News-based Equity Market Uncertainty and Crude Oil Volatility

Author(s): Dutta, Anupam; Bouri, Elie; Saeed, Tareq

Title: News-based Equity Market Uncertainty and Crude Oil Volatility

Year: 2021

Version: Accepted manuscript

Please cite the original version:

Dutta, A., Bouri, E. & Saeed, T. (2021). News-based Equity Market Uncertainty and Crude Oil Volatility. *Energy*. https://doi.org/10.1016/j.energy.2021.119930

News-based Equity Market Uncertainty and Crude Oil Volatility

Anupam Dutta

School of Accounting and Finance, University of Vaasa, Vaasa, Finland

Email: adutta@uwasa.fi

Elie Bouri

Adnan Kassar School of Business, Lebanese American University, Lebanon

Email: elie.elbouri@lau.edu.lb

Tareq Saeed

Nonlinear Analysis and Applied Mathematics (NAAM)-Research Group, Department of Mathematics, Faculty of Science, King Abdulaziz University, Jeddah, Saudi Arabia. Email: tsalmalki@kau.edu.sa

News-based Equity Market Uncertainty and Crude Oil Volatility

Abstract

Previous studies indicate that the US equity market implied volatility index (VIX) impacts the crude oil market volatility. However, the VIX typically reflects macroeconomic fluctuations, little affected by social media or investor perception changes. In this paper, we use recently introduced news-based equity market volatility (EMV) trackers to examine their impacts on crude oil volatility in its various states and their ability to predict oil volatility relative to that of the VIX. Applying quantile regressions, the results indicate a significant impact of EMV trackers on the oil market volatility during periods of high oil volatility, whereas the impact is mostly insignificant when the oil market is less volatile, which points to an asymmetry. Further analysis shows that various EMV trackers (EMV-overall, EMV-commodity, EMV-crises) have better forecasting power than VIX, economic policy uncertainty (EPU) and geopolitical risk (GPR) indexes. Our findings are relevant to asset pricing, oil portfolio formation, and risk management.

Keywords: US News-based equity market uncertainty (EMV); Crude oil volatility (OVX); VIX; oil volatility; Risk spillover; Quantiles

1. Introduction

Being one of the most important production inputs and a strategic commodity, crude oil plays a pivotal role in global economic development and international financial markets (e.g., Shi and Variam, 2017; Ji et al., 2018). Large swings in the prices of crude oil can induce huge losses to investors and serious concern for the economy and policymakers. On the one hand, uncertainty about crude oil prices has a significant impact on economic activity (Van Eyden et al., 2019) and can adversely shape current investment (Bernanke, 1983), which matters for regulatory and policy formulation. On the other hand, uncertainty about oil prices is closely linked to financial markets and investor sentiment (Bouri et al., 2018; Ji et al., 2018; Zhang and Li, 2019), which matters to the decision-making of investors. Furthermore, oil price volatility affects derivatives pricing, oil portfolio formation, hedging effectiveness, and risk measures such as the value at risk and the expected shortfall. Therefore, investors and policymakers are very keen to acquire precise knowledge of oil volatility and its forecasting (Manickavasagam et al., 2020).

The existing literature often relates uncertainty to oil price volatility (e.g., Liu et al., 2013; Reboredo and Uddin, 2016). Earlier studies indicate that the US equity market implied volatility index (henceforth, VIX) impacts the variance of crude oil prices (Liu et al., 2013; Dutta et al., 2017). They show that the oil market is closely linked with equity markets (e.g., Wang et al., 2018), which makes oil volatility influenced by equity market conditions (Liu et al., 2013; Tiwari et al., 2020). On the one hand, the VIX typically reflects macroeconomic fluctuations, little affected by social media or investor perception changes (Su at al., 2017; Mo et al., 2019; Zhu et al., 2019)[1].

[1] As Zhu et al. (2019) mention, the VIX 'is derived from option prices that can reflect the option market participants' expectation on future market volatility or risk, while various EMV trackers are basically calculated by counting the word frequencies of several specific keywords related to stock market volatility or risk appeared in newspapers published in present month. Thus, EMV can be considered as the public attention on future market volatility'.

Zhu et al. (2019) makes a breakthrough by providing evidence that equity market volatility (EMV) outperforms the US VIX in forecasting the volatility of US stock returns. However, this recently introduced text-based volatility measure, EMV, has not received much attention in the existing literature, although it includes an overall EMV tracker and various category-specific EMV trackers, such EMV-commodity, and EMV-crises, and seeks to capture the economic and financial uncertainty related to the US stock market (Baker et al., 2019). Only a few studies use this index for forecasting the volatility of US stock prices (Zhu et al., 2019; Alqahtani et al., 2020) and the impact of this EMV index on oil price volatility remains under-researched. On the other hand, the quest for a precise knowledge of oil price volatility such has been so far limited to the use of mean-based estimators that do not account for the fact that crude oil prices tend to react differently to diverse market conditions (i.e., bearish, normal and bullish states). This issue is important because the volatility of the crude oil market might exhibit a low or a high volatility regime, and thus considering one volatility regime in examining the impact of equity market uncertainty on the volatility of crude oil may lead to spurious results. For example, Choi and Hammoudeh (2010) claim that oil prices usually see an upturn during bullish stock market periods, whereas Balcilar et al. (2017) show that uncertainty variables exhibit asymmetric ability to predict oil returns and volatility under various conditions in the crude oil market.

Considering the above discussion and research gap, the purpose of this paper is to examine the impact of three EMV trackers (EMV-overall, EMV-commodity, and EMV-crises), recently constructed by Baker et al. (2019), on the volatility of crude oil prices under various conditions of oil volatility. We also assess the predictive power of those EMV trackers on oil volatility and compare it to that of the VIX, economic policy uncertainty (EPU), and geopolitical risk (GPR) indexes.

We contribute to the existing literature in several aspects. Firstly, this is the first study to examine the impacts of several EMV trackers on oil volatility and assess their ability to predict oil volatility relative to that of the VIX. The information on EMV trackers could be constructive as they tend to outperform other similar indexes such as the news implied volatility index (NVIX) (Baker et al., 2019) and use a much larger text corpus than the VIX. This nicely complements recent studies such as Zhu et al. (2019), which show that EMV outperforms the VIX in predicting the US equity market volatility without paying attention to the role of the EMV in the volatility of the oil market. Secondly, unlike previous studies focusing on the influence of macroeconomic and geopolitical risks on crude oil returns (Wei et al., 2017; Liu et al., 2019; Mei et al., 2020), we uncover the impact of the news-based equity market volatility on oil volatility. Notably, we use three alternative measures of oil market volatility: GARCH-based conditional volatility, range-based realized volatility (RV) and the oil price implied volatility index (henceforth, OVX). The use of a wide range of volatility measures could yield robust and reliable results while capturing the effects of stock market uncertainty on oil price volatility, which adds to Mei et al. (2020) and Liang et al. (2020). Thirdly, we estimate the impacts of EMV trackers on oil volatility during low, moderate, and high volatility states and make inferences about potential asymmetry (Xiao et al., 2018; Dawar et al., 2021), which extends previous studies that generally apply mean based models and avoid the asymmetric effect (e.g., Dutta et al., 2017; Wei et al., 2017; Liang et al., 2020; Mei et al., 2020). Our last contribution is based on the empirical findings. While earlier literature shows that VIX, EPU and GPR indexes are among the key determinants of crude oil volatility, our analysis indicates that EMV-trackers have better predictive power for oil volatility when compared to these indexes. This finding could be attributed to the fact that VIX index is mainly focused on the macroeconomic fluctuations, ignoring the vital role of public media and investor attentions, which is more flexible and timely than the economic data. Baker et al. (2019) also argue that unlike EPU and the GPR indexes, EMV-trackers capture people's perception on future uncertainty and make use of a much larger text corpus.

Our investigation plays a crucial role in risk analysis given that what matters for both market participants and policymakers is not market price variation per se, but its unpredictability and the resultant risks to producers, traders, consumers, and government agents. Given that precise estimates of oil price volatility are crucial to portfolio modelling and risk management, this study has important implications for oil market participants.

The rest of the paper is structured in the following fashion. The next section briefly reviews the related studies. Section 3 describes the dataset. The section that follows outlines the methodology. The results are presented and discussed in Section 5. We conclude the paper in Section 6.

2. Related studies

Over the past few years, a growing body of literature has used various news-based uncertainty indexes to measure the impact of macroeconomic risks on crude oil prices. Bekiros et al. (2015) provide evidence that information on US economic policy uncertainty can effectively predict variations in WTI oil prices. Using the GARCH-MIDAS approach, Wei et al. (2017) conclude that both the global EPU and US EPU indexes have certain predictive powers for the volatility of WTI oil spot prices. Su et al. (2018) use the NVIX, proposed by Manela and Moreira (2017), to observe the impact of news-based uncertainty on crude oil price changes. They report that the oil market is sensitive to fluctuations in the NVIX. Bakas and Triantafyllou (2019) also show that EPU and the NVIX are able to forecast the volatility of crude oil prices. Yang (2019) investigates the linkage between US EPU and crude oil prices across time scales. Using both WTI and Brent oil prices, Yang (2019) finds that EPU impacts both indexes, irrespective of the time scale, although the author shows that Brent prices are more influenced by EPU than the WTI index. Sun et al. (2020) employ the wavelet coherence model and scale-by-scale linear Granger causality tests to examine the relationship between EPU and oil prices for a group of countries (Canada, France, Germany, Italy, Japan, the United Kingdom, the United States, China, Brazil and Russia). Their results indicate a weak short-term linkage between EPU indexes and oil price changes. Sun et al. (2020), however, show that such an association is strengthened in the long-term. Qin et al. (2020) adopt the wavelet framework and document that oil prices react significantly to changes in US EPU. Moreover, Gao et al. (2020) consider the connectedness between EPU and the oil, gold, and stock markets in China. Using static and time-varying connectedness approaches, they report evidence that the volatility of the EPU index has a weak effect on the volatility of oil prices and that the global financial crisis can shape the dynamics of connectedness between EPU and the three markets under study. A recent study by Lyu et al. (2021) explores the effects of economic uncertainty shocks on the commodity market in China, highlighting the importance of using a local EPU index based on multiple Chinese newspapers. Besides, Liang et al. (2020) examine the ability of various economic uncertainty indices to predict the volatility of the crude oil market. Using standard regressions and shrinkage methods, they show the significant predictive power of both global economic policy uncertainty (GEPU) and US equity market volatility. Hailemariam et al. (2019) document a time-varying association between EPU and crude oil volatility. Additionally, Dutta et al. (2020) conclude that both oil market uncertainty and VIX play a pivotal role in forecasting crude oil volatility.

Another strand of literature explores the predictive power of the GPR index on crude oil price movements. Antonakakis et al. (2017) find that GPR has a negative impact on crude oil returns.

Employing the GARCH-MIDAS model, Liu et al. (2019) show that fluctuations in crude oil prices can be explained by geopolitical risk. Using a similar model, Mei et al. (2020) show that the information in the GPR index is useful for the prediction of oil market risk. In a similar line of research, Li et al. (2020) use GARCH-based models and show that uncertainty indices such as global and US EPUs, GPR, US monetary policy uncertainty, and equity market volatility contain predictive power oil price volatility. They notably show that EPU and monetary policy uncertainty indices contain useful information capable of predicting high oil volatility whereas equity market volatility. Additionally, Tiwari et al. (2020) report that GPR has a negative impact on WTI oil prices. Table 1 summarizes some recent studies on the effect of news-based uncertainty indexes on the crude oil market. Based on the above review of literature and its summary in Table 1, we note a lack of evidence in regard to the impact of the newly constructed EMV indexes on the volatility of WTI oil prices, especially under various states of the oil volatility. Furthermore, the related literature remains salient regarding the information content of the EMV index in forecasting the volatility of WTI oil prices relative to the VIX. In this paper, we address these research gaps while considering a variety of oil volatility measures (GARCH-based conditional volatility, range-based RV, and OVX) under various market states of oil volatility (low, moderate, and high). We also examine the volatility forecasting performance and conduct a robustness analysis.

3. Data

The current study uses monthly data of the news-based equity market volatility (EMV) index, VIX, OVX, and WTI crude oil prices for the period January 1990 to December 2019. Our reliance on monthly data is because only monthly observations are available for the EMV index and its various categories. Baker et al. (2019) construct the EMV index to capture the economic and financial uncertainty related to the stock market, by employing a procedure similar to that used to generate the EPU index of Baker et al. (2013). Specifically, the overall EMV tracker is constructed using scaled frequency counts of eleven major US newspapers[2] articles that contain specific terms in three sets E: {economic, economy, financial}, M: {"stock market", stock OR stocks, "equity market", equity OR equities, S&P OR "S & P", "Standard and Poors" OR "Standard and Poor's" OR "Standard and Poor" OR "Standard & Poors" OR "Standard & Poor's}, and V: {volatility OR volatile, "realized volatility", uncertain OR uncertainty, risk OR risky, variance, VIX}. Baker et al. (2019) obtain monthly counts of newspaper articles that include at least one term in each of the three sets, which is then scaled, standardized for each newspaper, and then averaged on a monthly basis. Finally, Baker et al. (2019) multiplicatively rescale the averaged series to match the average of the VIX over the period 1985-2015.

As for category specific EMV trackers, they are calculated based on the share of EMV articles in each category, which is multiplied by the contemporaneous EMV tracker value. They cover term sets related to Financial crises, Commodity Markets, and Financial Regulation. In fact, 30 category-specific EMV trackers are proposed. Based on the scope of our current study, we consider three of these EMV-trackers: (1) overall EMV (EMV-overall); (2) EMV related to commodity markets (EMV-commodity); and (3) EMV related to financial crises (EMV-crises). This choice is motivated by the fact that the overall EMV tracker captures the economic and financial uncertainty related to the stock market. The EMV commodity tracker represents the uncertainty related to the commodity markets that include the crude oil market. The EMV financial crises tracker reflects the effect of financial crises that have been shown to shape the crude oil market as evidenced by

[2] According to Baker et al. (2019), the eleven major US newspapers are: 'the Boston Globe, Chicago Tribune, Dallas Morning News, Houston Chronicle, Los Angeles Times, Miami Herald, New York Times, San Francisco Chronicle, USA Today, Wall Street Journal, and Washington Post'.

several studies indicating the high sensitivity of crude oil prices to economic and financial instability and adverse events. Besides, these EMV trackers are selected based on their leading article proportions in each category. Data on these EMV trackers are collected from the Economic Policy Uncertainty website.

Regarding data on the VIX, OVX and WTI oil prices, they are retrieved from DataStream. Both VIX and OVX are computed by the Chicago Board Options Exchange (CBOE). The VIX reflects the 30-day expected volatility of the S&P 500 index, based on mid-quote prices of call and put options. It is reported by financial media and closely followed by investors and policymakers as a daily market indicator. Following the same methodology of the VIX, the OVX measures the expected 30-day volatility of crude oil as priced by the US Oil Fund (USO). The availability of the OVX from May 2007 only restricts our analysis involving EMV/VIX and OVX to the period May 2007 to December 2019. Given that our empirical analysis involves stationary series, we use the log returns of WTI oil prices and the levels of the other indexes under study, which is motivated by the results of unit root tests (See Table 2).

Table 2 reports the summary statistics of the six indexes under study. The EMV-overall has higher mean and variance than the VIX. None of the indexes under study follow the normality assumption. The ADF and PP tests indicate the stationarity of the EMV indexes and the VIX and OVX at levels. However, the returns of WTI oil prices are stationary. Fig.1 shows the EMV-overall and the VIX.

4. Methodology

In this study, we employ quantile regressions to estimate the risk spillover effects between the US equity and WTI crude oil markets, allowing for a detailed examination under low and high volatility states of the crude oil market. However, as mentioned in the introduction section, three alternative measures of oil market volatility are used in this study: GARCH-based conditional volatility, range-based RV, and OVX. We present more details about the calculation of those three oil volatility measures in Section 4.1, and then present the quantile regression in Section 4.2.

4.1. Volatility measures for the crude oil market

For the conditional volatility measure, we first apply the asymmetric GARCH model to the WTI oil index and extract the GARCH variance series[3].

Based on various model selection criteria[4], our empirical analysis adopts the exponential GARCH (EGARCH) model proposed by Nelson (1991):

$$\ln(h_t^2) = \omega + \alpha \left|\frac{\varepsilon_{t-1}}{h_{t-1}}\right| + \gamma \frac{\varepsilon_{t-1}}{h_{t-1}} + \beta \ln(h_{t-1}^2) \quad (1)$$

where, h_t^2 indicates the conditional variance of WTI oil index returns at time *t*; α, β are the ARCH and GARCH parameters, respectively; and γ refers to the asymmetric term.

For the RV measure, we adopt the Parkinson (1980) method to compute the range-based RV for oil prices. According to Parkinson (1980), the RV is defined as:

$$RV_t = \frac{1}{4ln2}[\ln(H_t) - \ln(L_t)]^2 \quad (2)$$

where H_t and L_t refer to the high and low WTI oil prices at time *t*.

[3] A similar methodology is advocated by Bouri et al. (2019) for studying the effect of commodity market uncertainty on the BRIC sovereign risk.

[4] We choose the EGARCH model on the basis of the Akaike information criterion (AIC), Bayesian information criterion (BIC) and likelihood values.

As for the OVX, it is computed by the CBOE following the same methodology used to compute the VIX.

Each of the three volatility measures of the crude oil market is regressed on the news-based equity market volatility index using quantile regressions, as described the below section.

4.2. Quantile regression

In ordinary least squares (OLS), the conditional mean function defines how the mean of the dependent variable changes with the vector of independent variables. It thus allows for capturing the relation at the mean of the dependent variable's distribution only. However, it is often recognized that the independent variables can affect various parts of the conditional distribution of the dependent variable in an heterogenous way. Such a major shortcoming of the OLS can be addressed via the application of the quantile- regression (Koenker and Bassett, 1978). According to Koenker and Hallock (2001), the quantile regression represents a generalization of OLS to a set of models containing various conditional quantile functions. It has been extensively used in the finance literature (e.g., Bouri et al., 2019; Das and Dutta, 2019; Xiao et al., 2018, 2019; Dawar et al., 2021), given its ability to uncover non-linearity and asymmetric relationships between variables and to provide estimates that are robust to outliers, heteroskedasticity, and skewness on the dependent variable (Xiao et al., 2019).

Since one of our purposes is to examine the risk transmission relationship between the US equity and oil markets under various volatility states of the crude oil market, we apply the quantile regression. Notably, each of the three volatility measures of the crude oil market (defined in Section 4.1 as conditional, realized, and implied) is regressed against each of the three EMV trackers (EMV-overall, EMV-commodity, and EMV-crises) or the VIX and lagged values of the dependent variable.

We frame the quantile regression as:

$$Q_{OV_t}(\tau|OV_{t-1}, \Delta X_{t-1}) = \varphi(\tau) + \lambda(\tau)OV_{t-1} + \theta(\tau)\Delta X_{t-1} \quad (3)$$

where $Q_{OV_t}(\tau|OV_{t-1}, \Delta X_{t-1})$ signifies the τ conditional quantile of OV_t, with OV_t denoting each of the three oil volatility series (conditional/realized/implied, described in section 4.1.) at time *t*. In addition, $\varphi(\tau)$ accounts for the unobserved effect in the quantile model and ΔX_t refers to the first-order difference of EMV/VIX at time *t*.

For a given τ, we estimate Eq. (3) by minimizing the weighted absolute deviation:

$$arg \min_{\varphi(\tau),\lambda(\tau)+\theta(\tau)} \sum_{t=1}^{T} \rho_\tau \left(OV_t - \varphi(\tau) - \lambda(\tau)OV_{t-1} - \theta(\tau)\Delta X_{t-1}\right) \quad (4)$$

where, $\rho_\tau(u) = u(\tau - I(u < 0))$ with $\mathrm{I}(\cdot)$ being the indication function.

A positive and statistically significant $\theta(\tau)$ indicates that an increase in VIX or EMV leads to an upturn in the volatility of the WTI oil price index. However, if $\theta(\tau)$ is negative, there is an inverse relationship between the US equity and oil markets.

We consider seven quantiles, τ = (0.05, 0.10, 0.30, 0.50, 0.70, 0.90, 0.95). Note that the lower quantiles (i.e. 0.05, 0.10, 0.30) reflect low volatility states, whereas the higher quantiles (i.e. 0.70, 0.90, 0.95) indicate high volatility states. Considering these quantiles allows us to explore the impact of various EMV trackers and the VIX on the volatility of crude oil prices across low, normal, and high volatility regimes. Furthermore, we employ symmetric quantile tests to investigate whether the effects differ between upper and lower quantiles of the crude oil volatility.

5. Empirical results

5.1. Impact of news-based EMV and VIX

The results of our quantile regressions are reported in Tables 3-9. The impact of EMV/VIX on oil market volatility is reported in Tables 3-5, while the results of the symmetric quantiles tests for the changes in EMV and VIX are shown in Tables 6-9. Our results are presented in four panels: Panel A shows the impact of EMV-overall; Panel B shows the effect of EMV-commodity; Panel C shows the impact of EMV-crises; and Panel C shows the influence of the VIX.

Table 3 shows that EMV has a significant impact on the conditional volatility of crude oil prices, and that the VIX influences the oil volatility. Notably, we find no impact of these stock market uncertainty indexes on oil volatility at lower quantiles. In fact, the impacts are mainly significant when the oil market is highly volatile (see the estimates at the upper quantiles of 0.70, 0.90 and 0.95). Hence, risk transmits significantly from the US equity market to the WTI crude oil index during high volatility states of oil prices or when oil prices experience bearish periods. One would expect that, during the post financial crisis period, participants in the energy market would pay considerable attention to the macroeconomic fundamentals the ups and downs of which are immediately reflected by the equity sector volatility index. Accordingly, fluctuations in US stock market uncertainty can lead to significant changes in the expected volatility of the crude oil market during periods of turmoil (Liu et al., 2013).

Moreover, the volatility of oil prices is influenced by its own lagged volatility and the associated coefficients are positive and significant across all quantiles. The magnitude of these effects tends to increase as we move towards the higher quantiles. Notably, the impact of the EMV-commodity index is higher than the US VIX.

Table 4 shows similar effects of EMV trackers on the conditional volatility of the oil index. That is, there hardly exists any significant association when the oil market is less volatile. In other words, the impact is found to be insignificant at extreme lower quantiles (0.05 and 0.010) for the RV of crude oil prices. Therefore, the US equity market transmits its volatility to the WTI index during high volatility states of oil prices (i.e., when oil prices experience a downturn). We also find that the magnitude of such risk tends to increase for higher quantiles. However, the impact of EMV and VIX on the RV of oil prices is lower than the conditional volatility of the WTI market. It is also noteworthy that the estimates given in Table 4 are mostly insignificant, even for the own lagged volatilities of the WTI oil index.

Table 5 shows that the crude oil volatility index (as measures by the OVX) also reacts to various EMV trackers. We note that the effect of EMV-commodity is higher than that of EMV-overall or EMV-crises. For example, at the upper quantile of 0.95, the effects of EMV-overall, EMV-commodity, and EMV-crises amount to 0.31, 0.95 and 0.76, respectively. We also observe that each EMV tracker impacts the volatility of the WTI oil index at higher quantiles only. This latter finding is consistent with those reported in Tables 3 and 4, which suggests that EMV has a certain predictive power for the variance of WTI crude oil prices. One notable finding is that the VIX has no significant effect on the crude oil implied volatility index, which contradicts Liu et al. (2013) who report that variations in the VIX lead to significant changes in the expected volatility of the crude oil market during stress periods.

In summary, our findings suggest that, during periods of high uncertainty, the crude oil market receives volatility from the US equity market. The results generally indicate that the various EMV trackers and the VIX impact the volatility of crude oil prices, regardless of the volatility measures (with few exceptions). Figures 2-4, which demonstrate the influences of EMV and VIX on various measures of crude oil price volatility at different quantiles, show the same. As suggested by the magnitude of the effects, EMV-commodity and EMV-crises outperform the VIX in most cases for capturing the effects of US equity market uncertainty on WTI oil price volatility. These results are in line with Zhu et al. (2019) who document that the variation in the S&P 500 index is better predicted by EMV trackers than the VIX. Our analyses provide similar results for the volatility of the crude oil market. Overall, the results indicate that EMV trackers can be used as alternative measures of US equity market volatility.

5.2. Results of symmetric quantiles tests

This section reports the findings of the symmetric quantiles test for changes in EMV trackers and the VIX. Our objective is to investigate whether the upper quantiles (0.95, 0.90 and 0.70) have the same slopes as the lower quantiles (0.30, 0.10 and 0.05). Considering the pairs (0.05, 0.95), (0.10, 0.90) and (0.30, 0.70), Tables 6-9 show whether the impact of EMV and VIX on oil market volatility differs for upper and lower quantiles.

The slope parameters do vary for the extreme upper and extreme lower quantiles (i.e., 0.05 vs. 0.95). For other cases (0.10 vs. 0.90 and 0.30 vs. 0.70), all the tests appear to be insignificant. We document the findings for both conditional and realized oil volatility measures (see the estimates shown in Tables 6-9). We thus conclude that the effects of equity market volatility shocks tend to vary for high and low volatility states of crude oil prices. However, while estimating the volatility spillover effects between EMV/VIX and OVX, we do not find any significant results for the symmetric quantiles tests, which indicates that the slope parameters do not differ in this case.

5.3. Robustness analysis

This section assesses the robustness of our findings. To serve this purpose, we examine the effects of two widely used news-based uncertainty indexes - economic policy uncertainty (EPU) and geopolitical risk (GPR) - on the volatility of crude oil market. A strand of literature examines whether EPU and GPR exert any significant impact on oil volatility (Wei et al., 2017; Liu et al., 2019; Sun et al., 2020; Qin et al., 2020; Mei et al., 2020; Tiwari et al., 2020) and mostly shows that they have a predictive power. Wei et al. (2017), for instance, argue that an increase in policy uncertainty could cause an upsurge in oil price volatility given that oil suppliers can stock up as a result of precautionary motives. In addition, Liu et al. (2019) claim that GPR affects the oil supply policy of OPEC countries as well as the US and causes crude oil volatility to upsurge.

Table 10 shows the results of our robustness tests. These findings are important in several aspects. First, EPU impacts crude oil volatility only at upper quantiles of 0.90 and 0.95, while EMV trackers (e.g., EMV-overall and EMV-commodity) have substantial effects at both upper and lower quantiles as well (see Tables 3-5 and Fig. 2-6). This finding indicates that when crude oil market is less volatile, EPU does not have any predictive power for energy markets, which is, however, not the case for EMV trackers. Second, GPR does not impact crude oil conditional and realized volatility, albeit it exerts a negative effect on OVX at upper quantile of 0.95. Tiwari et al. (2020) also find that GPR affects oil volatility negatively. Third, the magnitude of the impact of EMV-trackers is much higher than that of EPU/GPR.

Overall, our robustness analysis shows that EMV-trackers have better predictive power for oil volatility when compared to EPU and GPR indexes. This finding could be attributed to the fact that, unlike EPU and the GPR indicators, EMV indexes capture people’s perception on future uncertainty and make use of a much larger text corpus (Baker et al., 2019).

5.4. Volatility forecasting performance

In this section, we examine whether various EMV trackers carry additional information (relative to VIX, EPU and GPR) that can be useful to forecast the volatility of crude oil prices more accurately. Accordingly, we estimate the regression[5]:

$$OV_{t+1} = a + bFV_t + \xi_t \tag{5}$$

where OV_{t+1} is the conditional/realized/implied volatility of oil returns at time $t+1$, FV_t denotes the volatility forecast at time t, and ξ_t refers to the forecast error term. FV_t is obtained from the estimates of the QR model, considering the EMV trackers/VIX/EPU/GPR as the explanatory variable. Note that the in-sample estimation period ranges from January 1990 to December, 2016, while the out-of-sample forecast period ranges from January 2017 to December, 2019. For the OVX index, the in-sample estimation period spans from May 2007 to December, 2016. The forecast performance is assessed by comparing the R^2 values.

The R^2 statistics obtained from Eq. (5) are shown in Table 11, in which Panel A shows the results at $\tau = 0.50$ and Panel B shows the results estimated at $\tau = 0.95$. Overall, the results confirm that the EMV trackers are superior. For example, the R^2 values involving the OVX, considering $\tau = 0.95$ (see Panel B) amount to 0.0611, 0.1175, 0.0142, 0.0013, 0.0533, and 0.0007 for EMV-overall, EMV-commodity, EMV-crises, VIX, EPU, and GPR respectively. These results indicate that the EMV trackers used in this study have better predictive power than the VIX. Quite similar results are reported in Panel A. Hence, we can conclude that these text-based measures of uncertainty provide additional information about how US equity market volatility impacts crude

[5] Kanas (2013) employs a similar model when forecasting the volatility of S&P 500 index using the VIX.

oil price volatility. These findings nicely complement previous findings (e.g., Su et al., 2018; Zhu et al., 2019; Alqahtani et al., 2020) highlighting the information content of the EMV indexes for the volatility of crude oil prices. It is also noteworthy that while GPR has the least predictive power for crude oil volatility, EPU outperforms the VIX index on each occasion.

5.5. Discussion

Crude oil appears to be a key global commodity whose demand is usually very high given its key role in both production and consumption. Being a liquid asset, crude oil is also widely traded at huge volumes by investors and speculators. Against this backdrop, fluctuations in oil prices are of great concerns to economic agents given that volatile oil prices have a significant impact on international financial markets. In particular, crude oil market volatility has an important influence on policymaking and investment decisions. As a result, market participants are very keen to acquire precise knowledge of oil price volatility and its prediction.

It is well-documented in the existing literature that many macro-level determinants have substantial impacts on oil price volatility. Of the various factors, global oil demand, supply, and speculation are often considered the most influential factors (Wei et al., 2017). Recent literature, however, documents that news-based uncertainty measures such as economic policy uncertainty and geopolitical risk indexes have also emerged as potential predictors of oil price variability. For example, Aloui et al. (2016) argue that variations in the EPU index can identify the supply-side, aggregate-demand, and oil-specific demand shocks, which directly leads the oil price to fluctuate. Thus, an upsurge (fall) in the EPU index could have a negative (positive) influence on the economy, which could decrease (increase) the demand and supply of crude oil, affecting oil market volatility. Balcilar et al. (2016) show that movements in oil prices are sensitive to changes in the levels of EPU index. Specifically, one would expect that increased EPU may lead to serious deviancy in the expectations of oil consumers, producers, and speculators simultaneously, which, in turn, impacts the demand, supply, or speculation in the crude oil market. Another strand of literature argues that GPR can also drive oil price volatility. Liu et al. (2019), for example, claim that increasing geopolitical risk could also exert impacts on oil prices by affecting the oil supply policy of OPEC countries. Overall, trading decisions as well as market sentiments may react significantly to EPU and GPR indexes, which could to an upsurge or a decline in oil prices.

However, it is not obvious that EPU or GPR appears to be the most informative factor in forecasting oil volatility. Besides, other news-based uncertainty indexes may contain additional predictive information for oil price volatility. In this paper, unlike previous studies, we explore the role of recently developed news-based volatility indexes in predicting oil market volatility. It is worth mentioning that various EMV trackers used in this study are calculated by counting the word frequencies of several specific keywords (e.g., volatility, volatile, uncertain, uncertainty, risk, risky) related to financial market volatility or risk appeared in newspapers published in present month. Thus, EMV, contrasting the EPU and GPR indexes, can be considered as the public attention on future market volatility. One could, therefore, postulate that the EMV trackers may reveal more information compared to EPU and GPR, which are often viewed as leading predictors of oil market volatility. Given that oil prices usually experience unexpected swings that could potentially change the sign and intensity of the impact of the uncertainty measures across different quantiles, this empirical research employs the flexible quantile regression framework to examine the risk spillover effects amongst the variables. The QR model has achieved immense popularity in prior literature as it can reveal information on the asymmetric and non-linear effects of conditional variables on the dependent variables. In our study, applying this approach has helped us to provide informative insights on the effects of various uncertainty indicators on oil market volatility under different market circumstances, including bearish (lower quantile) and bullish (upper quantile) markets.

Overall, our empirical analysis shows that the WTI crude oil market is substantially impacted by the news available from the US media and press and that newspaper information on commodity markets and financial crises is more useful than the information content of the VIX for forecasting the volatility of crude oil prices. This finding could be attributed to the fact that the VIX index is mainly focused on the macroeconomic fluctuations, ignoring the vital role of public media and investor attentions, which is more flexible and timely than the economic data. The results further indicate that the EMV indexes appear to be a better predictor of crude oil volatility than other observable economic uncertainty measures suggested in the literature, like the EPU and the GPR indexes.

6. Conclusion

Previous studies document the way US equity market uncertainty impacts the volatility of crude oil prices, but mostly rely on the implied volatility index (VIX) of the US stock market as a measure of stock market uncertainty. However, the VIX typically reflects macroeconomic fluctuations, little affected by social media or investor perception changes. Newly constructed news-based measures of equity market volatility (EMV) reflect a much larger text corpus than other uncertainty indexes, suggesting their ability to provide additional information about how US equity market uncertainty impacts crude oil volatility. In this paper, we uncover for the first time the impacts of EMV indexes on the volatility of WTI oil prices under various states of oil volatility.

Furthermore, we assess the ability of EMV to predict crude oil price volatility relative to that of the VIX.

Employing quantile regressions and using a variety of oil volatility measures, the results show a significant impact of US equity market uncertainty on volatility the WTI oil index during periods of high oil volatility, whereas such an impact appears to be insignificant when the oil market is less volatile. Further analysis involving the volatility forecasting performance indicates that the various EMV trackers have a better predictive power for oil price volatility than the VIX. Our findings thus provide empirical evidence that the crude oil market is substantially influenced by the news available from the US media and press. Therefore, when predicting crude oil price uncertainty, newspaper information on commodity markets and financial crises could be more useful than the information content of the VIX. Our results also show evidence of asymmetry, reflected in the fact that the effects of equity market volatility shocks vary for high and low volatility states of crude oil price, which is a general feature of financial markets because global investors tend to react more strongly to negative shocks than positive shocks.

Given that understanding crude oil price volatility is a fundamental issue that plays a major role in asset pricing, oil price formation, and risk management, our findings have important implications for investors, traders, and policymakers participating in the crude oil market. Investors and oil traders, for example, could forecast oil price volatility by utilizing the information content of the news-based measures of US equity market uncertainty during bearish periods. This suggests that they should closely follow stock price movements to realize potential threats, which would help them better understand the directions of oil market risk and thereby make more precise investment decisions. Furthermore, investors and oil traders could formulate appropriate hedging strategies during periods of high uncertainty in order to avoid the contagious shocks stemming from the US equity market. Further implications involve the econometric modelling of volatility in the crude oil market. In fact, the findings indirectly suggest that a joint econometric model should be used when analysing the impacts of volatility shocks from the US stock market (measured by the EMV trackers) to the crude oil market, while differentiating between high and low volatility states of crude oil prices. From a policy perspective, policymakers and regulators should exploit the information contents of EMV trackers to formulate optimal policies to maintain financial stability in the strategic oil market, especially when the oil market experiences high volatility.

Our current study is not free of limitations. Firstly, we concentrate on the impact of EMV on oil price volatility within a bivariate analysis. However, the nature of associations between crude oil and stocks markets suggests the possibility of including other variables in a multivariate framework which might affect the volatility dynamics of US stock uncertainty and oil prices, an interesting research path for future studies. Secondly, given that investors and traders might have different investment horizons, it would be an interesting topic for future studies to consider the application of a frequency-based approach capable of dismantling the risk spillovers from EMV to oil volatility across short- and long-term horizons.

References

Aloui, R., Gupta, R., & Miller, S.M. (2016). Uncertainty and crude oil returns. Energy Economics, 55, 92–100.

Alqahtani, A., Wither, M. J., Dong, Z., & Goodwin, K. R. (2020). Impact of news-based equity market volatility on international stock markets. Journal of Applied Economics, 23(1), 224-234.

Antonakakis, N., Gupta, R., Kollias, C., & Papadamou, S. (2017). Geopolitical risks and the oilstock nexus over 1899–2016. Finance Research Letters, 23, 165–173.

Bakas, D., & Triantafyllou, A. (2019). Volatility forecasting in commodity markets using macro uncertainty. Energy Economics, 81, 79–94.

Baker, S. R., Bloom, N., Davis, S. J., & Kost, K. (2019). Policy news and stock market volatility. NBER Working Paper No. 25720.

Baker, S., Bloom, N., & Davis, S. (2013). Measuring economic policy uncertainty. Chicago Booth Research Paper, 13–02. Stanford University, Department of Economics.

Balcilar, M., Bekiros, S., & Gupta, R. (2017). The role of news-based uncertainty indices in predicting oil markets: a hybrid nonparametric quantile causality method. Empirical Economics, 53(3), 879-889.

Bekiros, S., Gupta, R., and Paccagnini, A. (2015). Oil price forecastability and economic uncertainty. Economics Letters, 132, 125-128.

Bernanke, B. S. (1983). Irreversibility, uncertainty, and cyclical investment. The quarterly journal of economics, 98(1), 85-106.

Bouri, E., Jalkh, N., & Roubaud, D. (2019). Commodity volatility shocks and BRIC sovereign risk: A GARCH-quantile approach. Resources Policy, 61, 385-392

Bouri, E., Lien D., Roubaud, D. & Shahzad, S.J.H. (2018). Directional predictability of implied volatility: from crude oil to developed and emerging stock markets. Finance Research Letters, 27, 65-79.

Choi, K., & Hammoudeh, S. (2010). Volatility behavior of oil, industrial commodity and stock markets in a regime-switching environment. Energy Policy, 38, 4388-4399.

Das, D., & Dutta, A. (2019). Bitcoin's energy consumption: Is it the Achilles heel to miner's revenue?. Economics Letters, 186, 108530.

Dawar, I., Dutta, A., Bouri, E., & Saeed, T. (2021). Crude oil prices and clean energy stock indices: Lagged and asymmetric effects with quantile regression. Renewable Energy, 163, 288-299.

Dutta, A., Bouri, E. and Roubaud, D. (2020). Modelling the volatility of crude oil returns: jumps and volatility forecasts. International Journal of Finance and Economics, https://doi.org/10.1002/ijfe.1826.

Dutta, A., Nikkinen, J., & Rothovius, T. (2017). Impact of Oil Price Uncertainty on Middle East and African Stock Markets. Energy, 123, 189-197.

Gao, R., Zhao, Y., & Zhang, B. (2020). The spillover effects of economic policy uncertainty on the oil, gold, and stock markets: Evidence from China. International Journal of Finance & Economics. https://doi.org/10.1002/ijfe.1898

Hailemariam, A., Smyth, R., & Zhang, X. (2019). Oil prices and economic policy uncertainty: Evidence from a nonparametric panel data model. Energy Economics, 83, 40–51.

Ji, Q., Bouri, E., & Roubaud, D. (2018). Dynamic network of implied volatility transmission among US equities, strategic commodities, and BRICS equities. International Review of Financial Analysis, 57, 1-12.

Kanas, A. (2013). The Risk-Return Relation and VIX: Evidence from the S&P 500. Empirical Economics, 44(3), 1291-1314.

Koenker, R., & Hallock, K. F. (2001). Quantile regression. Journal of economic perspectives, 15(4), 143-156.

Koenker, R., & Bassett, G., (1978). Regression quantiles. Econometrika: journal of the Econometric Society, 46, 33–50.

Li, X., Wei, Y., Chen, X., Ma, F., Liang, C., & Chen, W. (2020). Which uncertainty is powerful to forecast crude oil market volatility? New evidence. International Journal of Finance & Economics. https://doi.org/10.1002/ijfe.2371

Liang, C., Wei, Y., Li, X., Zhang, X., & Zhang, Y., (2020). Uncertainty and crude oil market volatility: new evidence. Applied Economics, 52, 2945-2959.

Liu, J., Ma, F., Tang, Y., & Zhang, Y., (2019). Geopolitical risk and oil volatility: A new insight. Energy Economics 84, 104548.

Liu, ML, Ji, Q., & Fan, Y. (2013). How does oil market uncertainty interact with other markets: an empirical analysis of implied volatility index? Energy, 55, 860-8.

Lyu, Y., Yi, H., Hu, Y., & Yang, M. (2021) Economic uncertainty shocks and China's commodity futures returns: A time-varying perspective. Resources Policy, 70, 101979.

Manela, A., & Moreira, A., (2017). News implied volatility and disaster concerns. Journal of Financial Economics, 123 (1), 137–162.

Manickavasagam, J., Visalakshmi, S., & Apergis, N. (2020). A novel hybrid approach to forecast crude oil futures using intraday data. Technological Forecasting and Social Change, 158, 120126.

Mei, D., Ma, F., Liao, Y., & Wang, L. (2020). Geopolitical risk uncertainty and oil future volatility: Evidence from MIDAS models. Energy Economics, 86, 104624.

Mo, B., Mu, J., & Zhang, B. (2019). The relationship between news-based implied volatility and volatility of US stock market: What can we learn from multiscale perspective?, Physica A 526, 121003.

Nelson, D. B., (1991). Conditional heteroskedasticity in asset returns: A new approach, Econometrica 59, 347-370.

Parkinson, M., (1980). The extreme value method for estimating the variance of the rate of return. Journal of Business, 53 (1), 61-65.

Qin, M., Su, C. W., Hao, L. N., & Tao, R. (2020). The stability of U.S. economic policy: Does it really matter for oil price? Energy, 198, 117315.

Reboredo, J. C., & Uddin, G. S. (2016). Do financial stress and policy uncertainty have an impact on the energy and metals markets? A quantile regression approach. International Review of Economics and Finance, 43, 284–298.

Shi, X., & Variam, H. M. (2017). East Asia’s gas-market failure and distinctive economics—A case study of low oil prices. Applied energy, 195, 800-809.

Su, Z., Lu, M., & Yin, L. (2018). Oil prices and news-based uncertainty: novel evidence. Energy Economics, 72, 331–340.

Su, Z., Fang, T., & Yin, L. (2017). The role of news-based implied volatility among US financial markets, Economics Letters, 157, 24–27.

Sun, X, Chen, X, Wang, J, & Li, J. (2020). Multi-scale interactions between economic policy uncertainty and oil prices in time-frequency domains. The North American Journal of Economics and Finance, 51, 100854.

Tiwari, A.K., Aye, G.C., Gupta, R., & Gkillas, K. (2020). Gold-Oil Dependence Dynamics and the Role of Geopolitical Risks: Evidence from a Markov-Switching Time-Varying Copula Model. Energy Economics, 88, 104748

Van Eyden, R., Difeto, M., Gupta, R., & Wohar, M. E. (2019). Oil price volatility and economic growth: Evidence from advanced economies using more than a century's data. Applied Energy, 233, 612-621.

Wang, Y., Wei, Y., Wu, C., & Yin, L. (2018). Oil and the Short-term Predictability of Stock Return Volatility. Journal of Empirical Finance 47, 90–104.

Wei, Y.; Liu, J.; Lai, X.; Hu, Y. (2017). Which determinant is the most informative in forecasting crude oil market volatility: Fundamental, speculation, or uncertainty? Energy Economics, 68, 141–150.

Xiao, J., Hu, C., Ouyang, G., & Wen, F. (2019). Impacts of oil implied volatility shocks on stock implied volatility in china: Empirical evidence from a quantile regression approach. Energy Economics, 80, 297-309.

Xiao, J., Zhou, M., Wen, F., & Wen, F. (2018). Asymmetric impacts of oil price uncertainty on Chinese stock returns under different market conditions: evidence from oil volatility index. Energy Economics, 74, 777-786.

Yang, L., (2019). Connectedness of economic policy uncertainty and oil price shocks in a time domain perspective. Energy Economics, 80, 219–233.

Zhang, Y. J., & Li, S. H. (2019). The impact of investor sentiment on crude oil market risks: evidence from the wavelet approach. Quantitative Finance, 19(8), 1357-1371.

Zhu, S., Liu, Q., Wang, Y., Wei, Y., & Wei, G., (2019). Which fear index matters for predicting US stock market volatilities: Text-counts or option-based measurement? Physica A: Statistical Mechanics and its Applications, 536, 122567.

Table 1: Summary of important literature examining the impact of news-based uncertainty on crude oil markets

Reference	Econometric models used	Variables	Data frequency	Time period	Major Findings
Bekiros et al. (2015)	Different types of VAR models	EPU and WTI	Monthly	January, 2007 to February, 2014	EPU does impact crude oil price changes.
Antonakakis et al. (2017)	VAR-BEKK-GARCH approach	GPR and WTI	Monthly	January, 1899 to December, 2016	GPR has a negative effect on oil volatility.
Wei et al. (2017)	GARCH-MIDAS model	EPU and WTI	Daily and monthly	January, 1997 to April, 2016	EPU can predict the volatility of WTI index.
Su et al. (2018)	Wavelet coherence model	NVIX, WTI and Brent	Monthly	January, 1994 to March, 2016	Oil prices are sensitive to changes in NVIX.
Bakas and Triantafyllou (2019)	Realized volatility models	EPU, NVIX and a number of commodity indexes	Monthly	January, 1988 to December, 2016	Both EPU and NVIS have predictive power for crude oil volatility.
Yang (2019)	Diebold and Yilmaz spillover approach	EPU and WTI	Monthly	January, 1998 to December, 2017	Oil price volatility is sensitive to EPU.
Liu et al. (2019)	GARCH-MIDAS model	GPR and WTI	Daily and monthly	January, 1986 to May, 2017	The information on Geopolitical risk index is useful for predicting oil market volatility.
Liang et al. (2020)	Least absolute shrinkage and selection operator and elastic net models	Various news-based uncertainty indexes	Monthly	January, 1997 to July, 2017	The global EPU index plays a pivotal role in explaining oil volatility.

Mei et al. (2020)	MIDAS model	GPR and WTI	Daily	January 1, 2007 to July 15, 2016	GPR has a positive impact on crude oil realized volatility.
Qin et al. (2020)	Partial wavelet coherence approach	EPU and WTI	Monthly	January, 1986 to August, 2019	Oil prices react significantly to EPU.
Sun et al. (2020)	Wavelet coherence approach	EPU and oil prices for a group of countries	Monthly	January, 1997 to August, 2017	A strong long-term linkage is found between the variables.
Tiwari et al. (2020)	Markov-switching time-varying copula model	GPR, Gold and WTI	Daily	2 January 1985 to 30 November 2017.	GPR has a negative effect on the correlation between oil and gold.
Li et al. (2020)	GARCH-MIDAS model	GPR, EPU, US monetary policy uncertainty, and WTI	Daily	2 January 1997 to 31 July 2017	EPU has better predictive power than the rest.
Gao et al. (2020)	Spillover index approach	EPU, oil, gold and stock markets	Monthly	October, 2002 to May, 2017	EPU impacts crude oil volatility .

Notes: This table summarizes the recent literature investigating the role of various news-based uncertainty indicators in predicting oil market returns and volatility. These studies are also discussed in section 2. EPU = Economic Policy Uncertainty; GPR=Geopolitical Risk; NVIX=News VIX.

Table 2: Summary statistics of monthly data series

	WTI oil returns	EMV-overall	EMV-crises	EMV-commodity	VIX	OVX
Mean	0.29	20.17	2.07	8.63	19.16	36.05
Standard Deviation	9.48	7.68	2.56	3.33	7.40	13.19
Skewness	-0.19	2.48	3.32	2.25	1.79	1.46
Kurtosis	4.59	12.17	23.98	11.60	7.91	5.86
J-B test	38.41***	1562.57***	6965.31***	1358.19***	532.06***	106.36***
ADF test	-15.65***	-8.68***	-7.04***	-9.78***	-5.53***	-3.16**
PP test	-15.43***	-8.84***	-6.78***	-10.28***	-5.26***	-3.19**

Notes: The sample period is January 1990 - December 2019; WTI EMV(news-based equity market volatility) indices; VIX (US stock market implied volatility index; OVX (Crude oil implied volatility index); J-B indicates the Jarque-Bera test; ADF refers to the augmented Dickey-Fuller test; PP indicates Phillips-Perron test. ***$p<0.01$; **$p<0.05$.

Table 3: Impact of EMV/VIX on the conditional volatility of WTI index

Quantiles →	Q(0.05)	Q(0.10)	Q(0.30)	Q(0.50)	Q(0.70)	Q(0.90)	Q(0.95)
Panel A: EMV-overall							
Constant	**6.30**	**7.31**	2.64	5.14	-1.42	-13.30	**-34.23**
OV_{t-1}	**0.67**	**0.69**	**0.75**	**0.78**	**0.83**	**1.09**	**1.36**
EMV-overall	0.11	0.07	**0.33**	0.46	**0.96**	1.53	**2.43**
Panel B: EMV-commodity							
Constant	**6.31**	**6.67**	3.54	2.69	-4.23	-22.86	**-28.82**
OV_{t-1}	**0.68**	**0.69**	**0.74**	**0.77**	**0.83**	**1.03**	**1.22**
EMV-commodity	0.23	0.25	**0.72**	**1.41**	**2.72**	**5.78**	**5.91**
Panel C: EMV-crises							
Constant	**7.43**	**8.08**	**6.98**	**9.75**	**9.61**	6.07	4.72
OV_{t-1}	**0.68**	**0.70**	**0.75**	**0.81**	**0.89**	**1.12**	**1.38**
EMV-crises	0.26	0.05	0.75	0.66	**1.26**	**6.40**	**5.18**
Panel D: VIX							
Constant	**5.99**	**7.21**	5.07	3.62	0.11	-16.20	**-24.81**
OV_{t-1}	**0.67**	**0.70**	**0.75**	**0.77**	**0.80**	**0.93**	**1.15**
VIX	0.13	0.06	0.19	**0.62**	**1.04**	**2.80**	**2.98**

Notes: This table displays the estimates of Eq. (4)for the conditional volatility of WTI index. Panels A, B and C show the effects of EMV trackers, while Panel D exhibits the same for the VIX index. We consider seven quantiles, τ = (0.05, 0.10, 0.30, 0.50, 0.70, 0.90, 0.95). The lower quantiles (i.e. 0.05, 0.10, 0.30) reflect low volatility states, whereas the higher quantiles (i.e. 0.70, 0.90, 0.95) indicate high volatility states. OV refers to oil market volatility. Bold indicates statistical significance at the 5% level.

Table 4: Impact of EMV/VIX on the realized volatility of WTI index

Quantiles →	Q(0.05)	Q(0.10)	Q(0.30)	Q(0.50)	Q(0.70)	Q(0.90)	Q(0.95)
Panel A: EMV-overall							
Constant	0.14	-2.90	-14.57	-12.97	-22.24	-95.03	-197.62
OV_{t-1}	0.00	0.01	0.06	**0.08**	**0.11**	0.67	**1.50**
EMV-overall	0.01	0.20	**1.23**	**2.41**	**4.67**	**12.60**	**21.45**
Panel B: EMV-commodity							
Constant	0.47	-1.68	-16.02	-15.14	-32.35	-115.26	**-213.87**
OV_{t-1}	0.00	0.01	0.04	**0.06**	0.08	0.81	**1.03**
EMV-commodity	0.03	0.30	**3.25**	**6.07**	**12.62**	**32.75**	**57.55**
Panel C: EMV-crises							
Constant	0.18	0.21	2.75	**19.70**	**52.87**	**100.64**	**172.94**
OV_{t-1}	0.00	0.01	**0.08**	**0.09**	**0.18**	**0.83**	**1.52**
EMV-crises	0.03	0.27	1.70	**5.07**	5.75	27.68	**63.90**
Panel D: VIX							
Constant	0.42	0.06	-7.40	-22.72	**-39.18**	38.43	-233.59
OV_{t-1}	0.00	0.01	**0.07**	**0.07**	**0.09**	0.68	**0.93**
VIX	0.01	0.03	0.86	**3.04**	**6.39**	**10.40**	**29.18**

Notes: This table displays the estimates of Eq. (4) for the realized volatility of the WTI index. Panels A, B and C show the effects of EMV trackers, while Panel D exhibits the same for the VIX index. We consider seven quantiles, τ = (0.05, 0.10, 0.30, 0.50, 0.70, 0.90, 0.95). The lower quantiles (i.e. 0.05, 0.10, 0.30) reflect low volatility states, whereas the higher quantiles (i.e. 0.70, 0.90, 0.95) indicate high volatility states. OV refers to oil market volatility. Bold indicates statistical significance at the 5% level.

Table 5: Impact of EMV/VIX on the OVX

Quantiles →	Q(0.05)	Q(0.10)	Q(0.30)	Q(0.50)	Q(0.70)	Q(0.90)	Q(0.95)
Panel A: EMV-overall							
Constant	**4.53**	2.65	2.46	2.40	1.27	-0.20	5.79
OV_{t-1}	**0.56**	**0.67**	**0.81**	**0.80**	**0.87**	**0.95**	**0.96**
EMV-overall	0.13	0.11	0.09	0.18	**0.26**	**0.43**	**0.31**
Panel B: EMV-commodity							
Constant	**3.88**	3.81	1.46	**3.10**	2.40	0.88	7.26
OV_{t-1}	**0.55**	**0.63**	**0.79**	**0.78**	**0.84**	**0.95**	**0.90**
EMV-commodity	0.44	0.29	**0.41**	**0.46**	**0.58**	**0.98**	**0.84**
Panel C: EMV-crises							
Constant	**6.67**	3.04	3.42	2.24	2.07	-0.22	6.12
OV_{t-1}	**0.63**	**0.69**	**0.82**	**0.89**	**0.93**	**1.11**	**1.05**
EMV-crises	0.55	0.27	0.01	0.23	0.58	**0.93**	**0.76**
Panel D: VIX							
Constant	**5.33**	4.30	**3.38**	3.49	3.64	1.68	5.46
OV_{t-1}	**0.54**	**0.65**	**0.82**	**0.87**	**0.86**	**0.99**	**1.27**
VIX	0.11	0.06	0.00	0.03	0.16	0.31	0.15

Notes: This table presents the estimates of Eq. (4) for the crude oil volatility index (OVX). Panels A, B and C show the effects of EMV trackers, while Panel D exhibits the same for the VIX index. We consider seven quantiles, τ = (0.05, 0.10, 0.30, 0.50, 0.70, 0.90, 0.95). The lower quantiles (i.e. 0.05, 0.10, 0.30) reflect low volatility states, whereas the higher quantiles (i.e. 0.70, 0.90, 0.95) indicate high volatility states. OV refers to oil market volatility. Bold indicates statistical significance at the 5% level.

Table 6: Symmetric quantiles test for the changes in EMV-overall

Quantiles ↓	Restricted value	Standard error	*p*-value	Decision
Panel A: Conditional volatility of WTI				
0.05, 0.95	1.6214	0.5617	0.00	***
0.10, 0.90	0.6825	1.2042	0.57	Insignificant
0.30, 0.70	0.3666	0.3763	0.33	Insignificant
Panel B: Realized volatility of WTI				
0.05, 0.95	16.6369	9.8690	0.09	*
0.10, 0.90	7.9838	5.9908	0.18	Insignificant
0.30, 0.70	1.0800	1.1962	0.36	Insignificant
Panel C: OVX				
0.05, 0.95	0.0806	0.2274	0.72	Insignificant
0.10, 0.90	0.1762	0.2171	0.42	Insignificant
0.30, 0.70	-0.0172	0.1397	0.90	Insignificant

Notes: This table reports the findings of the symmetric quantiles test for changes in EMV-overall index. The objective of this test is to investigate whether the upper quantiles (0.95, 0.90 and 0.70) have the same slopes as the lower quantiles (0.30, 0.10 and 0.05). Considering the pairs (0.05, 0.95), (0.10, 0.90) and (0.30, 0.70), this table checks whether the impact of EMV-overall on oil market volatility differs for upper and lower quantiles. ***, ** and * indicate statistical significance at 1%, 5% and 10%, respectively.

Table 7: Symmetric quantiles test for the changes in EMV-commodity

Quantiles ↓	Restricted value	Standard error	p-value	Decision
Panel A: Conditional volatility of WTI				
0.05, 0.95	3.3324	1.1790	0.00	***
0.10, 0.90	3.2083	2.1639	0.14	Insignificant
0.30, 0.70	0.6241	0.7380	0.40	Insignificant
Panel B: Realized volatility of WTI				
0.05, 0.95	45.3726	18.4494	0.02	**
0.10, 0.90	20.9122	10.8010	0.06	*
0.30, 0.70	3.7293	2.6578	0.16	Insignificant
Panel C: OVX				
0.05, 0.95	0.3677	0.4816	0.44	Insignificant
0.10, 0.90	0.3581	0.4723	0.45	Insignificant
0.30, 0.70	0.0676	0.2295	0.77	Insignificant

Notes: This table reports the findings of the symmetric quantiles test for changes in EMV-commodity index. The objective of this test is to investigate whether the upper quantiles (0.95, 0.90 and 0.70) have the same slopes as the lower quantiles (0.30, 0.10 and 0.05). Considering the pairs (0.05, 0.95), (0.10, 0.90) and (0.30, 0.70), this table checks whether the impact of EMV-commodity on oil market volatility differs for upper and lower quantiles. ***, ** and * indicate statistical significance at 1%, 5% and 10%, respectively.

Table 8: Symmetric quantiles test for the changes in EMV-crises

Quantiles ↓	Restricted value	Standard error	*p*-value	Decision
Panel A: Conditional volatility of WTI				
0.05, 0.95	4.1256	1.0083	0.00	***
0.10, 0.90	5.1400	1.0207	0.00	***
0.30, 0.70	0.6995	0.6329	0.27	Insignificant
Panel B: Realized volatility of WTI				
0.05, 0.95	53.7847	15.2624	0.00	***
0.10, 0.90	17.8090	21.7746	0.41	Insignificant
0.30, 0.70	-2.6951	3.9100	0.49	Insignificant
Panel C: OVX				
0.05, 0.95	-0.2592	0.8004	0.75	Insignificant
0.10, 0.90	0.7248	0.7469	0.33	Insignificant
0.30, 0.70	0.0983	0.6075	0.87	Insignificant

Notes: This table provides the findings of the symmetric quantiles test for changes in EMV-crisis index. The objective of this test is to investigate whether the upper quantiles (0.95, 0.90 and 0.70) have the same slopes as the lower quantiles (0.30, 0.10 and 0.05). Considering the pairs (0.05, 0.95), (0.10, 0.90) and (0.30, 0.70), this table checks whether the impact of EMV-crisis on oil market volatility differs for upper and lower quantiles. ***, ** and * indicate statistical significance at 1%, 5% and 10%, respectively.

Table 9: Symmetric quantiles test for the changes in VIX

Quantiles ↓	Restricted value	Standard error	*p*-value	Decision
Panel A: Conditional volatility of WTI				
0.05, 0.95	1.8835	0.6011	0.00	***
0.10, 0.90	1.6398	1.0135	0.11	Insignificant
0.30, 0.70	0.0046	0.3233	0.99	Insignificant
Panel B: Realized volatility of WTI				
0.05, 0.95	23.0845	12.0418	0.06	*
0.10, 0.90	4.3531	3.1721	0.17	Insignificant
0.30, 0.70	1.1795	1.1555	0.31	Insignificant
Panel C: OVX				
0.05, 0.95	-0.1088	0.4474	0.81	Insignificant
0.10, 0.90	0.3082	0.4023	0.44	Insignificant
0.30, 0.70	0.0993	0.1699	0.56	Insignificant

Notes: This table reports the findings of the symmetric quantiles test for changes in VIX index. The objective of this test is to investigate whether the upper quantiles (0.95, 0.90 and 0.70) have the same slopes as the lower quantiles (0.30, 0.10 and 0.05). Considering the pairs (0.05, 0.95), (0.10, 0.90) and (0.30, 0.70), this table checks whether the impact of VIX on oil market volatility differs for upper and lower quantiles. ***, ** and * indicate statistical significance at 1%, 5% and 10%, respectively.

Table 10: Impact of EPU/GPR on crude oil volatility

Quantiles →	Q(0.05)	Q(0.10)	Q(0.30)	Q(0.50)	Q(0.70)	Q(0.90)	Q(0.95)
Panel A: Impact of EPU on the conditional volatility of WTI index							
Constant	**7.92**	**7.55**	**6.61**	**11.15**	**11.27**	6.41	15.42
OV_{t-1}	**0.68**	**0.70**	**0.77**	**0.80**	**0.91**	**1.23**	**1.30**
EPU	0.01	0.02	0.03	0.02	0.04	**0.15**	0.16
Panel B: Impact of EPU on the realized volatility of WTI index							
Constant	0.40	0.58	**6.21**	**26.86**	**64.02**	**149.18**	**259.47**
OV_{t-1}	0.001	0.01	**0.09**	**0.13**	0.21	**0.85**	**1.30**
EPU	-0.01	-0.02	0.07	0.08	0.12	0.53	**1.77**
Panel C: Impact of EPU on OVX							
Constant	5.28	4.28	**3.29**	3.24	3.26	**3.82**	**8.15**
OV_{t-1}	**0.61**	**0.69**	**0.83**	**0.89**	**0.96**	**1.10**	**1.06**
EPU	-0.002	-0.01	0.01	0.02	0.01	**0.04**	**0.06**
Panel D: Impact of GPR on the conditional volatility of WTI index							
Constant	**8.15**	**7.09**	**6.91**	**9.58**	**10.60**	10.52	6.94
OV_{t-1}	**0.68**	**0.71**	**0.78**	**0.82**	**0.92**	**1.17**	**1.42**
GPR	0.02	0.2	0.05	0.04	0.05	0.05	0.02
Panel E: Impact of GPR on the realized volatility of WTI index							
Constant	0.30	0.56	**6.77**	**28.23**	**62.86**	**132.22**	**278.37**
OV_{t-1}	0.002	0.01	**0.09**	**0.10**	**0.27**	**0.89**	**1.26**
GPR	0.006	0.007	0.04	0.06	-0.08	0.36	0.81
Panel F: Impact of GPR on OVX							
Constant	**5.33**	3.54	**3.51**	2.98	3.50	**6.31**	8.94
OV_{t-1}	**0.60**	**0.71**	**0.82**	**0.90**	**0.95**	**1.03**	**1.05**
GPR	0.01	0.02	-0.001	-0.01	-0.02	-0.04	**-0.05**

Notes: This table presents the impact of EPU/GPR on the volatility of WTI index. Panels A-C show the effects of EPU index, while Panels D-E exhibit the same for the GPR index. We consider seven quantiles, τ = (0.05, 0.10, 0.30, 0.50, 0.70, 0.90, 0.95). The lower quantiles (i.e. 0.05, 0.10, 0.30) reflect low volatility states, whereas the higher quantiles (i.e. 0.70, 0.90, 0.95) indicate high volatility states. OV refers to oil market volatility. Bold indicates statistical significance at the 5% level.

Table 11: Volatility forecasting performance

Volatility measures ↓	EMV-overall	EMV-commodity	EMV-crises	VIX	EPU	GPR
Panel A: $\tau = 0.50$						
Conditional volatility	0.2966	0.4000	0.0946	0.1376	0.1698	0.1077
Realized volatility	0.1397	0.1564	0.1977	0.1430	0.1543	0.1409
Implied volatility	0.3115	0.4613	0.0589	0.0756	0.2269	0.1829
Panel B: $\tau = 0.95$						
Conditional volatility	0.0558	0.0491	0.0280	0.0101	0.0217	0.0087
Realized volatility	0.0422	0.0600	0.0398	0.0269	0.0406	0.0211
Implied volatility	0.0611	0.1175	0.0142	0.0013	0.0533	0.0007

Notes: The numbers in this table indicate the values of the R^2 statistic estimated from Eq. (5). The forecast performance is assessed by comparing these R^2 values. We provide the results for quantiles 0.50 and 0.95. For other quantiles, we achieve similar results. The in-sample estimation period ranges from January 1990 to December, 2016, while the out-of-sample forecast period ranges from January 2017 to December, 2019. For the OVX index, the in-sample estimation period spans from May 2007 to December, 2016.

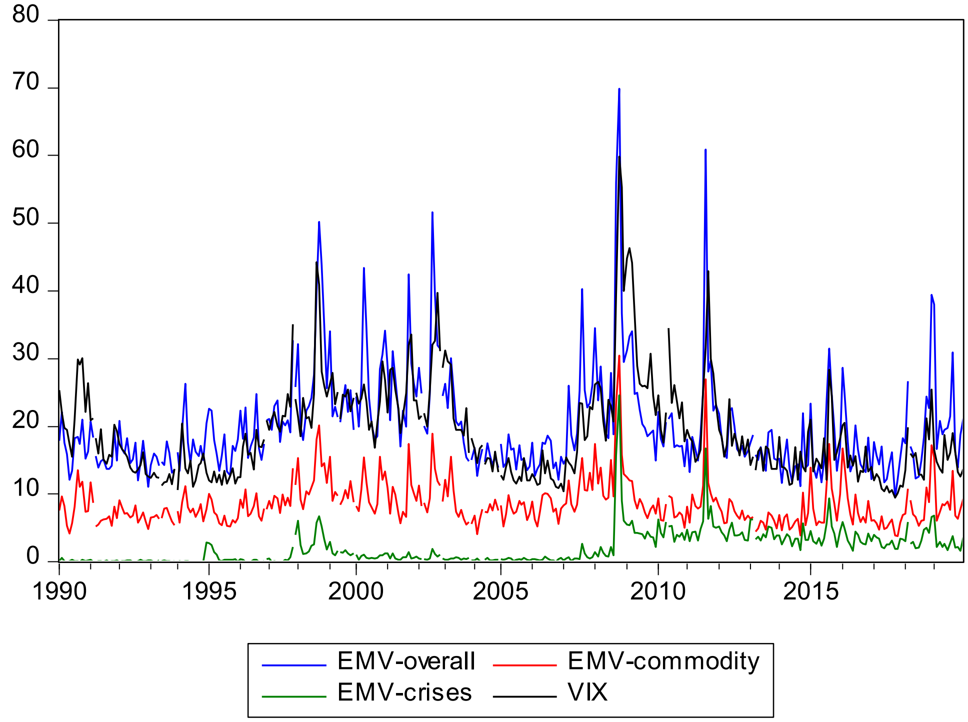

Fig. 1: Time-series plot for various EMV trackers and the VIX

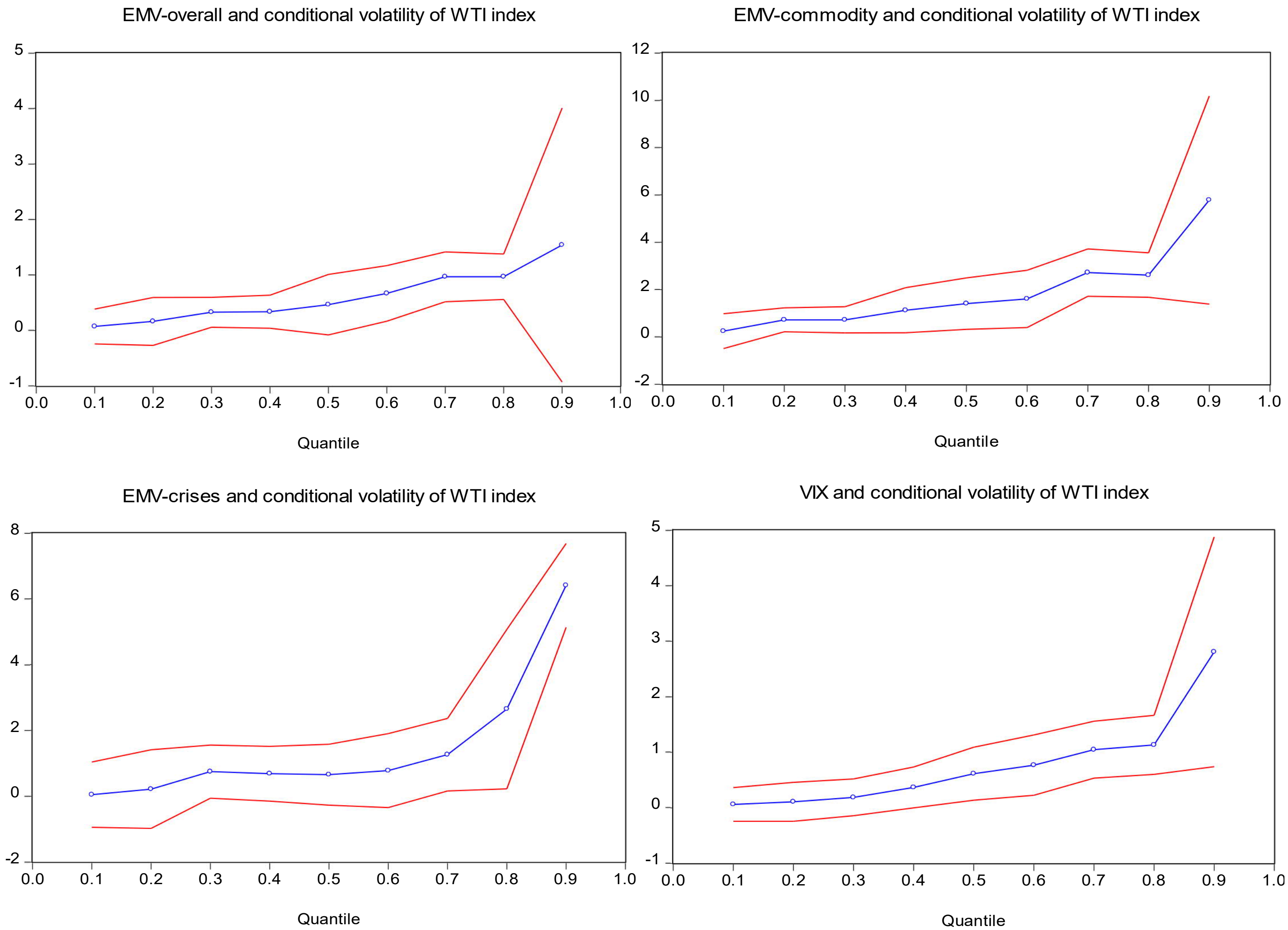

Fig. 2: Impact of EMV trackers and the VIX on the conditional volatility of the WTI index

Notes: This plot shows the contemporaneous impacts of various uncertainty indexes on crude oil conditional volatility across different quantiles. The blue solid line with circles denotes the point estimates and the two solid red lines present the 95% confidence bands.

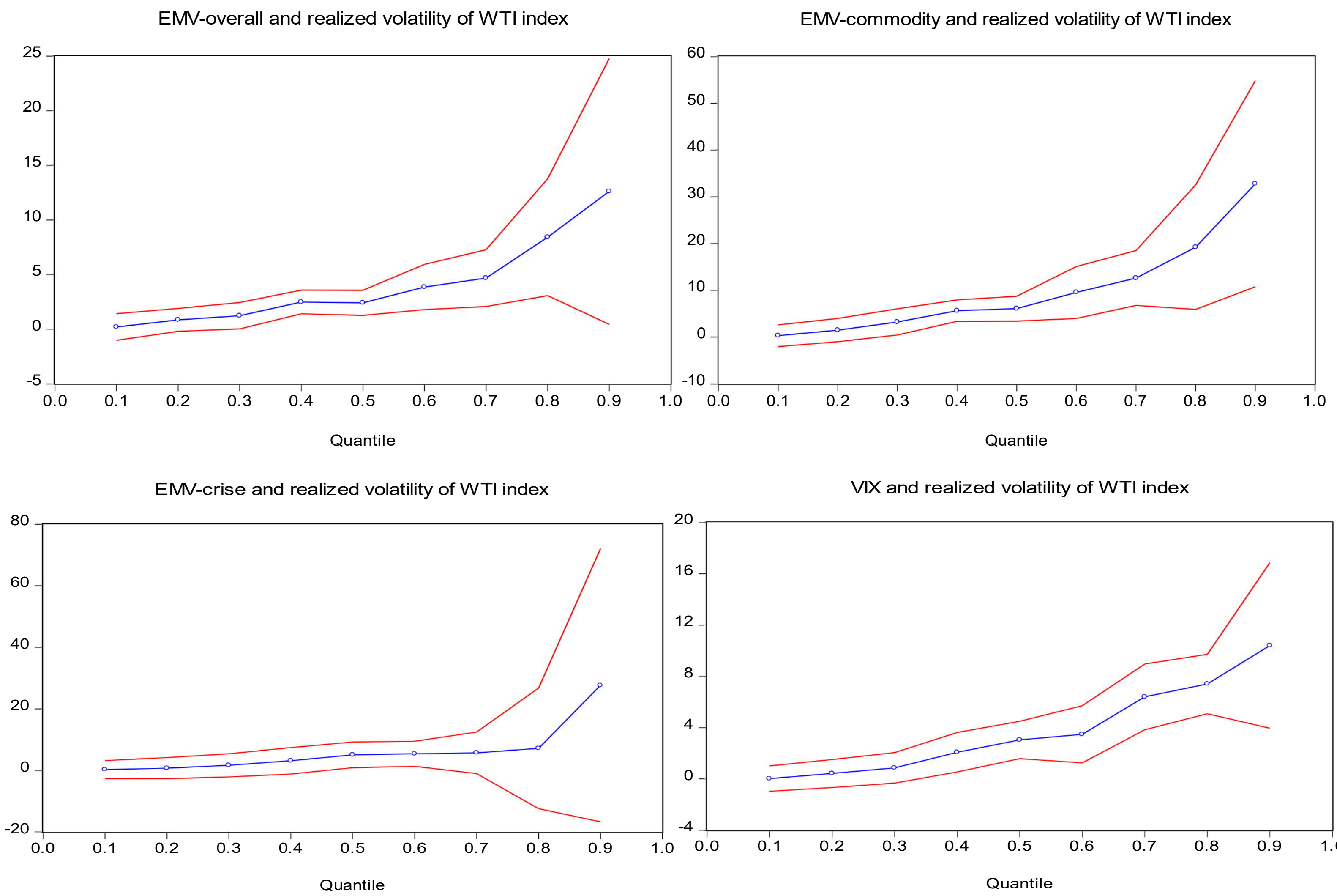

Fig. 3: Impact of EMV trackers and the VIX on the realized volatility of the WTI index

Notes: This plot shows the contemporaneous impacts of various uncertainty indexes on crude oil realized volatility across different quantiles. The blue solid line with circles denotes the point estimates and the two solid red lines present the 95% confidence bands.

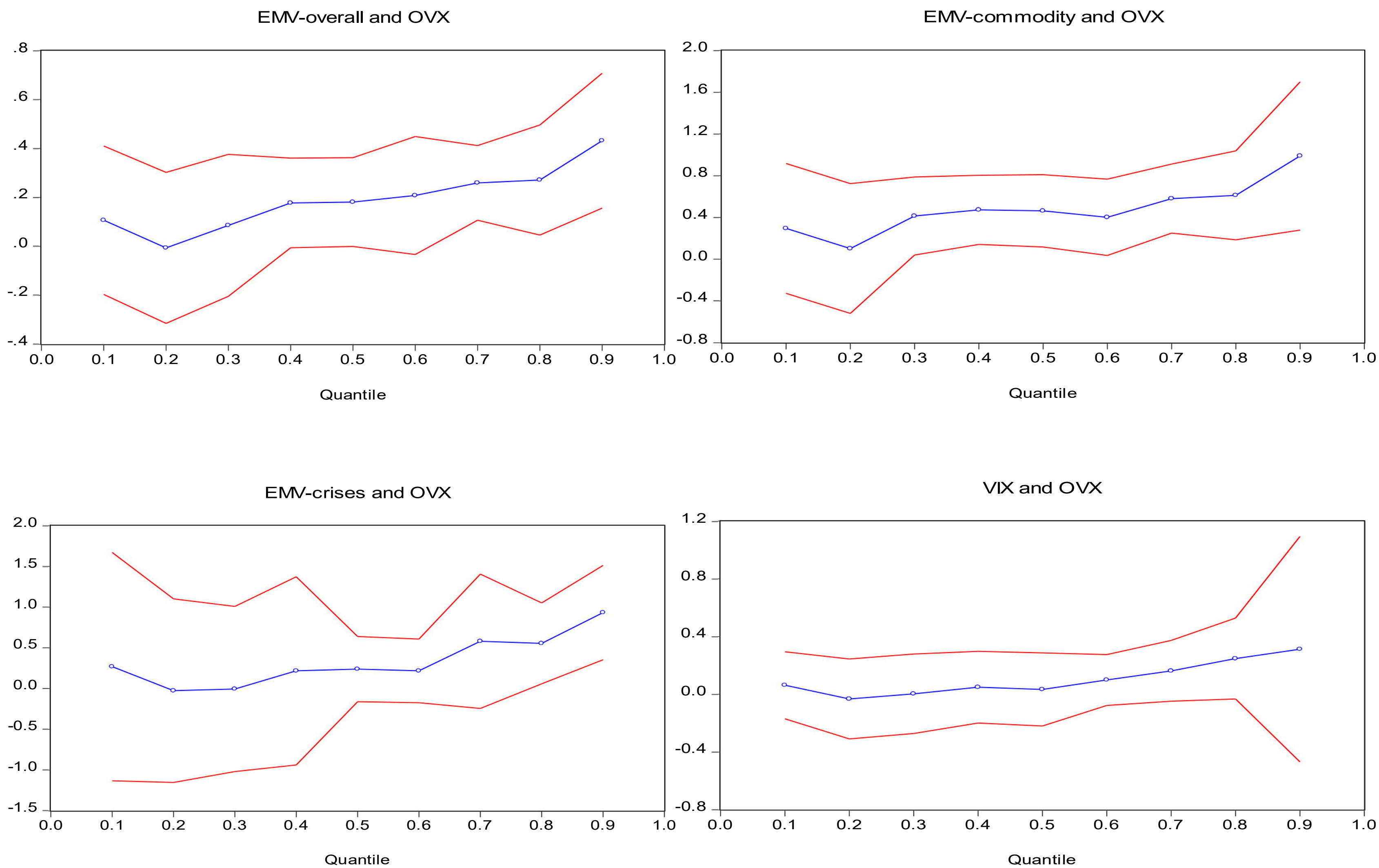

Fig. 4: Impact of EMV trackers and the VIX on the OVX

Notes: This plot shows the contemporaneous impacts of various uncertainty indexes on crude oil implied volatility across different quantiles. The blue solid line with circles denotes the point estimates and the two solid red lines present the 95% confidence bands.

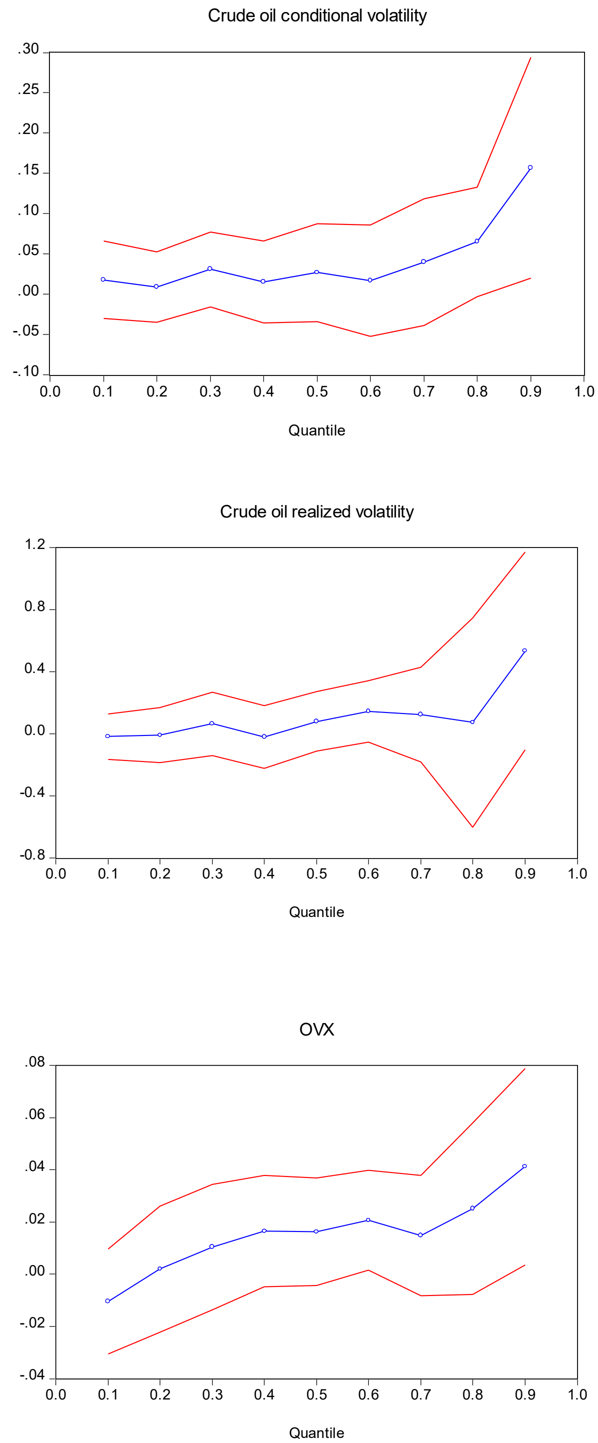

Fig. 5: Impact of EPU on crude oil volatility

Notes: This plot shows the contemporaneous impacts of EPU index on crude oil implied volatility across different quantiles. The blue solid line with circles denotes the point estimates and the two solid red lines present the 95% confidence bands.

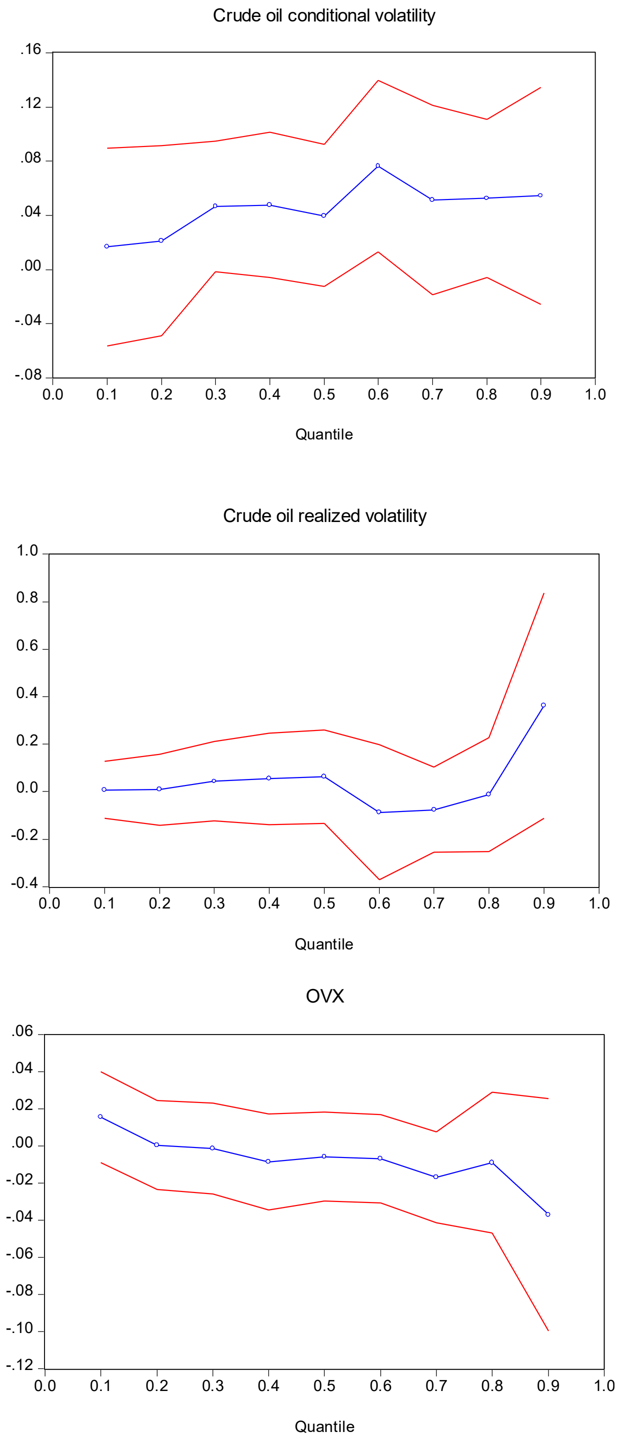

Fig. 6: Impact of GPR on crude oil volatility

Notes: This plot shows the contemporaneous impacts of GPR index on crude oil implied volatility across different quantiles. The blue solid line with circles denotes the point estimates and the two solid red lines present the 95% confidence bands.