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The predictive power of oil price shocks on realized volatility of oil: A note☆

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ARTICLE INFO

JEL classification:
C22
C53
Q02
Keywords:
Oil price shocks
Risk shocks
Oil
Realized volatility
Forecasting

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.

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 relationships between daily oil price shocks and intraday dynamics in financial and commodity asset returns. This paper contributes to the

☆ We would like to thank two anonymous referees for many helpful comments. However, any remaining errors are solely ours.
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1 See, for example, Kang et al. (2015), Bashir et al. (2018), Thorbecke (2019), Demirer et al. (2020) for recent applications.

https://doi.org/10.1016/j.resourpol.2020.101856
Received 24 May 2020; Received in revised form 25 July 2020; Accepted 4 September 2020
Available online 23 September 2020
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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 cautionary demand as traders become nervous about future supply (Hailemariam et al., 2019), demand shocks can be expected to reduce ering that uncertainty and oil market volatility are positively correlated unlike supply shocks (Degiannakis et al., 2018). Furthermore, consid- 2dation 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 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 simulta- neously 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 multi- variate models from the family of the Generalized Autoregressive Con- ditional Heteroskedasticity (GARCH) framework, and the Markov-switching multifractal (MSM) model (see Lux et al. (2016) Wang et al. (2016a, b), Dutta et al. (2020) for detailed reviews). 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

2 See for example, Haugom et al. (2014), Sévi (2014), Prokopczuk et al. (2013), Wen et al. (2016, 2019), Degiannakis and Fils (2017), Gong and Lin (2017, 2018a), Liu et al. (2018), Chen et al. (2019), Yang et al. (2019), Bonato et al. (2020) and Giakas et al. (2020).
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.\(^3\)

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 h 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-min prices (if the price is not available at the 1-min stamp, the previously available price is imputed) and we compute 5-min 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, 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.

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:

\[
X_t = AZ_t
\]

where \(X_t = [\Delta \text{oil}, R^\text{prod}_t, \xi_{\text{VIX}, t}']\) is a \(3 \times 1\) vector, \(\Delta \text{oil}\) denotes the change in oil price in period \(t\), \(R^\text{prod}_t\) is the return on the global stock index of oil producing firms, and \(\xi_{\text{VIX}, t}\) 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 \(3 \times 1\) vector of oil supply, demand and risk shocks represented by \(s_t, d_t\) and \(v_t\), respectively. Finally, \(A\) is a \(3 \times 3\) matrix of coefficients defined as:

\[
A = \begin{bmatrix} 1 & 1 & 1 \\ 0 & a_{22} & a_{23} \\ 0 & 0 & a_{33} \end{bmatrix}
\]

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

\[
A^{-1} \Sigma (A^{-1})'\]

where \(\Sigma_x\) denotes the covariance matrix of the variables in \(X_t\), while \(\sigma^2_s\), \(\sigma^2_d\) and \(\sigma^2_v\) 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

\(^3\) 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).

\(^4\) 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).
3.2.2. Heterogeneous autoregressive realized volatility (HAR-RV) model

Following Andersen 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:

\[
MRV, t = \frac{\pi}{6 - 4\sqrt{3}/3 + \pi} T \sum_{i = 2}^T \text{med}(|r_{t,i-1}|, |r_{t,i}|, |r_{t,i+1}|)^2
\]  

(4)

where \( r_{t,i} \) denotes intraday oil return \( i \) within day \( t \), and \( i = 1, ..., T \) is the number of intraday oil returns within a day. Andersen 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 behavior of commodity (oil) market volatility (Asai et al., 2019, 2020). In our application, the benchmark HAR-RV model is given by:

\[
RV_{i,h} = \beta_0 + \beta_RRV_i + \beta_{RV}RV_{i-1} + \beta_{RV}RV_{i-2} + \varepsilon_{i,h}
\]  

(5)

where the index \( h \) denotes \( h \)-days-ahead realized volatility, with \( h = 1 \), 5, and 22 in our context. In addition, \( RV_{i,h} \) is the average RV from day \( t-5 \) to day \( t-1 \), while \( RV_{i,h} \) 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 (\( \varepsilon \)), we obtain the following extended HAR-RV model which includes the set of predictors (Q):

\[
RV_{i,h} = \beta_0 + \beta_RRV_i + \beta_{RV}RV_{i-1} + \beta_{RV}RV_{i-2} + \theta_Q Q_{i,h} + \varepsilon_{i,h}
\]  

(6)

where, \( \theta \) and Q are \( p \times 1 \) vectors. In our forecasting exercise, we set \( Q_i = [s_i]; [d_i]; [r_i]; [s_i, d_i]; [s_i, r_i]; [d_i, r_i]; [s_i, d_i, r_i] \) 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 Fig. 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.\(^5\) 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 Fig. 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.

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 \( Q = [s, d, r] \) 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 \( \beta_R \), \( \beta_{RV} \), and \( \theta_Q \) 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 \( \theta_1, \theta_2, \) and \( \theta_3 \) 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.

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,\(^6\) for detailed statistics, see https://www.iea.org/reports/oil-informatio n-2019.

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\(^5\) 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.

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5. For detailed statistics, see https://www.iea.org/reports/oil-informatio n-2019.
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 $h = 1$, March 24, 2003, March 20, 2006, December 18, 2008, August 05, 2011, and September 30, 2014; (ii) for $h = 5$, March 27, 2003, March 06, 2006, December 18, 2008, August 05, 2011, and October 02, 2014; and (iii) for $h = 22$, April 17, 2003, March 20, 2006, January 01, 2009, August 03, 2011, and October 30, 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 ($\text{MSFE}_i$) augmented by the oil shocks as additional predictors, relative to the benchmark model ($\text{MSFE}_0$). Forecasting Gains (FG) are formulated as:

$$FG = \left( \frac{\text{MSFE}_0}{\text{MSFE}_i} - 1 \right) \times 100$$  (7)

where $\text{MSFE}_0$ and $\text{MSFE}_i$ 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,
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* | 1.1462* | 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: $RV_{t+h} = \beta_0 + \beta_1 RV_t + \beta_2 RV_{MVt} + \beta_3 RV_{MVt} \cdot Q_t + \epsilon_{t+h}$, where $Q_t = [s_t; d_t; [s_t d_t]; [s_t v_t]; [d_t v_t]; [s_t d_t v_t]]$ for Models 1 to 7 with $s$, $d$ and $v$ denoting oil supply, demand and risk shocks, respectively. For the benchmark HAR-RV model, $Q = [1]$. * indicates significance of the MSE-F test statistic at the 1 percent level.

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. 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 Qudan 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 Deggannakis 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.

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-run.

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 $h = 5$; (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 $h = 1$, 5, and 5 at the 5 percent level for $h = 22$. 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 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

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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.

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).
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 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.

CRediT authorship contribution statement

Riza Demirer: Supervision, Validation, Visualization, Roles, Writing - original draft, Writing - review & editing. Rangan Gupta: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Resources, Software, Roles, Writing - original draft. Christian Pierdzioch: Investigation, Methodology, Supervision, Validation, Visualization, Roles, Writing - original draft, Writing - review & editing. Syed Jawad Hussain Shahzad: Formal analysis, Investigation, Methodology, Resources, Software.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.resourp.2020.101856.

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