The Predictive Power of Oil Price Shocks on Realized Volatility of Oil: A Note[#]

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Highlights

- Predictive power of oil supply, demand and risk shocks for oil RV analyzed.
- HAR-RV model used.
- Particularly risk shock is important.
- Incorporating all three shocks simultaneously yields the largest forecasting gains.
- The predictive information captured by disentangled oil price shocks is highlighted.

Abstract

This paper examines the predictive power of oil supply, demand and risk shocks over the realized volatility of intraday oil returns. Utilizing the heterogeneous autoregressive realized volatility (HAR-RV) framework, we show that all shock terms on their own, and particularly financial market driven risk shocks, significantly improve the forecasting performance of the benchmark HAR-RV model, both in- and out-of-sample. Incorporating all three shocks simultaneously in the HAR-RV model yields the largest forecasting gains compared to all other variants of the HAR-RV model, consistently at short-, medium-, and long forecasting horizons. The findings highlight the predictive information captured by disentangled oil price shocks in accurately forecasting oil market volatility, offering a valuable opening for investors and corporations to monitor oil market volatility using information on traded assets at high frequency.

Keywords: Oil Price Shocks, Risk Shocks, Oil, Realized Volatility, Forecasting

JEL Codes: C22, C53, Q02

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1. Introduction

There is now ample evidence in the literature suggesting that one has to account for the different sources of oil price fluctuations by distinguishing between supply and demand related shocks in order to get a more accurate assessment of oil price dynamics (Kilian, 2009) and studies that do not take into account the source of oil price shocks will be biased towards finding insignificant results and/or an effect which is unstable over time (Kilian and Park, 2009). Clearly, as Herrera et al. (2019) note, oil price shocks are not only caused by supply disruptions, but also by demand related factors and accordingly, a growing strand of the literature on the oil-stock market nexus has examined the effect of disentangled oil price shocks on stock market returns and volatility.[1] The general conclusion from these studies is that the relationship between stock returns and oil price shocks primarily depends on the nature of the shock and that demand shocks are far more relevant than supply side shocks in stock market behavior.

Considering that oil supply shocks relate to unexpected changes in world oil production, perhaps driven by country specific or geopolitical factors, while oil demand shocks relate more to sentiment that drives their precautionary demand and/or the business cycle that drives aggregate demand, distinguishing between supply and demand driven components of oil price fluctuations can help improve the explanatory power of economic models. This is particularly important when it comes to forecasting applications, as accurate prediction of oil market volatility is not only vital for traders in their pricing and hedging models, but also for corporations in their earnings forecasts. The application of oil price shocks to econometric analysis, however, has largely been limited to low frequency models (i.e. monthly or quarterly) due to the availability of models that are designed to extract supply and demand driven components from oil price changes. In a recent study, Ready (2018) offers a high frequency alternative to disentangling oil price shocks into supply, demand and risk driven components obtained from traded asset prices on daily frequency. This opens up the opportunity to examine the relationship between daily oil price shocks and intraday dynamics in financial and commodity asset returns. This paper contributes to the literature by examining the predictive power of disentangled oil price shocks over oil market realized volatility obtained from intraday data. By doing so, the paper provides new insight to the relative roles of supply and demand driven factors over oil market volatility and whether distinguishing between these components improves the accuracy of forecasts for oil price fluctuations.

Understandably, accurate forecasts of oil market volatility are crucial for correctly pricing derivative assets that underlie energy-based commodities. Accurate volatility forecasts are also important for hedging applications as expectation of volatility is directly used in the calculation of the optimal hedge ratios. This is especially important for corporations, particularly those with earnings that are highly sensitive to energy price fluctuations, as the size of the hedge positions and the implementation of conditional hedging strategies are determined by volatility forecasts.

[1] See, for example, Kang et al. (2015), Basher et al. (2018), Thorbecke (2019), Demirer et al. (2020) for recent applications.

Not surprisingly, a large literature exists, which we summarize in the literature review section, on the predictability (both in- and out-of-sample) of daily oil-price volatility. Given that intraday data contains rich information and can lead to more accurate forecasts of daily volatility compared to models of conditional volatility based on daily data (McAleer and Medeiros, 2008), an increasing number of studies (for detailed reviews, see Mei et al., 2017 and Qiu et al., 2019) have used variations of the Heterogeneous Autoregressive (HAR) model of Corsi (2009) to forecast the realized volatility (RV) of various asset and commodity markets returns by utilizing the realized volatility estimates obtained from intraday data per Andersen and Bollerslev (1998). Against this backdrop, we aim to contribute to the existing research on oil market volatility based on high-frequency data by forecasting RV of oil returns, computed from 5-minute-interval intraday data, using an extended version of the HAR-RV model. In particular, the HAR-RV model now incorporates information on the various components of oil price fluctuations due to demand and supply related factors in the oil market, as well as, the innovations associated with financial market risks. To the best of our knowledge, this study is the first to analyze the role of disentangled oil price and financial market risk shocks for in- and out-of-sample predictability of daily realized oil return volatility, derived from intraday data.

Intuitively, one can expect disentangled oil price shocks to affect oil market volatility through various channels. As mentioned earlier, while oil supply shocks largely relate to geopolitical developments or country/region specific surprises, demand shocks reflect unexpected changes in the aggregate or precautionary demand for oil, driven by the market's expectation of future economic conditions or concerns regarding future supply shortfalls. Accordingly, it may not be as clear-cut when it comes to infer in what direction oil demand and supply shocks can affect volatility in the oil market as the nature of news that drives the shock would be the critical factor that determines the direction of the effect. For instance, an increase in oil returns due to a supply shock, would be associated with the slowdown of the economy (as has been shown to be historically the case by Gupta and Wohar, 2017), and this recessionary impact is likely to reduce the demand and trading activity in the oil sector to result in lower volatility. In the case of demand shocks, however, one can argue that demand shocks associated with an increase in oil price, due to a rise in aggregate oil demand following an economic expansion, have been shown to reduce macroeconomic uncertainty, unlike supply shocks (Degiannakis et al., 2018). Furthermore, considering that uncertainty and oil market volatility are positively correlated (Hailemariam et al., 2019), demand shocks can be expected to reduce volatility in the oil market due to positive underlying conditions. On the other hand, if demand shocks are driven by an unexpected rise in precautionary demand as traders become nervous about future supply shortfalls, it could have the opposite effect, driving up volatility in the oil market. Finally, risk shocks associated with unexpected fluctuations in financial market uncertainty can be expected to spill over to the oil market, thus resulting in an increase in oil price volatility (Bonaccolto et al., 2018). The spillover effects of financial risk shocks to the oil market could partially be driven by changes in investors' risk appetite due to uncertainty shocks that are not necessarily related to the oil market. Such a spillover effect could be further strengthened due to the greater participation of financial investors in the commodity market, so-called commodity financialization, creating a new channel that links financial trades to commodity trades. In sum, one can argue that while positive oil supply and demand shocks should generally reduce oil volatility, risk shocks associated with financial market uncertainty should have the opposite effect, driving up volatility in the oil market.

Our tests show that all shock terms on their own, and particularly financial market driven risk shocks, significantly improve the forecasting performance of the benchmark HAR-RV model. The forecasting performance is found to significantly improve when we combine the information content of the three shock terms in an augmented model, suggesting that oil price demand/supply shocks as well as risk shocks individually capture marginal predictive information for oil market volatility. In particular, when we incorporate all three shocks simultaneously in the HAR-RV model, the framework significantly outperforms all the other variants of the HAR-RV model, consistently at short-, medium-, and long forecasting horizons, implied by greater forecasting gains against all other variants of the HAR-RV model. The findings highlight the predictive information captured by disentangled oil price shocks in accurately forecasting oil market volatility, offering a valuable opening for investors and corporations to monitor oil market volatility using information on traded assets at high frequency.

The remainder of the paper is organized as follows: Section 2 provides a summary of the existing literature on forecasting oil market volatility, while Section 3 outlines the data and methodologies to compute oil price shocks as well as the HAR-RV model specification. Section 4 presents the empirical results and Section 5 concludes with a discussion of the implications of our results.

2. Literature Review

As pointed out earlier, due to the importance of accurate forecasts of oil market volatility from the perspective of investment decisions, a large number of studies has delved into the issue of predictability in the oil market. While providing an elaborate review is beyond the scope of this paper given its current objectives, we provide below a summary of the most important contributions in the strand of the literature that are most closely aligned with our particular study. The early studies on modelling and prediction of oil market volatility have largely relied on conditional volatility using different variants of univariate and multivariate models from the family of the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) framework, and the Markov-switching multifractal (MSM) model (see Lux et al., 2016 for a detailed review). Overall, these studies find that while the univariate GARCH-type models are able to produce more accurate forecasts, relative to other forms of GARCH models, the MSM model in general is the most preferred approach compared to all the other models considered (across majority of forecast horizons and sub-samples).

More recently, with the availability of intraday data, a growing number of studies have utilized variations of the HAR-RV model to forecast the realized volatility of oil-price returns.[2] The earlier studies of Haugom et al., (2014), Sévi (2014), Prokopczuk et al., (2015) have led to the conclusion that all models fail to beat the forecast accuracy of the simple HAR-RV model which utilizes only the information embedded in past realized volatility, while incorporating structural breaks to the model is found to help improve the predictive performance (Wen et al., 2016). Moreover, Gong and Lin (2017) indicate signed jumps contain forecasting information for good and bad RVs, derived from positive and negative oil returns respectively.

More recent studies, however, highlight the important forecasting role of various predictors in extended HAR-RV models. For instance, Degiannakis and Filis (2017) show that incorporating information on the exogenous volatilities of four different asset classes (stocks, currencies, commodities and macroeconomic policy) improves the forecast accuracy of the standard HAR-RV model. Similarly, Gkillas et al., (2020) argue that forecast accuracy is improved when the baseline linear HAR-RV model is extended to incorporate an index of financial stress since financial stress as an additional predictors helps to explain the possible asymmetry of the loss function of a forecaster. To some extent, under the same theme, the role of various metrics capturing financial and oil market uncertainty and sentiment, has been stressed by numerous other studies including Gong and Lin (2018a), Wen et al., (2019), Yang et al., (2019), and Bonato et al., (2020). Gong and Lin (2017) and Wen et al., (2016). At the same time, Liu et al., (2018) and Chen et al., (2019) argue that the benchmark HAR-RV model can be outperformed when considering the time-variation and asymmetric volatility jumps and co-jumps with the equity (S&P 500) market.

Our paper aims to add to this burgeoning literature on oil market volatility using intraday data by looking at, for the first time, the role of oil demand and supply shocks, as well as financial market risk shocks, derived from a structural model, in forecasting oil returns RV. To the best of our knowledge, such a study of whether the shocks originating in the oil market itself can possibly be used to predict future high-frequency oil volatility has not been pursued before.[3]

[2] See for example, Haugom et al. (2014), Sévi (2014), Prokopczuk et al. (2015), Wen et al., (2016, 2019), Degiannakis and Filis (2017), Gong and Lin (2017, 2018a), Liu et al. (2018), Chen et al. (2019), Yang et al., (2019), Bonato et al., (2020) and Gkillas et al. (2020).

[3] The study of Pan et al., (2017) is to some extent related to our study, whereby the authors looked at the role of low frequency macro variables related to oil market decisions in forecasting daily conditional volatility based on a regime-switching GARCH model with mixed data sampling (MIDAS).

3. Data and Methodology

3.1. Data

Daily realized oil volatility (RV) values are computed from intraday data on oil futures traded on NYMEX over a 24 hour trading day (pit and electronic). The futures price data, in continuous format, is obtained from: www.disktrading.com and www.kibot.com. Close to expiration of a contract, the position is rolled over to the next available contract, provided that activity has increased. For intraday returns, last-tick interpolation gives 1-minute prices (if the price is not available at the 1-minute stamp, the previously available price is imputed) and we compute 5-minute returns by taking the log-differences of these prices. These returns are then used to calculate the realized oil volatility estimate for the day, as formulated in Equation (4). Separately, daily returns are computed as the end of day (New York time) price difference (close to close).

The information captured by demand and supply related oil factors is highlighted in an early study by Kilian (2009), noting that one has to account for the different sources of oil price fluctuations by distinguishing between supply and demand related shocks in order to get a more accurate assessment of oil price dynamics. Demirer et al. (2020) note that the decomposition method of Kilian (2009) has several shortcomings in that it tends to give too much weight to oil-specific demand shocks relative to supply shocks. The most limiting aspect of this decomposition method, however, is that it is limited to monthly frequency only and does not allow for higher frequency analysis. The decomposition method recently introduced by Ready (2018) overcomes these limitations by computing supply/demand related shocks based on traded asset prices, thus allowing us to perform our analysis at daily frequency. In our case, this framework offers an appropriate setting as it allows us to match daily oil price shocks with the daily realized volatility estimates obtained from intraday oil data.

In order to compute oil price demand/supply as well as risk shocks per Ready (2018), we collect daily price data for the world integrated oil and gas producer index[4], the nearest maturity NYMEX crude-light sweet oil futures contract, and the Chicago Board Options Exchange (CBOE) volatility index (VIX). These data are all derived from the Datastream database maintained by Thomson Reuters. Following Ready (2018), we use the first nearest maturity NYMEX crude-light sweet oil futures contract as a proxy for the price of crude oil. Finally, we use the innovations in VIX, obtained as the residuals from an ARMA (1,1) model estimated for the VIX index, to capture shocks related to changes in the market discount rate that tends to co-vary with attitudes towards risk. Our analysis covers the daily period of 5th January, 2000 to 30th May, 2017, with the start and end dates governed by the availability of data on price shocks and the intraday price data on oil futures.

[4] The world integrated oil and gas producer index represents the stock prices of global oil producer companies and includes large publicly traded oil producing firms (i.e., BP, Chevron, Exxon, Petrobras or Repsol), but not nationalized oil producers (such as ADNOC or Saudi Aramco).

3.2. Methodologies

The econometric framework we use in our empirical analysis consists of two components. First, we rely on the methodology introduced by Ready (2018) to decompose oil price changes into demand, supply and risk driven shocks. Second, we use the HAR-RV model developed by Corsi (2009) to forecast realized oil volatility by incorporating the information on the three shocks.

3.2.1. Identification of Oil Price Shocks

Ready (2018) defines demand shocks as the portion of returns on a global stock index of oil producing firms that is orthogonal to the innovations to the VIX. The innovations to the VIX are considered to control for aggregate changes in market discount rates that affect stock returns of oil producing companies and are used as a proxy for risk shocks. Supply shocks, in turn, are represented by the residual component of oil-price changes that is orthogonal to both demand shocks and risk shocks. To be more specific, the decomposition model by Ready (2018) takes the following matrix form:

$$X_t = AZ_t \tag{1}$$

where $X_t = \left[\Delta oil_t, R_t^{Prod}, \xi_{VIX,t}\right]'$ is a 3×1 vector, Δoil_t denotes the change in oil price in period t, R_t^{Prod} is the return on the global stock index of oil producing firms, and $\xi_{VIX,t}$ stands for the innovation to the VIX, based on an ARMA(1,1) specification. Our focus is $Z_t = [s_t, d_t, v_t]'$, which is a 3×1 vector of oil supply, demand and risk shocks represented by s_t, d_t and v_t, respectively. Finally, A is a 3×3 matrix of coefficients defined as:

$$A = \begin{bmatrix} 1 & 1 & 1 \\ 0 & a_{22} & a_{23} \\ 0 & 0 & a_{33} \end{bmatrix} \tag{2}$$

Ready (2018) imposes the following condition to achieve orthogonality among the three types of shocks as follows:

$$A^{-1}\Sigma_X(A^{-1})^T = \begin{bmatrix} \sigma_s^2 & 0 & 0 \\ 0 & \sigma_d^2 & 0 \\ 0 & 0 & \sigma_v^2 \end{bmatrix} \tag{3}$$

where Σ_X denotes the covariance matrix of the variables in X_t, while σ_s^2, σ_d^2 and σ_v^2 are the variance of the supply, demand and risk shocks, respectively. The specification in Eq. (3) represents a renormalization of the standard orthogonalization applied to construct structural shocks in an SVAR model. Note that the volatility of oil-price shocks is not normalized to one, but, instead, the sum of the three shocks has to be, by their very construction, equal to the total variation in the oil price. This method of decomposing oil-price shocks defines an oil supply shock as the component of oil-price fluctuations that cannot be explained by changes in global aggregate demand and changes in financial-market uncertainty.[5]

[5] As Demirer et al. (2020) argue, supply shocks in this framework relate to region-specific or event-specific information that cannot be accounted for by stock-market related pricing effects.

3.2.2. *Heterogeneous Autoregressive Realized Volatility (HAR-RV) Model*

Following Anderson et al., (2012), we measure the daily realized oil volatility by the median realized variance (MRV), constructed using intraday data. *MRV* is a jump-robust estimator of integrated variance computed as follows:

$$MRV_t = \frac{\pi}{6-4\sqrt{3}+\pi} \frac{T}{T-2} \sum_{i=2}^{T-1} med\left(|r_{t,i-1}|, |r_{t,i}|, |r_{t,i+1}|\right)^2 \quad (4)$$

where $r_{t,i}$ denotes intraday oil return i within day t, and $i = 1, \dots, T$ is the number of intraday oil returns within a day. Anderson et al., (2012) argue that *MRV* is less biased in the presence of market-microstructure noise than other measures of realized volatility.

In the case of forecasting analysis, we use variants of the widely-studied HAR-RV framework of Corsi (2009) to model and forecast daily realized oil volatility. While the HAR-RV model apparently has a simple structure, it has become increasingly popular in the literature because it is able to capture long memory and multi-scaling behaviour of commodity (oil) market volatility (Asai et al., 2019; 2020). In our application, the benchmark HAR-RV model is given by:

$$RV_{t+h} = \beta_0 + \beta_d RV_t + \beta_w RV_{w,t} + \beta_m RV_{m,t} + \varepsilon_{t+h} \quad (5)$$

where the index h denotes h-days-ahead realized volatility, with h = 1, 5, and 22 in our context. In addition, $RV_{w,t}$ is the average RV from day $t-5$ to day $t-1$, while $RV_{m,t}$ denotes the average RV from day $t-22$ to day $t-1$. The model in Equation (5) represents the benchmark HAR-RV model that we compare against the variants of the augmented model with various combinations of oil price shocks. When we augment the benchmark forecasting model with oil supply (s), demand (d) and risk shocks (v), we obtain the following extended HAR-RV model which includes the set of predictors (Q):

$$RV_{t+h} = \beta_0 + \beta_d RV_t + \beta_w RV_{w,t} + \beta_m RV_{m,t} + \theta' Q_t + \varepsilon_{t+h} \quad (6)$$

where, θ and Q are $p\times 1$ vectors. In our forecasting exercise, we set Q_t = [s_t]; [d_t]; [v_t]; [s_t, d_t]; [s_t, v_t]; [d_t, v_t]; [s_t, d_t, v_t] to explore variants of the HAR-RV model with various combinations of shocks included in the model.

4. Empirical Results

Table 1 provides the summary statistics for the daily realized volatility estimates and the three oil shock series, with the time series plots presented in Figure 1. Clearly, the component of oil returns due to financial risk shocks are highly volatile compared to demand and supply driven components. Risk shocks have on average 1.62% contribution to oil price changes whereas the average contribution of supply and demand shocks are relatively smaller than risk shocks. While both supply and demand driven components of oil price changes are less volatile, we observe that both shock series have negative mean values, suggesting that, on average, demand and supply factors had a negative impact on oil price changes. Given that the sample period covers the post-global financial crisis period, it is possible that the negative average contribution of supply/demand shocks on oil price changes is due to the slump in oil demand, particularly by OECD economies, observed following the global financial crash, while oil supply was largely unaffected.[6] Not surprisingly, all the variables under consideration are non-normal – a standard feature of high-frequency data. At the same time, daily realized volatility series presented in Figure 1 exhibit a rather volatile pattern with the RV estimates spiking to almost 50% during the 2007-2009 global crash period. Similar observation can also be drawn for the oil demand and supply shocks, while the risk shocks have been consistently higher since early 2006.

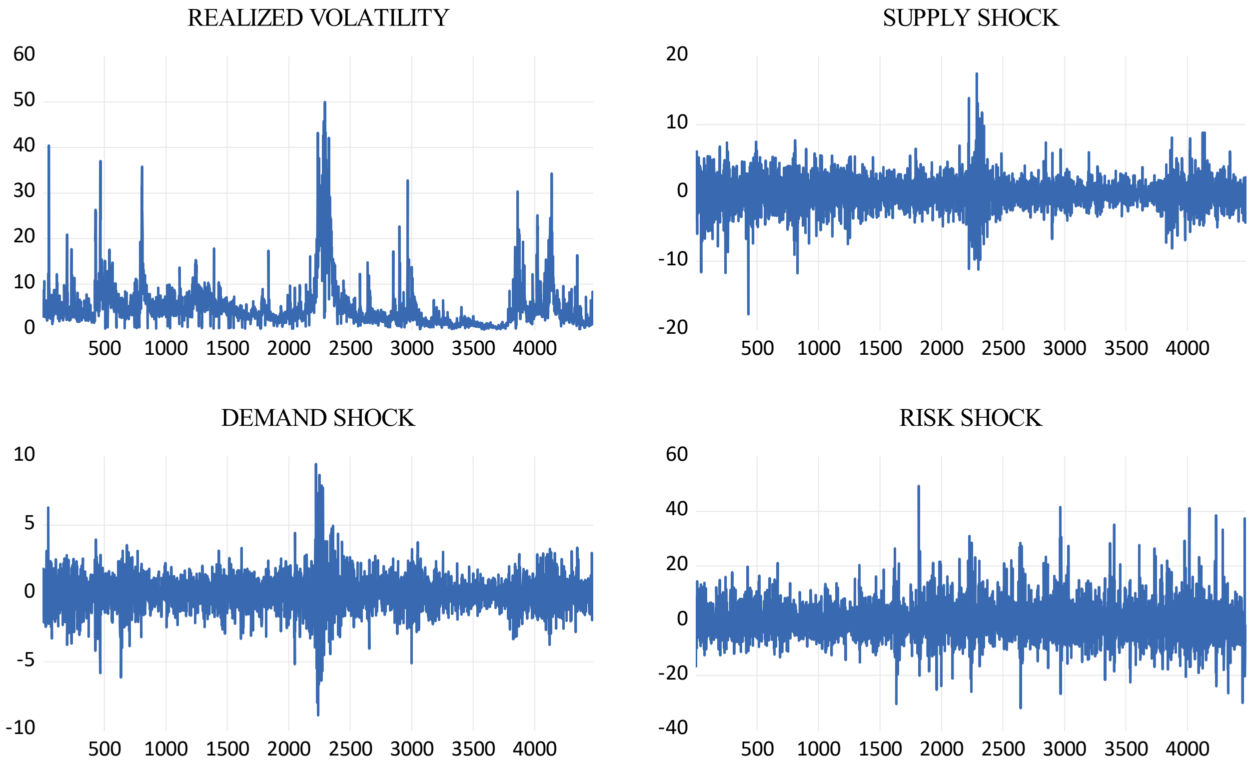
Table 1. Summary Statistics.

Statistic	Realized Volatility	Supply Shock	Demand Shock	Risk Shock
Mean	4.9271	-0.0026	-0.0020	0.0162
Median	3.7278	-0.0031	0.0244	-0.4467
Maximum	49.9654	17.4887	9.4707	49.2950
Minimum	0.0521	-17.7642	-8.9221	-31.9383
S.D.	5.0391	2.1123	1.1788	6.5295
Skewness	3.4928	-0.0634	-0.0552	0.7867
Kurtosis	19.4241	8.4397	9.4929	7.4374
Jarque-Bera	59356.1500	5516.7420	7857.7220	4130.2120
p-value	0.0000	0.0000	0.0000	0.0000
Observations		4472		

Note: S.D. stands for standard deviation; *p*-value corresponds to the null hypothesis of normality associated with the Jarque-Bera test.

[6] For detailed statistics, see https://www.iea.org/reports/oil-information-2019

Figure 1. Data Plots.



Note: The figures present the time-series plots for the daily realized volatility estimates for oil as well oil supply, demand and risk shocks.

Considering that the ultimate test of any predictive model (in terms of the econometric methodologies and predictors employed) is in its out-of-sample performance (Campbell, 2008), we focus on the forecasting exercise from an out-of-sample perspective. However, for the sake of completeness, we provide in Table 2 the full-sample estimation results for Eq. (6), with Q = [s, d, v] for h = 1, 5 and 22. Consistent with the empirical evidence on financial market returns, the persistence of the realized volatility series is confirmed by the highly significant and positive β_d, β_w and β_m estimates in the table. At the same time, all three types of oil price shocks are found to have a significant effect on oil realized volatility, implied by the highly significant θ_1, θ_2, and θ_3 estimates across all forecast horizons. Since we standardize the oil shock series with their respective standard deviations for the in-sample analysis, we see that, in absolute terms, financial risk shocks carry the highest strength in predicting oil market volatility, followed by demand shocks, barring the one-week-ahead horizon. Not surprisingly, financial market-related risk shocks are found to increase intraday return volatility in the oil market. One possible explanation for the positive effect of risk shocks on oil volatility could be that risk sentiment in financial markets, captured by the innovations in the volatility index, spill over to commodity markets as financial investors move funds in and out of the relatively riskier commodity positions. It is also possible that investors increase their hedge positions by taking on additional oil futures positions, thus contributing to volatility in the oil market as the sign of the hedge positions are driven by investors’ underlying positions as well as risk expectations. At the same time, however, we observe that oil supply and demand shocks have a negative marginal effect on realized volatility, possibly as they capture information regarding future economic conditions or uncertainty, as discussed earlier.

Table 2. In-Sample Predictability Results.

	Parameter Estimates						
Horizon	β_0	β_d	β_w	β_m	θ_1	θ_2	θ_3
h = 1	0.2117*	0.3225*	0.0841*	0.0097*	-0.1977*	-0.2133*	0.3006*
h = 5	0.2439**	0.6916*	0.8442*	0.0017*	-0.2303*	-0.1772*	0.2627*
h = 22	-0.0046	0.2649*	0.1874*	0.9453*	-0.1647*	-0.2351*	0.3117*

Note: The table presents the estimates for: $RV_{t+h} = \beta_0 + \beta_d RV_t + \beta_w RV_{w,t} + \beta_m RV_{m,t} + \theta_1 s_t + \theta_2 d_t + \theta_3 v_t + \varepsilon_{t+h}$, where s, d and v are oil supply, oil demand and risk shocks respectively. * and ** indicate significance at the 1 percent and 5 percent levels respectively.

Having observed a significant in-sample effect of oil price shocks on realized volatility, we next turn our attention to the primary objective of our research, i.e., the role of oil supply/demand and risk shocks in forecasting the realized volatility of intraday oil price changes. Out-of-sample predictability is examined via a recursive estimation approach over the out-of-sample period, which covers the period of 24th March, 2003 to 26th May, 2017. In order to determine the out-of-sample period, we first conduct the multiple structural break test of Bai and Perron (2003) on the HAR-RV model including all three oil shock series. Note that the importance of accounting for structural breaks in forecasting volatility, including that of commodity futures, is important to avoid model misspecification (Wen et al., 2016; Gong and Lin, 2018b). The structural break test yields the following breaks: (i) for h = 1, 24/03/2003, 20/03/2006, 18/12/2008, 05/08/2011, and 30/09/2014; (ii) for h = 5, 27/03/2003, 06/03/2006, 18/12/2008, 05/08/2011, and 02/10/2014; and (iii) for h = 22, 17/04/2003, 20/03/2006, 01/01/2009, 03/08/2011, and 30/10/2014. Baumeister and Kilian (2016) note that the structural breaks in 2003 coincide with the heightening tensions in Iraq during this period, resulting in the U.S. invasion of Iraq in early 2003, while the regime changes in 2008 and 2014 coincide with sharp declines in oil prices due to weakening of global demand. Similarly, the breaks in 2006 are generally attributed to price increases due to a series of events such as Hurricane Katrina, supply disruptions in Iraq due to its ongoing conflict and geopolitical tensions resulting from North Korea's missile launch. Finally, the break in 2011 is likely to have resulted from the political turmoil due to the Arab Spring, which drove oil prices up. It must be noted that the breaks in 2008 and 2011 could also be driven by the financial market driven risk shocks as these were the periods corresponding to the peaks of the Global Financial and the European sovereign debt crises. Nevertheless, given that the earliest break occurred on 24th March, 2003, we start our recursive estimation from this point onwards and compute the Mean Squared Forecast Errors (MSFEs) from the benchmark HAR-RV model and its seven possible extensions for h =1, 5 and 22. We then use the MSE-F test of McCracken (2007) to compare the forecast accuracy of the extended versions of the HAR-RV models with the nested benchmark, i.e., the basic HAR-RV model in Eq. (5), which does not include any of the shock variables.

Clearly, since our focus is on the forecast errors, a lower MSFE value implies a better performing forecasting model. In Table 3, we report the out-of-sample forecasting gains from a particular extended version of the HAR-RV model ($MSFE_1$) augmented by the oil shocks as additional predictors, relative to the benchmark model ($MSFE_0$). Forecasting Gains (FG) are formulated as:

$$FG = \left(\frac{MSFE_0}{MSFE_1} - 1\right) \times 100 \tag{7}$$

where $MSFE_0$ and $MSFE_1$ are the Mean Squared Forecast Errors (MSFEs) of the benchmark HAR-RV model (without any shocks) and its extended version, given the general forecasting model presented in Eq. (6). As mentioned earlier, we examine seven different model variants with various predictor combinations where $Q_t = [s_t]; [d_t]; [v_t]; [s_t, d_t]; [s_t, v_t]; [d_t, v_t]; [s_t, d_t, v_t]$ for Models 1 to 7, with s, d and v denoting oil supply, demand and risk shocks, respectively. Given the formulation in Eq. (7), a positive (negative) entry in the table indicates the forecasting gain (loss) in percentages.

The first observation that strikes the eye in Table 3 is that all entries in the table are positive, indicating that all variants of the extended HAR-RV model with various combinations of oil and risk shocks incorporated to the model result in gains in forecasting accuracy. This means that HAR-RV models that incorporate the information captured by oil price and risk shocks produce lower MSFEs relative to the benchmark HAR-RV specification.[7] Clearly, each type of oil price shock captures valuable predictive information individually regarding the future pattern of oil market volatility. Second, comparing the forecasting power of each oil shock in Models 1-3, we see that financial risk shocks provide the greatest forecasting gain when incorporated into the benchmark model. Compared to the extended models that include only the supply (Model 1) or the demand (Model 2) shock, Model 3 that includes the risk shock results in the highest reduction in forecasting errors, consistently at all the three forecast horizons of h =1, 5 and 22. This suggests that financial market-related shocks tend to capture more predictive information over oil market volatility compared to oil market specific demand and supply factors. Although not entirely expected, this result is in fact in line with the recent finding by Qadan and Idilbi-Bayaa (2020) that financial market shocks are more important than fundamental oil supply and demand shocks in driving the first and second moments of oil price changes. The dominant role of financial risk shocks on oil market volatility is also consistent with a number of studies including Degiannakis and Filis (2017), Wen et al., (2019) and Gkillas et al., (2020), that also highlight the role of financial market volatility, uncertainty and stress, respectively in accurately forecasting the realized volatility of oil.

[7] The absolute MSFEs from the benchmark HAR-RV model for h = 1, 5 and 22 are found to be 2.45 percent, 3.12 percent and 3.71 percent, respectively. These values can, in turn, be used to recover the absolute MSFEs of the extended versions of the HAR-RV model by interested readers.

Table 3. Out-of-Sample Forecasting Gains.

	Forecasting Models						
Horizon	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
$h = 1$	0.6936*	0.8169*	2.0541*	1.4162*	2.7688*	2.7719*	3.3909*
$h = 5$	0.7562*	0.3019*	0.9967*	0.9996*	1.7660*	1.2483*	1.9600*
$h = 22$	0.1214*	0.4885*	0.8453*	0.5695*	0.9632*	1.2779*	1.3560*

Note: Entries correspond to forecasting gains, i.e., $FG = \left(\frac{MSFE_0}{MSFE_1} - 1\right)\times 100$, where $MSFE_0$ and $MSFE_1$ are Mean Squared Forecast Errors (MSFEs) of the benchmark HAR-RV model (excluding oil price shocks) and its extended version that includes oil shocks in various combinations, respectively. The general forecasting model takes the form: $RV_{t+h} = \beta_0 + \beta_d RV_t + \beta_w RV_{w,t} + \beta_m RV_{m,t} + \theta' Q_t + \varepsilon_{t+h}$, where $Q_t = [s_t]; [d_t]; [v_t]; [s_t, d_t]; [s_t, v_t]; [d_t, v_t]; [s_t, d_t, v_t]$ for Models 1 to 7 with s, d and v denoting oil supply, demand and risk shocks, respectively. For the benchmark HAR-RV model, $Q = []$. * indicates significance of the MSE-F test statistic at the 1 percent level.

Comparing Models 4-6 where we combine two shocks at a time with Models 1-3 that include only one shock at a time, we observe that including the additional shock terms indeed improves the forecasting performance. The best-performing models including two shock terms are found to produce higher forecasting gains than the best-performing one-shock models at respective forecasting horizons, clearly indicating that the oil market demand and supply shock terms provide additional forecasting power. Interestingly, the model that includes demand and risk shocks provide the best forecasting performance at the shortest and longest forecasting horizons, while the model with supply and risk shocks performs the best at $h = 5$. This is consistent with our in-sample results, where the predictive power of risk shocks dominates in all horizons, followed by the demand shock at short- and medium-runs. Finally, we see that the model that incorporates all three shocks (Model 7) outperforms all other extended HAR-RV model variants, consistently at h =1, 5 and 22 although the gains diminish as the forecasting horizon increases. Clearly, both risk and oil price demand/supply shocks capture valuable predictive information over oil market volatility and including these shocks in the forecasting model results in smaller forecast errors at all forecasting horizons.

Overall, our results suggest that disentangled oil price shocks carry significant predictive information regarding the future path of return volatility in the oil market. While financial market driven risk shocks are important on their own in forecasting realized oil volatility, the forecasting performance can be significantly improved by supplementing the model with the information captured by oil price shocks driven by supply- and demand-related factors. Finally, and more importantly, the forecasting gains from all seven variants of the extended HAR-RV model are statistically significant at the 1 percent level of significance using the MSE-F statistic, confirming the importance of the predictive information captured by these shocks. Although not explicitly reported in Table 3, when we compare the two best performing models at each forecast horizon, namely: (i) HAR-RV with s+d+v against HAR-RV with d+v for $h=1$; (ii) HAR-RV with s+d+v against HAR-RV with s+v for $h=5$; and (iii) HAR-RV with s+d+v against HAR-RV with d+v for $h=22$, we obtain the MSE-F statistics to be 22.0733, 6.9847, and 2.8285 respectively, which are again significant at the 1 percent level for h=1, and 5, and at the 5 percent level for h=22.[8] This result further supports our earlier conclusion that the model that incorporates all three shock terms not only statistically outperforms the benchmark HAR-RV model, but also dominates all other variants of the extended HAR-RV model.

The finding that financial risk shocks contain significant predictive power over oil market realized volatility over and above that is contained in oil demand and supply shocks highlights the importance of spillover effects across the oil and stock markets. Considering the increasing participation of financial investors in commodity trades, one can argue that that predictive information captured by financial shocks reflects changes in investors' risk appetite toward the risky commodity trades. Nevertheless, these findings have clear implications for not only oil traders, but also corporations in the implementation of their volatility forecasting models. From an investment perspective, the results suggest that traders can incorporate high frequency, disentangled oil price shocks based on traded asset prices to improve their volatility forecasts, which in turn can be used to price derivative contracts underlying oil related assets. These forecasts can also be used to determine optimal hedge positions as ignoring the information captured by oil price shocks can lead to sub-optimally hedged oil positions. At the corporate level, the results can be used to improve hedging strategies to mitigate the negative effect of oil price uncertainty on business operations, particularly for firms whose revenues are highly sensitive to oil price fluctuations (e.g. airlines, transportation companies). Finally, given the role of financial risk shocks as an important predictor of oil realized volatility, it is important for market regulators to consider cross-market spillover effects in their models to monitor unusual trading activity and excessive market volatility. Specifically, the role of financial traders as a possible driver of volatility in commodity markets could be closely monitored in order to avoid unusual fluctuations in commodity prices.

5. Conclusion

This paper explores the predictive power of oil demand/supply shocks as well as financial market risk shocks for the realized volatility of oil returns derived from intraday data. Utilizing a recently proposed model to decompose oil price shocks into supply and demand related components, as well as shocks due to financial market related risks, we examine the in- and out-of-sample forecasting performance of various HAR-RV models per Corsi (2009) by incorporating disentangled oil price shocks as predictors in various combinations. In the process, we extend the existing literature on forecasting of realized oil price volatility by accounting for fundamental shocks to the oil market over and above the shocks related to the financial market.

We find that all shock terms on their own, and particularly financial market driven risk shocks, significantly improve the forecasting performance of the benchmark HAR-RV model. More

[8] The critical values at 10 percent, 5 percent and 1 percent are 0.1270, 1.6120, and 4.1840 respectively, as derived from Table 4 of McCracken (2007, p. 732).

importantly, we show that the forecasting performance can be significantly improved when we combine the information content of the three shock terms in an augmented model, suggesting that oil price demand/supply shocks as well as risk shocks individually capture marginal predictive information for oil market volatility. In particular, when we incorporate all three shocks simultaneously in the HAR-RV model, the framework significantly outperforms all the other variants of the HAR-RV model, consistently at short-, medium-, and long forecasting horizons, implied by greater forecasting gains against all other variants of the HAR-RV model. The findings highlight the predictive information captured by disentangled oil price shocks in accurately forecasting oil market volatility, offering a valuable opening for investors and corporations to monitor oil market volatility using information on traded assets at high frequency.

Given the importance of accurate volatility forecasts in the computation of optimal investment positions and pricing of derivatives, our findings suggest that incorporating supply and demand driven oil price shocks, over and above financial risk shocks in forecasting models, can help improve the design of portfolios that include oil as a hedge against financial market risks across various investment horizons. Such a predictability relationship is also important at the aggregate market level as oil market volatility (uncertainty) tends to negatively impact the macroeconomy (Elder and Serletis, 2010; van Eyden et al., 2019). Naturally, high-frequency forecasts of oil volatility can be incorporated into mixed data sampling (MIDAS) models by policymakers to predict the future path of low frequency real activity and nominal variables, and then accordingly undertake monetary and fiscal policy decisions to counteract the possible recessionary impact on the economy. In this regard, it must be noted that while we concentrate on the WTI oil market, given that oil volatility across the various regional markets are connected with each other (Liu and Gong, 2020), policy authorities around the world should closely monitor the importance of these shocks in determining uncertainty and associated negative impact on their respective domestic economies.

As part of future research, it would be interesting to extend our study to other popular safe havens like U.S. Treasuries, the Swiss franc and Japanese yen, and even the cryptocurrency Bitcoin, which too has recently gained some popularity as a hedge against financial market risks. Another line of research can examine the hedging and pricing implications of our findings by comparing models that utilize volatility forecasts from a benchmark model with those obtained from an augmented forecasting model that incorporates disentangled oil price shocks. Finally, given the ongoing wide-ranging impact of COVID-19, it would be interesting to extend our data set to the current period, and analyze the role of this pandemic on the recent volatility of the oil market. Understandably, the virus outbreak has affected oil demand and supply, and financial risks, and our model specification would be able to capture the current situation adequately. Based on intraday data availability, this would be a very relevant research question to venture in the future.

References

Andersen, T.G., Dobrev, D., and Schaumburg, E. (2012). Jump-robust volatility estimation using nearest neighbor truncation. Journal of Econometrics, 169, 75-93.

Antonakakis, N., Chatziantoniou, I., and Filis, G. (2014). Dynamic spillovers of oil price shocks and economic policy uncertainty. Energy Economics, 44, 433-447.

Asai, M. Gupta, R., and McAleer, M. (2019). The Impact of Jumps and Leverage in Forecasting the Co-Volatility of Oil and Gold Futures. Energies, 12, 3379.

Asai, M. Gupta, R., and McAleer, M. (2020). Forecasting Volatility and co-volatility of crude oil and gold futures: Effects of leverage, jumps, spillovers, and geopolitical risks. International Journal of Forecasting. DOI: https://doi.org/10.1016/j.ijforecast.2019.10.003.

Bai, J. and Perron, P. (2003). Computation and analysis of multiple structural change models. Journal of Applied Econometrics, 18, 1-22.

Basher, S.A., Haug, A.A. and Sadorsky, P. (2018). The impact of oil-market shocks on stock returns in major oil-exporting countries. *Journal of International Money and Finance*, 86, 264-280.

Baumeister, C., and Kilian, L. (2016). Forty Years of Oil Price Fluctuations: Why the Price of Oil May Still Surprise Us. Journal of Economic Perspectives, 30(1), 139–160.

Bonaccolto, M., Caporin, M., and Gupta, R. (2018). The dynamic impact of uncertainty in causing and forecasting the distribution of oil returns and risk? Physica A: Statistical Mechanics and its Applications, 507, 446-469.

Bonato, M., Gkillas, K., Gupta, R., and Pierdzioch, C. (2020). Investor Happiness and Predictability of the Realized Volatility of Oil Price. Sustainability 2020, 12(10), 4309.

Campbell, J.Y. (2008). Viewpoint: estimating the equity premium. Canadian Journal of Economics, 41, 1-21.

Chen, Y., Ma, F., and Zhang, Y. (2019). Good, bad cojumps and volatility forecasting: new evidence from crude oil and the U.S. stock markets. Energy Economics, 81, 52-62.

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

Degiannakis, S., and Filis, G. (2017). Forecasting oil price realized volatility using information channels from other asset classes. Journal of International Money and Finance, 76, 28-49.

Degiannakis, S., Filis, G., and Panagiotakopoulou, S. (2018). Oil price shocks and uncertainty: How stable is their relationship over time? Economic Modelling, 72(C), 42-53.

Demirer, R., Ferrer Lapeña, R., Shahzad, S.J.H (2020). Oil Price Shocks, Global Financial Markets and Their Connectedness. Energy Economics 88, 104771.

Elder, J., and Serletis, A. (2010). Oil price uncertainty. Journal of Money, Credit and Banking, 42, 1137−1159.

Gkillas, K., Gupta, R., and Pierdzioch, C. (2020). Forecasting realized oil-price volatility: The Role of financial stress and asymmetric loss. Journal of International Money and Finance 104, 102137.

Gong, X., and Lin, B. (2017). Forecasting the good and bad uncertainties of crude oil prices using a HAR framework. Energy Economics, 67(C), 315-327.

Gong, X., and Lin, B. (2018a). The incremental information content of investor fear gauge for volatility forecasting in the crude oil futures market. Energy Economics, 74(C), 370-386.

Gong, X., and Lin, B. (2018b). Structural breaks and volatility forecasting in the copper futures market. Journal of Futures Markets, 38(3), 290-339.

Gupta, R., and Wohar, M.E. (2017). Forecasting oil and stock returns with a Qual VAR using over 150 years of data. Energy Economics, 62(C), 181-186.

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

Herrera, A.M., Karaki, M.B. and Rangaraju, S.K. (2019). Oil price shocks and U.S. economic activity. Energy Policy, 129, 89-99.

Kang, W., Ratti, R.A. and Yoon, K.H. (2015). Time-varying effect of oil market shocks on the stock market. Journal of Banking & Finance, 61(2), S150-S163.

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

Kilian, L., and Park, C. (2009). The impact of oil prices shocks and the U.S. stock market. International Economic Review, 50, 1267-1287.

Liu, T., and Gong, X. (2020). Analyzing time-varying volatility spillovers between the crude oil markets using a new method. Energy Economics, 87(C), 104711.

Liu, J., Ma, F., Yang, K., and Zhang, Y. (2018). Forecasting the oil futures price volatility: large jumps and small jumps. Energy Economics, 72, 321-330.

Lux, T., Segnon, M., and Gupta, R. (2016). Forecasting crude oil price volatility and value-atrisk: Evidence from historical and recent data. Energy Economics, 56, 117-133.

McAleer, M., and Medeiros, M.C. (2008). Realized volatility: A review. Econometric Reviews, 27, 10-45.

McCracken, M.W. (2007). Asymptotics for out of sample tests of Granger causality. Journal of Econometrics, 140, 719-752.

Mei, D., Liu, J., Ma, F., and Chen, W. (2017). Forecasting stock market volatility: Do realized skewness and kurtosis help?, Physica A, 481, 153−159.

Pan, Z., Wang, Y., Wu, C., and Yin, L. (2017). Oil price volatility and macroeconomic fundamentals: A regime switching GARCH-MIDAS model. Journal of Empirical Finance, 43, 130-142.

Prokopczuk, M., Symeonidis, L., and Wese Simen, C. (2015). Do jumps matter for volatility forecasting? Evidence from energy markets. Journal of Futures Markets, 36, 758-792.

Qadan, M., and Idilbi-Bayaa, Y. (2020). Risk appetite and oil prices, Energy Economics, 85, 104595.

Qiu, Y., Zhang, X., Xie, T., and Zhao, S. (2019). Versatile HAR model for realized volatility: A least square model averaging perspective. Journal of Management Science and Engineering, 4(1), 55-73.

Ready, R.C. (2018). Oil prices and the stock market. Review of Finance, 22(1), 155-176.

Sévi, B. (2014). Forecasting the volatility of crude oil futures using intraday data. European Journal of Operational Research, 235, 643-659.

Thorbecke, W. (2019). Oil prices and the U.S. Economy: Evidence from the stock market. Discussion papers 19003, Research Institute of Economy, Trade and Industry (RIETI).

van Eyden, R., Difeto, M., Gupta, R., and Wohar, M.E. (2019). Oil price volatility and economic growth: Evidence from advanced OECD countries using over one century of data. Applied Energy, 233/234, 612−621.

Wen, F., Gong, X., and Cai, S. (2016). Forecasting the volatility of crude oil futures using HAR type models with structural breaks. Energy Economics, 59, 400–413.

Wen, F., Zhao, Y., Zhang, M., and Hu, C. (2019). Forecasting realized volatility of crude oil futures with equity market uncertainty. Applied Economics, 51(59), 6411–6427.

Yang, C., Gong, X., Zhang, H. (2019). Volatility forecasting of crude oil futures: The role of investor sentiment and leverage effect. Resources Policy, 61, 548–563.