January 2010 to August, 2017.

Table V: Predictability of variance risk premiums I: natural gas

		xm^{UNG}						
		2w	1m	2m	3m	6m	9m	12m
1	Const.	-0.009*	-0.014	-0.021	-0.028	-0.047*	-0.037	-0.017
		(-1.76)	(-1.31)	(-1.30)	(-1.46)	(-1.73)	(-1.14)	(-0.45)
	vrp	2.741	3.952	5.985**	8.395**	15.573***	13.830***	9.026
		(1.10)	(1.40)	(2.14)	(2.54)	(3.78)	(2.97)	(1.63)
	Adj. R^2(%)	2.11%	2.05%	2.90%	4.04%	7.72%	4.72%	1.61%
2	Const.	-0.006	-0.009	-0.013	-0.017	-0.026	-0.019	-0.006
		(-0.88)	(-0.73)	(-0.82)	(-0.87)	(-0.95)	(-0.58)	(-0.15)
	vrp^u	4.904	5.355	9.016**	11.632**	16.889**	9.877	5.694
		(1.21)	(1.11)	(2.09)	(2.27)	(2.95)	(1.46)	(0.73)
	Adj. R^2(%)	2.67%	1.46%	2.58%	3.03%	3.51%	0.89%	0.19%
3	Const.	-0.007	-0.013	-0.019	-0.026	-0.049	-0.044	-0.022
		(-1.21)	(-1.26)	(-1.15)	(-1.36)	(-1.83)	(-1.39)	(-0.61)
	vrp^d	1.752	3.970	5.227*	8.216**	19.270***	22.250***	15.378**
		(0.88)	(1.62)	(1.84)	(2.41)	(4.07)	(3.85)	(2.17)
	Adj. R^2(%)	0.35%	0.93%	0.99%	1.77%	5.49%	5.48%	2.10%
4	Const.	-0.007	-0.013	-0.019	-0.026	-0.049*	-0.044	-0.022
		(-1.26)	(-1.29)	(-1.18)	(-1.39)	(-1.84)	(-1.40)	(-0.61)
	vrp^u	4.717	4.770	8.307**	10.437**	13.737**	5.513	2.441
		(1.23)	(1.02)	(2.02)	(2.11)	(2.48)	(0.86)	(0.33)
	vrp^d	1.038	3.248	3.982	6.630**	17.153***	21.261***	14.912**
		(0.66)	(1.52)	(1.55)	(2.07)	(3.72)	(3.92)	(2.27)
	Adj. R^2(%)	2.75%	2.04%	3.12%	4.12%	7.73%	5.70%	2.07%

Note: The table shows the predictability of cumulative forward UNG returns (xm^{UNG}) which is defined as Eq.(14), by using the variance risk premium (vrp, given by Eq.(7)), the upside variance risk premium (vrp^u, given by Eq.(8)) and the downside variance risk premium (vrp^d, given by Eq.(8)). The forecasting horizon spans from 2 weeks (2w) to 12 months (12m). The t-statistics are computed according to Newey and West (1987). We use $*$, $**$ and $***$ to denote the significance level of 5%, 1% and 0.1% respectively. The daily observations range from January 2010 to August, 2017.

Table VI: Predictability of variance risk premiums II: natural gas

xm^{UNG}

		2w	1m	2m	3m	6m	9m	12m
1	Const.	-0.009*	-0.014	-0.021	-0.028	-0.046*	-0.036	-0.016
		(-1.73)	(-1.30)	(-1.28)	(-1.44)	(-1.69)	(-1.11)	(-0.44)
	vrp	2.740	3.929	5.908**	8.276**	15.415***	13.787***	9.075
		(1.09)	(1.39)	(2.11)	(2.51)	(3.75)	(2.95)	(1.64)
	Δfed	3.346	-1.892	4.082	4.662	42.711	75.962	68.651
		(0.36)	(-0.14)	(0.21)	(0.18)	(1.04)	(1.64)	(1.19)
	Δdef	12.981	-20.186	-71.012*	-118.998***	-147.309**	-74.588	5.201
		(0.71)	(-0.68)	(-1.94)	(-2.66)	(-2.18)	(-0.94)	(0.06)
	$\Delta term$	8.110*	2.572	7.365	7.854	23.103	5.973	-4.698
		(1.74)	(0.31)	(0.80)	(0.64)	(1.40)	(0.30)	(-0.21)
	Adj. R^2(%)	2.07%	1.90%	3.01%	4.39%	8.11%	4.67%	1.44%
2	Const.	-0.007	-0.013	-0.018	-0.026	-0.048*	-0.043	-0.022
		(-1.25)	(-1.28)	(-1.15)	(-1.37)	(-1.80)	(-1.36)	(-0.59)
	vrp^u	4.699	4.742	8.214**	10.298**	13.526**	5.436	2.507
		(1.22)	(1.01)	(2.00)	(2.08)	(2.45)	(0.84)	(0.34)
	vrp^d	1.054	3.230	3.922	6.530**	17.037***	21.232***	14.935**
		(0.67)	(1.51)	(1.53)	(2.05)	(3.70)	(3.91)	(2.26)
	Δfed	3.253	-1.930	4.033	4.414	42.288	72.505	66.431
		(0.34)	(-0.14)	(0.21)	(0.17)	(1.02)	(1.62)	(1.20)
	Δdef	12.964	-20.193	-71.048*	-118.986***	-147.336**	-77.021	3.083
		(0.70)	(-0.68)	(-1.91)	(-2.64)	(-2.20)	(-1.00)	(0.03)
	$\Delta term$	7.568	2.348	6.723	7.324	23.557	8.171	-2.961
		(1.58)	(0.29)	(0.73)	(0.60)	(1.43)	(0.42)	(-0.13)
	Adj. R^2(%)	2.69%	1.90%	3.22%	4.48%	8.12%	5.66%	1.90%

Note: The table shows the predictability of cumulative forward UNG returns (xm^{UNG}) which is defined as Eq.(14), by using the variance risk premium (vrp, given by Eq.(7)) with control variables such as Δfed, Δdef and $\Delta term$. It also shows the predictability of the upside variance risk premium (vrp^u, given by Eq.(8)) and the downside variance risk premium (vrp^d, given by Eq.(8)) jointly with the same set of control variables. The forecasting horizon spans from 2 weeks (2w) to 12 months (12m). The t-statistics are computed according to Newey and West (1987). We use $*$, $**$ and $***$ to denote the significance level of 5%, 1% and 0.1% respectively. The daily observations range from January 2010 to August, 2017.

Table VII: Predictability of variance risk premiums I: gold

		xm^{GLD}						
		2w	1m	2m	3m	6m	9m	12m
1	Const.	6.940e-05	0.0005	-0.001	-2.640e-04	-0.005	-0.009	-0.015
		(0.03)	(0.14)	(-0.31)	(-0.05)	(-0.65)	(-0.95)	(-1.34)
	vrp	-1.112	-2.410	-7.506**	-7.950***	-16.543***	-17.755***	-24.539***
		(-0.67)	(-0.99)	(-2.04)	(-2.61)	(-4.08)	(-3.39)	(-3.73)
	Adj. R^2(%)	0.10%	0.32%	1.92%	1.46%	3.31%	2.43%	3.68%
2	Const.	2.130e-04	0.001	-2.470e-05	0.002	-4.370e-04	-0.004	-0.007
		(0.11)	(0.23)	(-0.01)	(0.30)	(-0.06)	(-0.37)	(-0.61)
	vrp^u	-3.416	-7.884	-19.691***	-18.626***	-34.212***	-32.545***	-43.134***
		(-1.11)	(-1.56)	(-4.01)	(-3.23)	(-4.38)	(-3.45)	(-3.45)
	Adj. R^2(%)	0.35%	1.01%	3.55%	2.16%	3.76%	2.16%	2.98%
3	Const.	0.002	0.001	3.740e-04	0.001	-0.003	-0.009	-0.015
		(0.21)	(0.44)	(0.07)	(0.20)	(-0.42)	(-0.86)	(-1.27)
	vrp^d	2.625	-0.754	-5.350	-7.055	-17.526***	-21.510***	-31.011***
		(-0.18)	(-0.21)	(-0.81)	(-1.48)	(-3.02)	(-2.65)	(-3.21)
	Adj. R^2(%)	-0.05%	-0.04%	0.37%	0.45%	1.55%	1.49%	2.48%
4	Const.	0.001	0.002	0.001	0.001	-0.003	-0.008	-0.014
		(0.24)	(0.47)	(0.13)	(0.25)	(-0.34)	(-0.79)	(-1.17)
	vrp^u	-3.952	-9.386*	-20.934***	-18.358***	-30.439***	-25.393**	-31.603**
		(-1.15)	(-1.65)	(-4.14)	(-2.87)	(-3.77)	(-2.42)	(-2.42)
	vrp^d	0.926	2.596	2.146	-0.463	-6.485	-12.211	-19.454*
		(0.32)	(0.66)	(0.30)	(-0.09)	(-1.10)	(-1.37)	(-1.97)
	Adj. R^2(%)	0.32%	1.10%	3.55%	2.10%	3.88%	2.49%	3.70%

Note: The table shows the predictability of cumulative forward GLD returns (xm^{GLD}) which is defined as Eq.(14), by using the variance risk premium (vrp, given by Eq.(7)), the upside variance risk premium (vrp^u, given by Eq.(8)) and the downside variance risk premium (vrp^d, given by Eq.(8)). The forecasting horizon spans from 2 weeks (2w) to 12 months (12m). The t-statistics are computed according to Newey and West (1987). We use $*$, $**$ and $***$ to denote the significance level of 5%, 1% and 0.1% respectively. The daily observations range from January 2010 to August, 2017.

Table VIII: Predictability of variance risk premiums II: gold

		xm^{GLD}						
		2w	1m	2m	3m	6m	9m	12m
1	Const.	-1.260e-05	3.950e-04	-0.002	-3.970e-04	-0.005	-0.009	-0.016
		(-0.01)	(0.12)	(-0.32)	(-0.07)	(-0.66)	(-0.95)	(-1.36)
	vrp	-1.036	-2.326	-7.486**	-8.014***	-16.343***	-17.394***	-24.409***
		(-0.63)	(-0.95)	(-2.03)	(-2.63)	(-4.07)	(-3.31)	(-3.71)
	Δfed	0.281	1.635	2.778	4.041	-2.326	-10.607	-24.453
		(0.09)	(0.33)	(0.47)	(0.55)	(-0.20)	(-0.66)	(-1.24)
	Δdef	-6.136	-5.016	-8.034	-17.269*	-0.644	14.333	2.470
		(-1.22)	(-0.66)	(-0.92)	(-1.66)	(-0.04)	(0.67)	(0.10)
	$\Delta term$	-6.734***	-6.340***	-5.548**	-7.698**	-8.391*	-6.285	-5.437
		(-4.11)	(-2.78)	(-2.00)	(-2.54)	(-1.70)	(-0.95)	(-0.74)
	Adj. R^2(%)	1.13%	0.66%	1.99%	1.69%	3.29%	2.34%	3.56%
2	Const.	4.320e-04	0.001	0.001	0.001	-0.003	-0.008	-0.014
		(0.20)	(0.45)	(0.11)	(0.23)	(-0.34)	(-0.79)	(-1.19)
	vrp^u	-3.858	-9.289	-20.867***	-18.316***	-30.290***	-25.185**	-31.509**
		(-1.12)	(-1.62)	(-4.11)	(-2.85)	(-3.75)	(-2.39)	(-2.41)
	vrp^d	0.998	2.692	2.172	-0.570	-6.203	-11.710	-19.273*
		(0.35)	(0.69)	(0.30)	(-0.11)	(-1.05)	(-1.31)	(-1.95)
	Δfed	0.300	1.680	2.883	4.167	-2.171	-10.221	-24.374
		(0.10)	(0.34)	(0.49)	(0.57)	(-0.19)	(-0.64)	(-1.25)
	Δdef	-5.841	-4.290	-6.605	-16.174	0.816	15.206	3.290
		(-1.17)	(-0.59)	(-0.77)	(-1.61)	(0.05)	(0.72)	(0.14)
	$\Delta term$	-6.752***	-6.383***	-5.631**	-7.770***	-8.547*	-6.390	-5.506
		(-4.13)	(-2.82)	(-2.05)	(-2.58)	(-1.74)	(-0.97)	(-0.75)
	Adj. R^2(%)	1.35%	1.45%	3.61%	2.31%	3.86%	2.40%	3.58%

Note: The table shows the predictability of cumulative forward GLD returns (xm^{GLD}) which is defined as Eq.(14), by using the variance risk premium (vrp, given by Eq.(7)) with control variables such as Δfed, Δdef and $\Delta term$. It also shows the predictability of the upside variance risk premium (vrp^u, given by Eq.(8)) and the downside variance risk premium (vrp^d, given by Eq.(8)) jointly with the same set of control variables. The forecasting horizon spans from 2 weeks (2w) to 12 months (12m). The t-statistics are computed according to Newey and West (1987). We use $*$, $**$ and $***$ to denote the significance level of 5%, 1% and 0.1% respectively. The daily observations range from January 2010 to August, 2017.

Table IX: Predictability of variance risk premiums I: silver

		xm^{SLV}						
		2w	1m	2m	3m	6m	9m	12m
1	Const.	0.002	0.001	-0.002	-1.390e-03	-0.009	-0.014	-0.029
		(0.52)	(0.18)	(-0.21)	(-0.14)	(-0.59)	(-0.66)	(-1.18)
	vrp	0.968	-0.184	-1.517	-0.606	-3.956**	-1.496	-1.028
		(1.38)	(-0.19)	(-1.06)	(-0.39)	(-2.12)	(-0.64)	(-0.37)
	Adj. R^2(%)	0.51%	-0.05%	0.27%	-0.03%	0.67%	-0.002%	-0.04%
2	Const.	0.001	0.001	-7.920e-04	-0.001	-6.592e-03	-0.013	-0.029
		(0.32)	(0.19)	(-0.10)	(-0.10)	(-0.43)	(-0.63)	(-1.21)
	vrp^u	1.962	-0.669	-3.643	-1.727	-10.220***	-5.633	-5.909
		(1.52)	(-0.41)	(-1.35)	(-0.53)	(-2.68)	(-1.03)	(-0.93)
	Adj. R^2(%)	0.46%	-0.03%	0.37%	0.004%	1.05%	0.14%	0.11%
3	Const.	0.002	0.001	-1.337e-03	-0.001	-0.008	-0.012	-0.027
		(0.49)	(0.21)	(-0.16)	(-0.11)	(-0.51)	(-0.59)	(-1.10)
	vrp^d	1.112	-0.071	-1.474	-0.458	-3.512	-0.473	0.651
		(1.08)	(-0.05)	(-0.65)	(-0.20)	(-1.33)	(-0.14)	(0.17)
	Adj. R^2(%)	0.29%	-0.06%	0.09%	-0.05%	0.21%	-0.06%	-0.06%
4	Const.	0.002	0.001	-0.001	-0.001	-0.007	-0.012	-0.026
		(0.46)	(0.22)	(-0.13)	(-0.09)	(-0.45)	(-0.57)	(-1.06)
	vrp^u	1.549	-0.792	-3.383	-1.810	-10.040**	-6.795	-8.143
		(1.27)	(-0.47)	(-1.07)	(-0.51)	(-2.26)	(-1.01)	(-1.09)
	vrp^d	0.616	0.183	-0.388	0.123	-0.267	1.727	3.301
		(0.61)	(0.12)	(-0.14)	(0.05)	(-0.08)	(0.40)	(0.71)
	Adj. R^2(%)	0.49%	-0.09%	0.32%	-0.06%	0.99%	0.11%	0.14%

Note: The table shows the predictability of cumulative forward SLV returns (xm^{SLV}) which is defined as Eq.(14), by using the variance risk premium (vrp, given by Eq.(7)), the upside variance risk premium (vrp^u, given by Eq.(8)) and the downside variance risk premium (vrp^d, given by Eq.(8)). The forecasting horizon spans from 2 weeks (2w) to 12 months (12m). The t-statistics are computed according to Newey and West (1987). We use $*$, $**$ and $***$ to denote the significance level of 5%, 1% and 0.1% respectively. The daily observations range from January 2010 to August, 2017.

Table X: Predictability of variance risk premiums II: silver

		xm^{SLV}						
		2w	1m	2m	3m	6m	9m	12m
1	Const.	0.002	0.001	-0.002	-0.002	-0.009	-0.014	-0.030
		(0.48)	(0.16)	(-0.22)	(-0.16)	(-0.61)	(-0.68)	(-1.21)
	vrp	0.931	-0.245	-1.623	-0.755	-3.956**	-1.379	-0.891
		(1.34)	(-0.25)	(-1.14)	(-0.49)	(-2.12)	(-0.60)	(-0.33)
	Δfed	-2.571	-2.116	-1.657	-4.264	-17.381	-32.206	-44.881
		(-0.50)	(-0.30)	(-0.19)	(-0.35)	(-0.80)	(-0.88)	(-0.93)
	Δdef	-17.838*	-22.091	-35.271*	-52.426**	-7.005	32.216	42.148
		(-1.69)	(-1.44)	(-1.84)	(-2.25)	(-0.20)	(0.65)	(0.84)
	$\Delta term$	-5.914**	-1.974	0.312	-2.659	-10.091	-13.576	-11.911
		(-2.31)	(-0.49)	(0.05)	(-0.40)	(-0.92)	(-0.94)	(-0.77)
	Adj. R^2(%)	0.86%	-0.03%	0.35%	0.18%	0.56%	-0.07%	-0.12%
2	Const.	0.001	0.001	-0.001	-0.001	-0.007	-0.012	-0.027
		(0.43)	(0.20)	(-0.14)	(-0.11)	(-0.47)	(-0.59)	(-1.09)
	vrp^u	1.466	-0.907	-3.573	-2.085	-10.092**	-6.649	-7.955
		(1.21)	(-0.54)	(-1.13)	(-0.58)	(-2.26)	(-0.99)	(-1.06)
	vrp^d	0.608	0.155	-0.446	0.048	-0.247	1.819	3.394
		(0.61)	(0.10)	(-0.17)	(0.02)	(-0.08)	(0.42)	(0.74)
	Δfed	-2.523	-2.175	-1.823	-4.359	-17.837	-32.256	-45.323
		(-0.49)	(-0.31)	(-0.21)	(-0.35)	(-0.82)	(-0.88)	(-0.93)
	Δdef	-17.654*	-22.320	-35.936*	-52.880**	-9.149	30.407	39.416
		(-1.66)	(-1.45)	(-1.92)	(-2.28)	(-0.26)	(0.62)	(0.79)
	$\Delta term$	-5.907**	-1.983	0.283	-2.684	-10.258	-13.791	-12.159
		(-2.31)	(-0.50)	(0.05)	(-0.40)	(-0.92)	(-0.96)	(-0.78)
	Adj. R^2(%)	0.84%	-0.06%	0.40%	0.15%	0.88%	0.04%	0.05%

Note: The table shows the predictability of cumulative forward SLV returns (xm^{SLV}) which is defined as Eq.(14), by using the variance risk premium (vrp, given by Eq.(7)) with control variables such as Δfed, Δdef and $\Delta term$. It also shows the predictability of the upside variance risk premium (vrp^u, given by Eq.(8)) and the downside variance risk premium (vrp^d, given by Eq.(8)) jointly with the same set of control variables. The forecasting horizon spans from 2 weeks (2w) to 12 months (12m). The t-statistics are computed according to Newey and West (1987). We use $*$, $**$ and $***$ to denote the significance level of 5%, 1% and 0.1% respectively. The daily observations range from January 2010 to August, 2017.

Table XI: Predictability of signed jump risk premium: crude oil

		xm^{USO}						
		2w	1m	2m	3m	6m	9m	12m
1	Const.	-0.010**	-0.021***	-0.042***	-0.058***	-0.102***	-0.143***	-0.212***
		(-2.42)	(-2.94)	(-4.10)	(-4.58)	(-5.43)	(-6.48)	(-7.60)
	$sjrp$	1.871	3.860**	6.885***	6.532**	2.769	0.148	8.026
		(1.59)	(1.96)	(2.82)	(2.09)	(0.64)	(0.02)	(1.04)
	Adj. R^2(%)	0.73%	1.45%	2.17%	1.28%	0.07%	-0.07%	0.48%
2	Const.	-0.010**	-0.021***	-0.042***	-0.058***	-0.102***	-0.142***	-0.212***
		(-2.40)	(-2.92)	(-4.09)	(-4.59)	(-5.45)	(-6.49)	(-7.61)
	$sjrp$	1.834	3.799**	6.833***	6.422**	2.633	-0.022	7.844
		(1.56)	(1.93)	(2.80)	(2.06)	(0.61)	(0.00)	(1.01)
	Δfed	-5.236	-4.125	2.318	-15.527	-25.507	-19.183	-34.025
		(-0.76)	(-0.42)	(0.22)	(-1.19)	(-1.38)	(-0.68)	(-0.91)
	Δdef	-2.035	-10.288	-10.600	-26.983	-34.292	-54.675	-31.189
		(-0.20)	(-0.71)	(-0.53)	(-1.11)	(-1.06)	(-1.41)	(-0.66)
	$\Delta term$	11.403***	13.644***	12.508**	7.783	7.510	1.099	9.108
		(4.28)	(3.36)	(2.26)	(1.13)	(0.81)	(0.10)	(0.66)
	Adj. R^2(%)	1.49%	1.91%	2.24%	1.28%	0.03%	-0.12%	0.35%

Note: The table shows the predictability of cumulative forward USO returns (xm^{USO}) which is defined as Eq.(14), by using the the signed jump risk premium ($sjrp$, given by Eq.(9)) alone, and the signed jump risk premium with control variables such as Δfed, Δdef and $\Delta term$. The forecasting horizon spans from 2 weeks (2w) to 12 months (12m). The t-statistics are computed according to Newey and West (1987). We use $*$, $**$ and $***$ to denote the significance level of 5%, 1% and 0.1% respectively. The daily observations range from January 2010 to August, 2017.

Table XII: Predictability of signed jump risk premium: natural gas

		xm^{UNG}						
		2w	1m	2m	3m	6m	9m	12m
1	Const.	-0.003	-0.007	-0.009	-0.013	-0.027	-0.026	-0.011
		(-0.30)	(-0.54)	(-0.55)	(-0.65)	(-0.98)	(-0.80)	(-0.29)
	$sjrp$	1.542	0.346	1.530	1.036	-3.339	-8.986**	-6.969*
		(1.20)	(0.17)	(0.82)	(0.43)	(-1.12)	(-2.52)	(-1.69)
	Adj. R^2(%)	0.43%	-0.05%	0.08%	-0.02%	0.19%	1.30%	0.59%
2	Const.	-0.002	-0.007	-0.009	-0.013	-0.026	-0.025	-0.010
		(-0.29)	(-0.53)	(-0.54)	(-0.63)	(-0.95)	(-0.76)	(-0.28)
	$sjrp$	1.523	0.341	1.518	1.024	-3.379	-9.023**	-6.963*
		(1.19)	(0.17)	(0.82)	(0.42)	(-1.14)	(-2.54)	(-1.69)
	Δfed	2.922	-2.389	3.431	2.170	31.075	59.684	54.416
		(0.30)	(-0.18)	(0.18)	(0.09)	(0.77)	(1.31)	(1.02)
	Δdef	8.843	-25.904	-79.664**	-130.676***	-168.369**	-94.805	-10.356
		(0.56)	(-0.90)	(-2.19)	(-2.94)	(-2.53)	(-1.23)	(-0.11)
	$\Delta term$	8.442*	3.558	8.530	9.866	28.772*	12.656	-0.144
		(1.85)	(0.45)	(0.94)	(0.80)	(1.69)	(0.64)	(-0.01)
	Adj. R^2(%)	0.37%	-0.17%	0.26%	0.45%	0.74%	1.30%	0.41%

Note: The table shows the predictability of cumulative forward UNG returns (xm^{UNG}) which is defined as Eq.(14), by using the the signed jump risk premium ($sjrp$, given by Eq.(9)) alone, and the signed jump risk premium with control variables such as Δfed, Δdef and $\Delta term$. The forecasting horizon spans from 2 weeks (2w) to 12 months (12m). The t-statistics are computed according to Newey and West (1987). We use $*$, $**$ and $***$ to denote the significance level of 5%, 1% and 0.1% respectively. The daily observations range from January 2010 to August, 2017.

Table XIII: Predictability of signed jump risk premium: gold

		xm^{GLD}						
		2w	1m	2m	3m	6m	9m	12m
1	Const.	0.001	0.003	0.005	0.005	0.005	2.770e-04	-0.003
		(0.56)	(0.93)	(0.89)	(0.94)	(0.63)	(0.03)	(-0.27)
	$sjrp$	-1.797	-4.551	-7.561	-4.961	-4.235	1.302	4.967
		(-0.70)	(-1.19)	(-1.15)	(-0.92)	(-0.65)	(0.15)	(0.57)
	Adj. R^2(%)	0.10%	0.46%	0.72%	0.17%	0.02%	-0.06%	-0.01%
2	Const.	0.001	0.003	0.005	0.005	0.005	1.580e-04	-0.004
		(0.51)	(0.91)	(0.88)	(0.93)	(0.62)	(0.02)	(-0.29)
	$sjrp$	-1.835	-4.623	-7.650	-4.964	-4.577	0.811	4.585
		(-0.72)	(-1.22)	(-1.16)	(-0.92)	(-0.70)	(0.09)	(0.52)
	Δfed	0.303	1.688	2.898	4.236	-1.036	-9.429	-21.644
		(0.10)	(0.35)	(0.50)	(0.57)	(-0.09)	(-0.57)	(-1.06)
	Δdef	-4.981	-2.307	-0.976	-10.463	12.058	26.526	19.454
		(-1.01)	(-0.33)	(-0.12)	(-1.02)	(0.75)	(1.21)	(0.77)
	$\Delta term$	-6.912***	-6.752***	-6.678**	-8.836***	-10.638**	-8.575	-8.610
		(-4.05)	(-2.88)	(-2.42)	(-2.91)	(-2.11)	(-1.30)	(-1.14)
	Adj. R^2(%)	1.16%	0.85%	0.84%	0.39%	0.13%	-0.03%	-0.05%

Note: The table shows the predictability of cumulative forward GLD returns (xm^{GLD}) which is defined as Eq.(14), by using the the signed jump risk premium ($sjrp$, given by Eq.(9)) alone, and the signed jump risk premium with control variables such as Δfed, Δdef and $\Delta term$. The forecasting horizon spans from 2 weeks (2w) to 12 months (12m). The t-statistics are computed according to Newey and West (1987). We use $*$, $**$ and $***$ to denote the significance level of 5%, 1% and 0.1% respectively. The daily observations range from January 2010 to August, 2017.

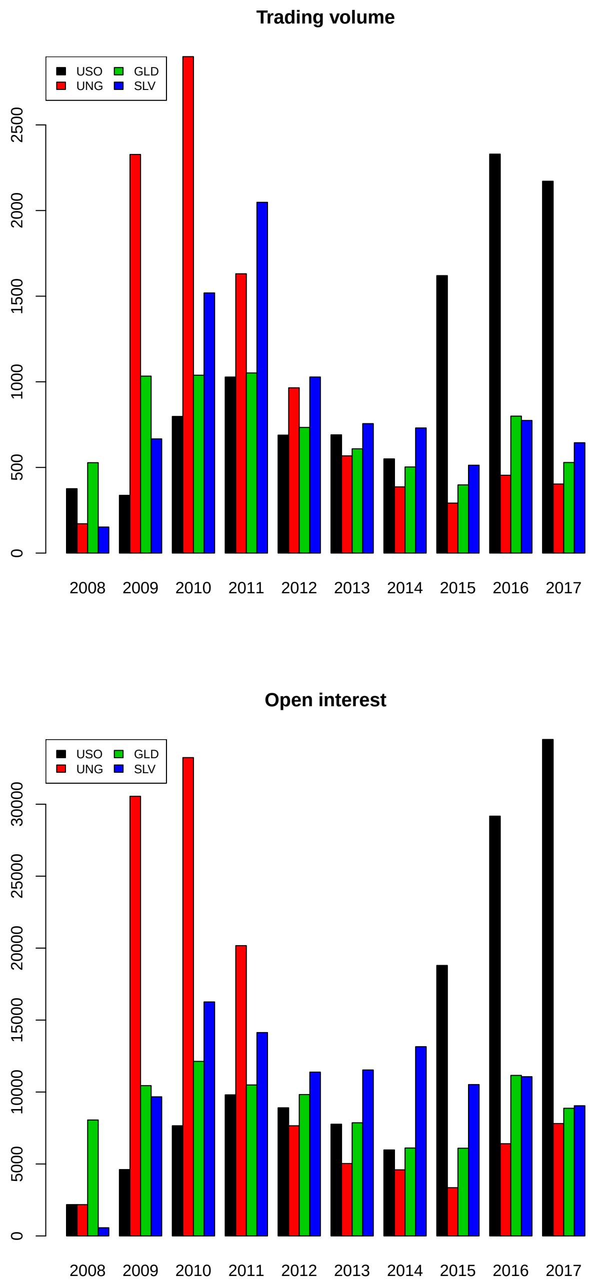
Table XIV: Predictability of signed jump risk premium: silver

		xm^{SLV}						
		2w	1m	2m	3m	6m	9m	12m
1	Const.	0.001	0.001	2.060e-04	-4.050e-04	-0.003	-0.010	-0.024
		(0.24)	(0.25)	(0.02)	(-0.04)	(-0.21)	(-0.47)	(-0.99)
	$sjrp$	-0.209	-0.297	-0.321	-0.440	-1.660	-2.683	-4.207
		(-0.23)	(-0.21)	(-0.12)	(-0.18)	(-0.52)	(-0.60)	(-0.88)
	Adj. R^2(%)	-0.05%	-0.05%	-0.06%	-0.05%	-0.01%	0.02%	0.09%
2	Const.	0.001	0.001	2.080e-04	-4.540e-04	-0.004	-0.010	-0.025
		(0.21)	(0.24)	(0.02)	(-0.04)	(-0.23)	(-0.50)	(-1.02)
	$sjrp$	-0.217	-0.297	-0.312	-0.432	-1.692	-2.734	-4.250
		(-0.24)	(-0.21)	(-0.12)	(-0.18)	(-0.53)	(-0.61)	(-0.89)
	Δfed	-2.664	-2.124	-1.559	-4.199	-16.051	-31.375	-44.345
		(-0.52)	(-0.30)	(-0.18)	(-0.34)	(-0.74)	(-0.86)	(-0.92)
	Δdef	-19.732*	-21.565	-31.908*	-50.837**	1.370	35.264	44.331
		(-1.78)	(-1.42)	(-1.69)	(-2.20)	(0.04)	(0.71)	(0.88)
	$\Delta term$	-5.736**	-2.045	-0.045	-2.849	-11.112	-14.167	-12.490
		(-2.24)	(-0.51)	(-0.01)	(-0.43)	(-1.01)	(-0.98)	(-0.80)
	Adj. R^2(%)	0.35%	-0.03%	-0.03%	0.13%	-0.12%	-0.04%	0.02%

Note: The table shows the predictability of cumulative forward SLV returns (xm^{SLV}) which is defined as Eq.(14), by using the the signed jump risk premium ($sjrp$, given by Eq.(9)) alone, and the signed jump risk premium with control variables such as Δfed, Δdef and $\Delta term$. The forecasting horizon spans from 2 weeks (2w) to 12 months (12m). The t-statistics are computed according to Newey and West (1987). We use $*$, $**$ and $***$ to denote the significance level of 5%, 1% and 0.1% respectively. The daily observations range from January 2010 to August, 2017.

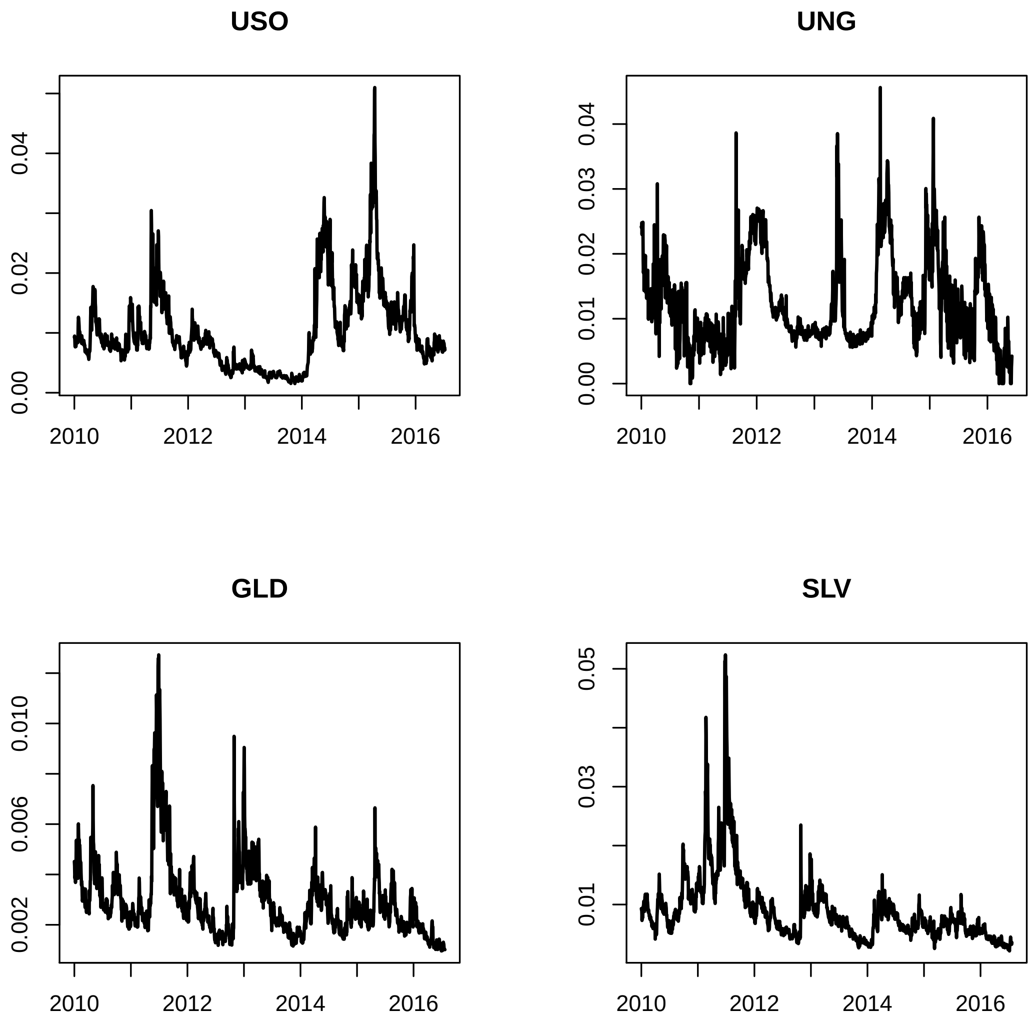
B Figures

Figure 1: Trading volume and open interest of commodity options



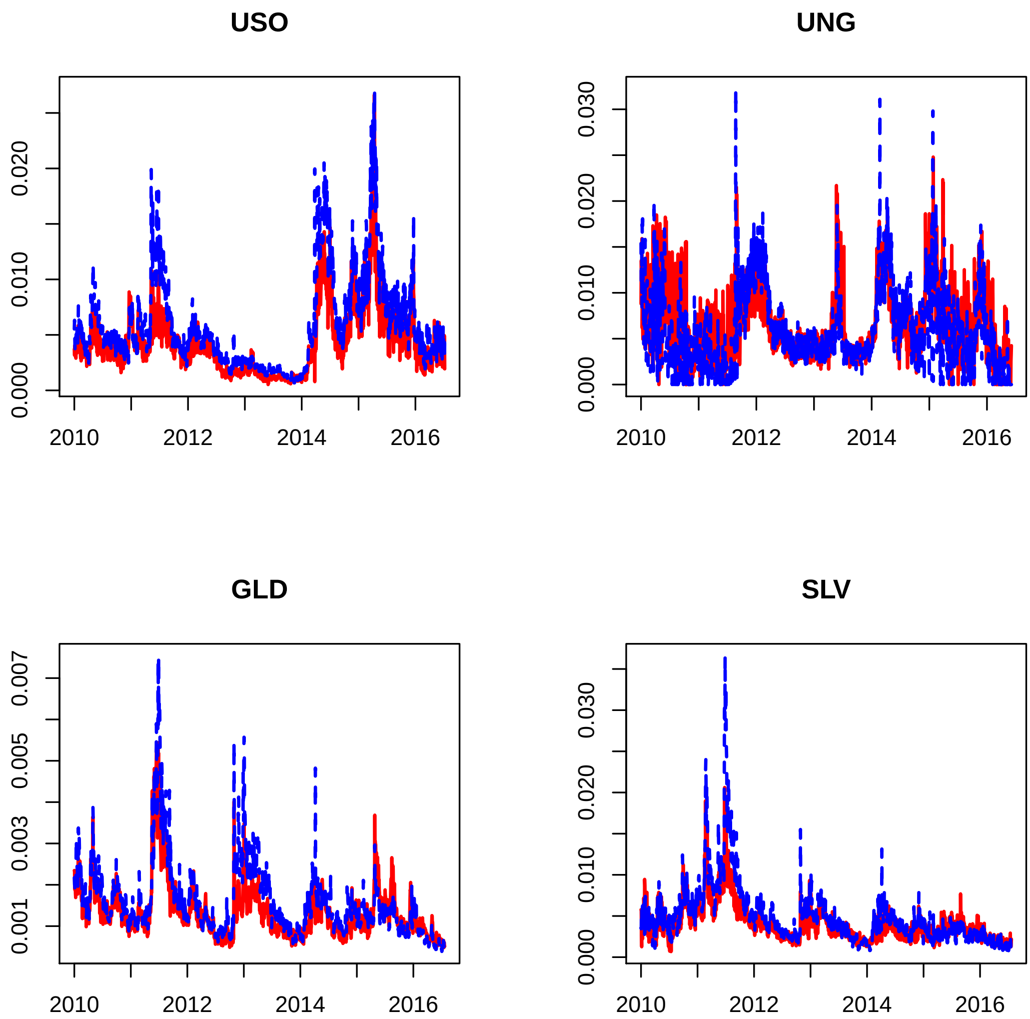
Note: The above histogram shows the trading volumes of the four commodity ETF options from 2008 to 2017. And the below histogram shows their open interests of the same period.

Figure 2: Evolution of total risk neutral variance



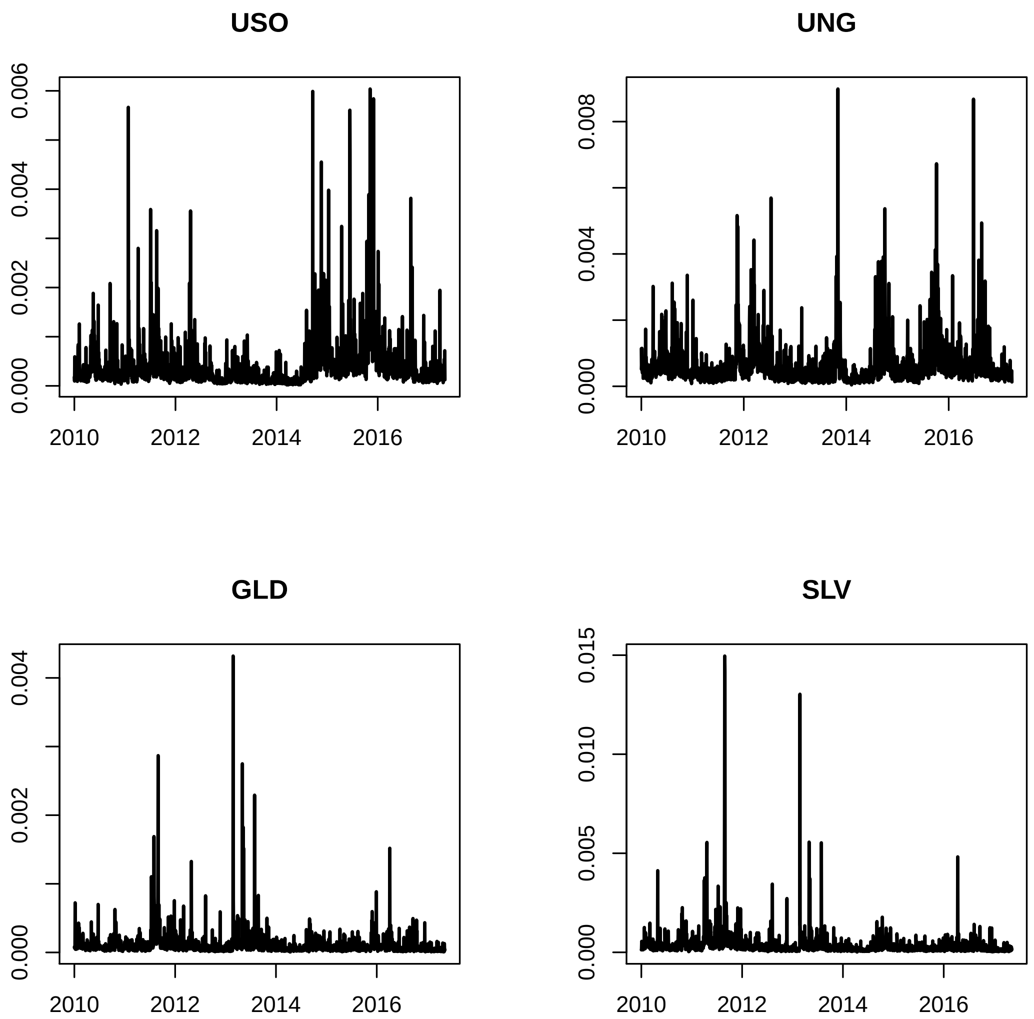
Note: The figure shows the evolution of total neutral variance (iv, given by Eq.(1)) of four commodity markets, namely USO (crude oil ETF), UNG (natural gas ETF), GLD (gold ETF) and SLV (silver ETF), from January 2010 to August, 2017.

Figure 3: Evolution of upside and downside risk neutral variances



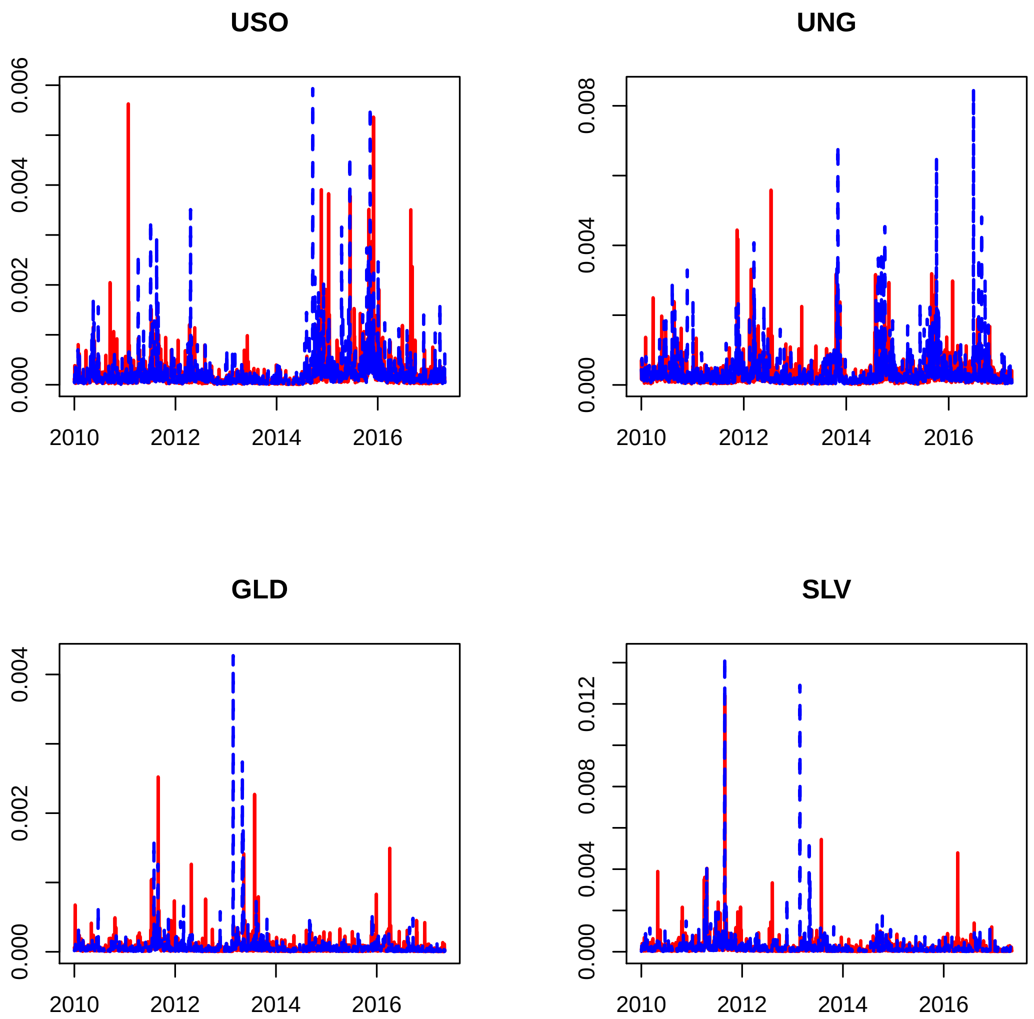
Note: The figure shows the evolution of upside risk neutral variance (iv^u, plotted in red solid line, given by Eq.(2)) and downside risk neutral variance (iv^d, plotted in blue dashed line, given by Eq.(2)) of four commodity markets, namely USO (crude oil ETF), UNG (natural gas ETF), GLD (gold ETF) and SLV (silver ETF), from January 2010 to August, 2017.

Figure 4: Evolution of total realized variance



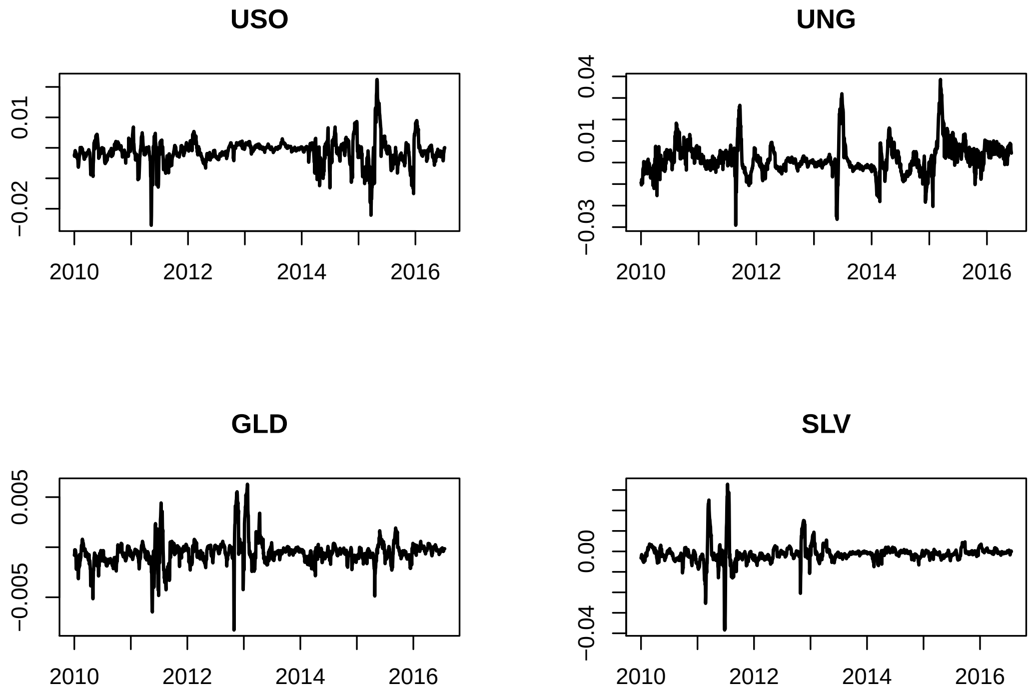
Note: The figure shows the evolution of total realized variance (rv, given by Eq.(5)) of four commodity markets, namely USO (crude oil ETF), UNG (natural gas ETF), GLD (gold ETF) and SLV (silver ETF), from January 2010 to August, 2017.

Figure 5: Evolution of upside and downside realized variances



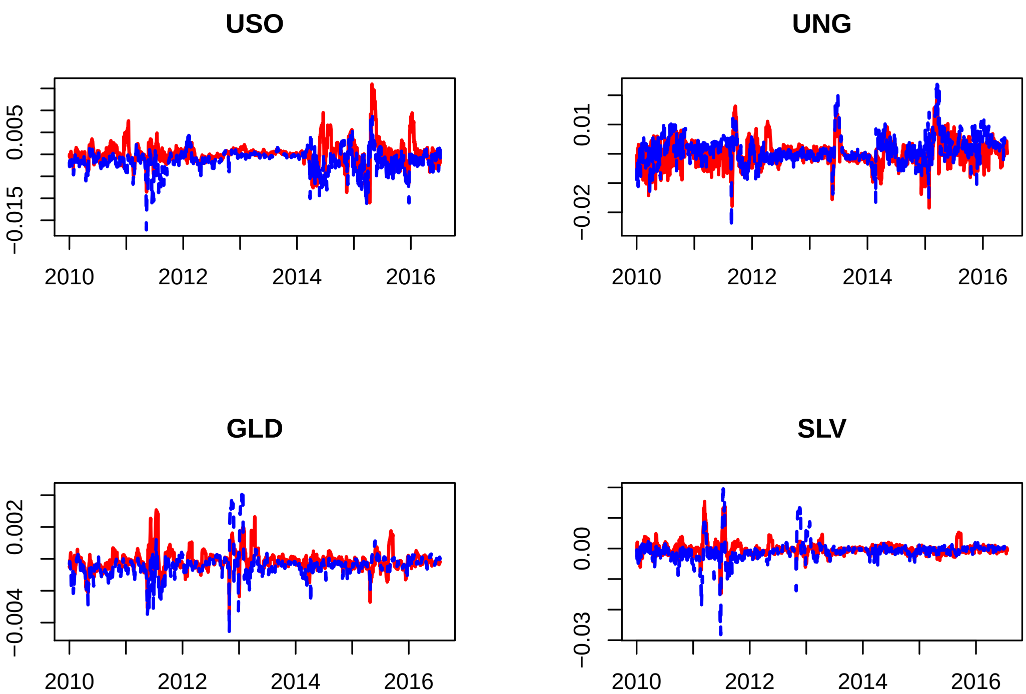
Note: The figure shows the evolution of upside realized variance (rv^u, plotted in red solid line, given by Eq.(6)) and downside realized variance (rv^d, plotted in blue dashed line, given by Eq.(6)) of four commodity markets, namely USO (crude oil ETF), UNG (natural gas ETF), GLD (gold ETF) and SLV (silver ETF), from January 2010 to August, 2017.

Figure 6: Evolution of total variance risk premium



Note: The figure shows the evolution of total variance risk premium (vrp, given by Eq.(7)) of four commodity markets, namely USO (crude oil ETF), UNG (natural gas ETF), GLD (gold ETF) and SLV (silver ETF), from January 2010 to August, 2017.

Figure 7: Evolution of upside and downside variance risk premiums



Note: The figure shows the evolution of upside variance risk premium (vrp^u, plotted in red solid line, given by Eq.(8)) and downside realized variance (vrp^d, plotted in blue dashed line, given by Eq.(8)) of four commodity markets, namely USO (crude oil ETF), UNG (natural gas ETF), GLD (gold ETF) and SLV (silver ETF), from January 2010 to August, 2017.