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Zhuo Huang, Fang Liang, Chen Tong, and Xiaoyong Cui*

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**Keywords:** volatility spillover, the HAR (heterogeneous autoregressive) model, realized volatility, forward curve, crude oil futures

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## 1. Introduction

Futures markets have two important roles in financial economics theory. First, they provide instruments for hedging risk, and second, they contribute to the price discovery process (Working, 1948). Due to characteristics such as higher liquidity, greater transparency, and lower transaction costs, futures markets react more quickly than the underlying spot markets to new information (Working, 1962; Black, 1976).

In this study, we explore the price discovery process along the forward curve of the WTI crude oil futures by examining the volatility spillover effects between nearby contracts and contracts with distant maturities. The idea of studying volatility spillover to shed light on the price discovery process comes from the literature. Volatility is often interpreted as a proxy for information flow (e.g. Chan et al., 1991). It is natural to be concerned with how information, and therefore volatility, may flow from one market to another. The theory of volatility spillovers based on the GARCH models, was first introduced and named “meteor showers” by Engle et al. (1990). Chan et al. (1991) then provided a detailed discussion of the need to focus on volatility spillovers as an alternative measure of information transmission. Thus, in this paper, we choose volatility spillover as an indicator of information flow and investigate the causal relationships between volatilities along the forward curve of crude oil futures.

As many assets are traded based on the price of crude oil futures, it is important for financial market participants to understand the volatility transmission mechanism in the crude oil market to facilitate optimal portfolio allocation decisions. In particular, crude oil futures are a tool financial market participants can use to hedge against portfolio risk, and because the volatility of crude oil prices is a key determinant of hedging effectiveness, it is important to understand the nature of the volatility dynamics in the crude oil futures market. Furthermore, the strength of volatility spillover may also shed light on risk management strategies.

Volatility spillovers in the crude oil futures market have been extensively examined in the literature. Evidence of volatility spillovers among different crude oil futures, between crude oil futures and other energy assets, and between the crude oil market and other financial markets has been widely documented. Chang et al. (2010) examined the spillover effects among the four major benchmarks in the international oil market, namely West Texas Intermediate, Brent, Dubai/Oman, and Tapis, and presented some volatility spillover effects from Brent and WTI returns, and from the Brent and WTI crude oil markets to the Dubai and Tapis markets. Ewing, Malik, and Ozfidan (2002) examined the transmission of volatility between the oil and natural gas markets using daily returns data. Their findings indicate that volatility in oil returns is affected by both its own volatility and the volatility in natural gas returns, although the volatility in natural gas returns is only affected by the volatility of oil returns and not by its own volatility.

In terms of volatility transmission between the crude oil market and other financial markets, Souček and Todorova (2013) investigated the volatility spillover mechanisms among the S&P 500, WTI crude oil, and US$/EUR futures markets by applying a multivariate version of the HAR model. The causality analysis in their study indicates that the S&P 500 futures and US$/EUR futures volatilities lead the volatility of crude oil, which can be attributed to the financial uncertainty emerging from the financial markets over the last decade. Also, the HAR estimation shows that, in the case of the S&P 500 futures, the highest parameter estimate is assigned to the own short-term volatility component, while in the case of crude oil and US$/EUR, the weekly and monthly components seem to contain the majority of the information. Nazlioglu et al. (2013) examined volatility transmission between oil and selected agricultural commodity prices (wheat, corn, soybeans, and sugar). The findings indicate no volatility spillover between oil and agricultural commodity markets before the food price crisis, whereas after the food price crisis, oil volatility transmits to the wheat, corn, and soybean markets.

The current literature focuses on the volatility spillover effects between crude oil futures and other financial assets; however, the volatility spillover effects have rarely been studied along the forward curve within the crude oil market. The so-called forward curves, which are formed by the futures or forward prices for a particular commodity for all available maturities at a given point in time, are an essential input to the pricing models of complex energy derivatives (see Pilipovic, 2007). The financial value of a multi-commodity position is a function of the forward curves. As the volatility of futures prices is a key determinant of hedging effectiveness, it is important to understand the nature of volatility dynamics along the forward curves.

In this paper, we examine the volatility spillover effects among crude oil futures with different maturities. More specifically, we study whether volatilities have spillover effects between the one-month and three-month contracts of crude oil futures. By describing the interaction of the volatilities between particular points in the same forward curve, this study may enable us to evaluate the relative informational roles of volatilities of near and distant maturities futures and their information processing ability in the crude oil futures market.

In the broad tradition of Andersen and Bollerslev (1998), we choose realized volatility (RV) as the measure of volatility, and study whether RVs have a spillover effect among contracts with different maturities. Realized volatility calculated from high frequency data is easy to implement, model-free, and lends itself to relatively parsimonious forecasting models which capture the long-memory feature of volatility.

The methodological contributions of the present paper involve the use of high-frequency data and recent statistical techniques for the realized measures, and to allow these to have different impacts at different frequencies when constructing the RVs of contracts with different maturities. To achieve this, we apply the HAR model for RV analysis, taking advantage of the superposition of different frequencies in the model. In the HAR framework, we include RVs backed out from the prices of contracts with a different maturity as additional regressors. We also assess the structure of the volatility transmission using the Granger causality tests. The dataset used in this paper is the 5-min price data from the light crude oil futures covering the period from January 4, 2010 to March 29, 2016.

We find that the daily RVs of nearby contracts have stronger power in forecasting the daily RV of distant contracts, relative to the lagged daily RV of the latter, indicating that the one-month futures market is more informative than the three-month futures market. In fact, the RVs of the three-month contracts possess little additional information in forecasting the RV of the front contracts. The results of the Granger causality tests confirm that the RVs of nearby contracts contain important information when forecasting the RVs of distant contracts, even after controlling for the lagged RV of the latter. However, the converse is not true. The findings support the volatility spillover effects among contracts along the crude oil forward curve, and the direction of the volatility spillover is from nearby to distant maturities contracts.

The out-of-sample results also provide supportive evidence for the volatility spillover from front contracts to three-month contracts. The models using the lagged RV of front contracts beat the standard HAR model for three-month RV. Their stronger forecasting power comes mainly from the lagged daily RV of the front contracts.

The crude oil inventory data is released every Wednesday by the U.S. Energy Information Administration (EIA). We have shown that the inventory announcements have a significant effect on both the spillover effect and the magnitude of volatility. On the announcement day, the volatility spillover between the front and three-month contracts becomes bi-directional, and the RVs become significantly larger for both front and three-month contracts.

To check whether our findings are sensitive to the chosen model specifications, we use the autoregressive framework on weekly RVs as a robustness check, and the findings hold closely in the AR settings.

In addition to the methodological contributions mentioned above, this study also contributes to the literature in the following way. Although many previous studies have explored volatility spillovers among different energy futures (e.g., Karali and Ramirez, 2014) or between the energy market and other financial markets (e.g., Wu, Guan, and Myers, 2010), volatility spillover effects along the forward curve of the crude oil futures have not to our knowledge been thoroughly examined. In this respect, our study fills this gap and sheds light on optimal portfolio allocation, hedging effectiveness, and risk management among futures contracts with different maturities.

The rest of the paper is organized as follows. Section 2 introduces the notation and derivation of the model. Section 3 describes the dataset used in the empirical study. Section 4 reports the in-sample estimation results of our forecasting models, while section 5 compares the out-of-sample performance of different forecasting models. Section 6 studies the announcement-day effect of the crude oil inventory data on the volatility spillover and the magnitude of the RV, section 7 provides some robustness checks, and section 8 concludes. We report some complementary descriptions of our dataset in the Appendix.

## 2. The Model

A variety of models can be used to test for volatility spillover effects. One approach is to use the time series vector autoregressive (VAR) framework formalized by Diebold and Yilmaz (2009, 2012), who model volatility spillovers using VAR models and variance decompositions, and construct a spillover index based on return and volatility spillovers. Badshah et al. (2013) examine the contemporaneous spillover effects among the implied volatility indices for stocks, gold, and exchange rates. As the impulse responses of the structural VAR model suggest that the responses to shocks originating in either gold or exchange rate volatility are seriously overestimated in traditional VARs, they use a multivariate GARCH model to identify the causal spillover effects among stock, gold, and exchange rate volatility.

The research on volatility spillover has increased greatly with the development of the generalized autoregressive conditional heteroscedasticity (GARCH) model framework and its multivariate extensions. However, the various multivariate GARCH (MGARCH) specifications used by most studies use returns sampled at a daily or lower frequency, which results in much noisier volatility estimates than the RV based on high-frequency data.

According to Corsi (2009), financial data show evidence of scaling and multiscaling, and standard GARCH and stochastic volatility models are not able to reproduce all of these features. The observed data contain noticeable fluctuations in the size of price changes at all time scales, while standard GARCH and stochastic volatility short-memory models appear as white noise when aggregated over longer time periods. Hence, it is important to consider the long-memory characteristic when modeling volatilities.

The HAR model proposed by Corsi (2009) is able to reproduce this stylized fact of financial data. The model is also parsimonious and easy to estimate. Thus, we apply the HAR model to the RV of crude oil futures, and investigate the volatility spillover mechanisms among futures contracts with different maturities. The most common HAR model specification considers volatility as a linear function of daily (d), average weekly (w), and monthly (m) RVs. Based on the basic idea of the HAR model, we derive our regression models as shown below.

Assume that M+1 evenly spaced intra-period observations for day t are available on the log price $p_{t,j}$. The continuously compounded intraday returns are

$$r_{t,j} = p_{t,j} - p_{t,j-1}, j = 1,\ldots,M, t = 1,\ldots,T, \tag{1}$$

where T is the number of observation days in the sample. The RV for day t is given by

$$RV_{d,t} = \sqrt{\sum_{j=1}^{M} r_{t,j}^2}, t = 1,\ldots,T. \tag{2}$$

Following Corsi (2009), we also consider the RV viewed over different time horizons longer than one day. Specifically, we make use of weekly and monthly aggregation. In our notation, the weekly RV at day t is given by the average

$$RV_{w,t} = \frac{1}{5}\sum_{j=0}^{4} RV_{d,t-jd}, \tag{3}$$

and the monthly RV at day t is given by

$$RV_{m,t} = \frac{1}{22}\sum_{j=0}^{21} RV_{d,t-jd}. \tag{4}$$

We include a set of additional regressors $z_t$ in the standard HAR-RV model for three-month and one-month futures contracts

$$RV^{(3)}_{d,t+1d} = c + \gamma_d RV^{(3)}_{d,t} + \gamma_w RV^{(3)}_{w,t} + \gamma_m RV^{(3)}_{m,t} + \beta z_t + \varepsilon_{t+1d} \tag{5}$$

$$RV^{(1)}_{d,t+1d} = c + \gamma_d RV^{(1)}_{d,t} + \gamma_w RV^{(1)}_{w,t} + \gamma_m RV^{(1)}_{m,t} + \beta z_t + \varepsilon_{t+1d} \tag{6}$$

where $z_t = (z_{1t}, z_{2t}, \ldots z_{kt})$ is a K-dimensional vector of the additional regressors. Among the latter, we include the following variables in equation (5): daily, weekly, and monthly RVs backed out from the prices of the relevant one-month futures contracts, denoted by $RV^{(1)}_{d,t}$, $RV^{(1)}_{w,t}$, and $RV^{(1)}_{m,t}$, respectively. Similarly, we also include $RV^{(3)}_{d,t}$, $RV^{(3)}_{w,t}$, and $RV^{(3)}_{m,t}$ as additional regressors in equation (6). The motivation for using these additional regressors is to take into account possible unidirectional or bidirectional volatility spillovers between nearby futures and distant maturity futures.

Following such manners, our modified HAR models are

$$RV^{(3)}_{d,t+1d} = c + g_d RV^{(3)}_{d,t} + g_w RV^{(3)}_{w,t} + g_m RV^{(3)}_{m,t} + b_d RV^{(1)}_{d,t} + b_w RV^{(1)}_{w,t} + b_m RV^{(1)}_{m,t} + e_{t+1d} \quad (7)$$

$$RV^{(1)}_{d,t+1d} = c + g_d RV^{(1)}_{d,t} + g_w RV^{(1)}_{w,t} + g_m RV^{(1)}_{m,t} + b_d RV^{(3)}_{d,t} + b_w RV^{(3)}_{w,t} + b_m RV^{(3)}_{m,t} + e_{t+1d} \quad (8)$$

where $e_{t+1d}$ is the daily forecasting error. When a variable is not included in the specific regression, $b_p = 0, p = d, w, m$ or $g_q = 0, q = d, w, m$ is imposed.

As noted in Andersen et al. (2007), the logarithmic daily RVs are approximately unconditionally normally distributed. This empirical regularity motivated Andersen et al. (2007) to model the logarithmic RVs, in turn allowing for the use of standard normal distribution theory. The same transformation has been applied in many other studies, such as Koopman, Jungbacker and Hol (2005), and Martens, van Dijk, and de Pooter (2004). Guided by the same idea, we also use the logarithmic HAR-RV models. The logarithmic models to be estimated are as follows.

$$\begin{aligned}\ln RV^{(3)}_{d,t+1d} &= c + g_d \ln RV^{(3)}_{d,t} + g_w \ln RV^{(3)}_{w,t} + g_m \ln RV^{(3)}_{m,t} \\ &+ b_d \ln RV^{(1)}_{d,t} + b_w \ln RV^{(1)}_{w,t} + b_m \ln RV^{(1)}_{m,t} + e_{t+1d}\end{aligned} \quad (9)$$

$$\begin{aligned}\ln RV^{(1)}_{d,t+1d} &= c + g_d \ln RV^{(1)}_{d,t} + g_w \ln RV^{(1)}_{w,t} + g_m \ln RV^{(1)}_{m,t} \\ &+ b_d \ln RV^{(3)}_{d,t} + b_w \ln RV^{(3)}_{w,t} + b_m \ln RV^{(3)}_{m,t} + e_{t+1d}\end{aligned} \quad (10)$$

As before, $b_p = 0, p = d, w, m$ or $g_q = 0, q = d, w, m$ is imposed when a variable is not included in the specific regression.

## 3. Data

In this study, we use the 5-min price data from the crude oil futures markets covering the period from January 4, 2010 to March 29, 2016. Our data include the transaction price of one-month, two-month, and three-month contracts and we interpolate the missing values.[1] All of the price data are

[1] We interpolate the 5-min price series of two-month and three-month contracts, and the percentages of missing values interpolated are 0.044% and 1.205%, respectively. The percentages of missing prices before and after the interpolation are reported in the Appendix.

from Tick Data Inc.

Our work is based on the advances in model-free volatility measurements using high-frequency data (see for example Nielsen and Shephard, 2007). We compute the daily RV measure using the intraday data, and aggregate the daily RV at weekly and monthly scales to have comparable RV measures over different horizons.

Table 1 provides the summary statistics for the unconditional distribution of the daily RVs of contracts with maturities. In particular, for each RV series, we report the sample mean, median, standard deviation, skewness, kurtosis, and the p-value of the Jarque-Bera test for normality. The distributions of the RVs are skewed to the right and leptokurtic relative to the normal distribution, as indicated in the fifth and sixth rows in Table 1. The Jarque-Bera statistic rejects the null hypothesis of a Gaussian distribution for each RV series at the 1% significance level.

**Table 1** RV summary statistics

| | 1-month contract | 2-month contract | 3-month contract |
|---|---|---|---|
| Mean | 0.013 | 0.013 | 0.013 |
| Median | 0.012 | 0.011 | 0.012 |
| Std. dev. | 0.007 | 0.006 | 0.006 |
| Skewness | 1.564 | 1.508 | 1.626 |
| Kurtosis | 6.359 | 6.178 | 7.213 |
| JB stat. | 0.001 | 0.001 | 0.001 |
| Obs. | 1594 | 1594 | 1594 |

*Notes*. This table reports the descriptive statistics for the realized volatilities of contracts with different maturities. Specifically, for each RV series, we report the sample mean, median, standard deviation, skewness, kurtosis, and the p-value of the Jarque-Bera test for normality. The sample covers the period from January 4, 2010 to March 29, 2016. The last row reports the number of trading days.

We also use this dataset to generate the out-of-sample forecast. A rolling window method is employed to obtain the forecast series. Specifically, we use an initial window consisting of 450 daily observations to estimate the first set of coefficients, and obtain the first out-of-sample one-step ahead forecast. Thereafter, the estimating sample rolls by adding a new observation and dropping the first observation in the previous window. The results are reported in section 5.

## 4. In-Sample Estimation

Following the recent literature on RV, we can consider all of the terms in equations (7) and (8) as observed and then estimate their parameters by applying linear regression. The standard OLS regression estimators are consistent and normally distributed. To account for the possible presence of serial correlation and heteroscedasticity in the data, we use the Newey-West covariance correction. We also estimate the logarithmic HAR models in equations (9) and (10), and the results are reported for comparison.

Table 2 shows the estimation results for the HAR-RV model on the RVs of three-month crude oil futures contracts. We report the coefficient estimates, the t-statistics based on standard errors computed after the Newey-West adjustment for the serial correlation of order 20, and the adjusted $R^2$. Panel A reports the results for models using the RV levels, and panel B reports the results for the logarithmic settings.

In panel A, the result of the standard HAR model is reported in column 1, which is similar to that of previous studies for other assets (see for example Corsi, 2009). Next, the one-month daily RVs are added to the information set at time t in the standard HAR regression (column 2). When the three-month monthly, weekly, and daily RVs are included together with the daily RVs of front contracts, the three-month daily RV coefficient becomes insignificant, and the daily RV of front contracts becomes the most significant regressor in both the economic and statistical sense. Furthermore, the adjusted $R^2$ improves when using the one-month daily RV as an additional regressor. In column 3, when the three-month daily, weekly, and monthly RVs are included with those of front contracts, both the three-month daily and weekly RVs lose their forecasting power; however, the daily RV of front contracts still contains important forecasting information. The results shown in panel B are very similar to those of panel A, and the logarithmic models are superior in model fitness, as indicated by the larger adjusted $R^2$ s.

Table 2 provides strong evidence that the RVs of the nearby contracts contain additional information when forecasting the RVs of distant maturity contracts. In fact, the results in Table 3 indicate that the RVs of distant maturity contracts possess little additional information when forecasting the RVs of nearby contracts.

Specifically, Table 3 shows the results for the augmented HAR-RV model for one-month crude oil futures. When adding three-month daily, weekly, and monthly RV to the standard HAR model for front-contract RVs as additional regressors, neither of the coefficients of the three-month RV shows any significance (columns 2 and 3). As expected, the magnitude and significance of all of the coefficients of the one-month RV are hardly affected. Furthermore, the adjusted $R^2$ of the above two columns are almost unchanged compared with that of the standard HAR model for front-contract RV (column 1). The findings hold closely in panel B.

**Table 2** HAR-RV estimation for three-month contracts

| | $RV^{(3)}_{d,t+1d}$ | | | | $\ln RV^{(3)}_{d,t+1d}$ | | |
|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | | (4) | (5) | (6) |
| C | 0.001 | 0.001 | 0.001 | C | -0.228 | -0.288 | -0.362 |
| | (3.102) | (4.443) | (4.105) | | (-2.972) | (-3.881) | (-4.182) |
| $RV^{(3)}_{d,t}$ | 0.260 | -0.010 | 0.028 | $\ln RV^{(3)}_{d,t}$ | 0.232 | 0.003 | 0.063 |
| | (4.439) | (-0.258) | (0.887) | | (6.421) | (0.063) | (1.451) |
| $RV^{(3)}_{w,t}$ | 0.400 | 0.344 | 0.149 | $\ln RV^{(3)}_{w,t}$ | 0.364 | 0.345 | 0.134 |
| | (7.513) | (5.758) | (1.148) | | (5.266) | (4.842) | (1.196) |
| $RV^{(3)}_{m,t}$ | 0.277 | 0.218 | 0.345 | $\ln RV^{(3)}_{m,t}$ | 0.358 | 0.310 | 0.157 |
| | (4.645) | (4.142) | (2.229) | | (5.249) | (5.641) | (1.378) |
| $RV^{(1)}_{d,t}$ | | 0.348 | 0.298 | $\ln RV^{(1)}_{d,t}$ | | 0.282 | 0.182 |
| | | (7.398) | (6.318) | | | (7.199) | (4.727) |
| $RV^{(1)}_{w,t}$ | | | 0.219 | $\ln RV^{(1)}_{w,t}$ | | | 0.281 |
| | | | (1.766) | | | | (2.622) |
| $RV^{(1)}_{m,t}$ | | | -0.141 | $\ln RV^{(1)}_{m,t}$ | | | 0.107 |
| | | | (-0.962) | | | | (0.910) |
| Adj. $R^2$ | 0.595 | 0.609 | 0.609 | Adj. $R^2$ | 0.670 | 0.680 | 0.684 |

*Notes.* This table reports the in-sample estimation results of the HAR-RV model for three-month futures data. Panel A reports the results for models using the level of realized volatilities, and panel B is for the logarithmic settings. The sample covers the period from January 2010 to March 2016, including 1594 daily observations. The t-statistics reported in parentheses are based on the standard errors computed after the Newey-West adjustment for the serial correlation of order 20. The last row of the table reports the adjusted $R^2$.

**Table 3** HAR-RV estimation for one-month contracts

| | $RV^{(1)}_{d,t+1d}$ | $\ln RV^{(1)}_{d,t+1d}$ |
|---|---|---|

| | (1) | (2) | (3) | | (4) | (5) | (6) |
|---|---|---|---|---|---|---|---|
| C | 0.001 | 0.001 | 0.001 | C | -0.191 | -0.168 | -0.162 |
| | (2.664) | (2.629) | (2.761) | | (-2.791) | (-2.425) | (-2.171) |
| $RV_{d,t}^{(1)}$ | 0.334 | 0.320 | 0.310 | $\ln RV_{d,t}^{(1)}$ | 0.233 | 0.182 | 0.193 |
| | (7.026) | (6.834) | (6.900) | | (6.888) | (4.590) | (4.346) |
| $RV_{w,t}^{(1)}$ | 0.400 | 0.399 | 0.429 | $\ln RV_{w,t}^{(1)}$ | 0.448 | 0.437 | 0.389 |
| | (6.669) | (6.618) | (4.733) | | (10.393) | (10.199) | (5.417) |
| $RV_{m,t}^{(1)}$ | 0.218 | 0.219 | 0.239 | $\ln RV_{m,t}^{(1)}$ | 0.280 | 0.278 | 0.299 |
| | (4.628) | (4.679) | (1.740) | | (6.826) | (6.844) | (3.112) |
| $RV_{d,t}^{(3)}$ | | 0.016 | 0.027 | $\ln RV_{d,t}^{(3)}$ | | 0.069 | 0.055 |
| | | (0.545) | (0.877) | | | (1.611) | (1.240) |
| $RV_{w,t}^{(3)}$ | | | -0.033 | $\ln RV_{w,t}^{(3)}$ | | | 0.057 |
| | | | (-0.409) | | | | (0.830) |
| $RV_{m,t}^{(3)}$ | | | -0.024 | $\ln RV_{m,t}^{(3)}$ | | | -0.026 |
| | | | (-0.170) | | | | (-0.264) |
| Adj. $R^2$ | 0.693 | 0.693 | 0.693 | Adj. $R^2$ | 0.710 | 0.710 | 0.710 |

*Notes.* This table reports the in-sample estimation results of the HAR-RV model for the front contracts of crude oil futures. Panel A reports the results for models using the level of realized volatilities, and panel B is for the logarithmic settings. The sample covers the period from January 2010 to March 2016, including 1594 daily observations. The t-statistics reported in parentheses are based on the standard errors computed after the Newey-West adjustment for the serial correlation of order 20. The last row of the table reports the adjusted $R^2$.

To formally test the direction of the volatility spillover effects, we apply the Granger causality tests to test for causality between the RVs of nearby and distant maturity contracts. The results are presented in Table 4. Panel A shows whether the RVs of front contracts cause the RVs of three-month contracts, and panel B shows the converse. Specifically, Table 4 reports the F-statistics for the joint significance tests of the coefficients of daily, weekly, and monthly RV in the first column, based on the estimated model (7) for panel A and (8) for panel B.

In panel A, the Granger causality tests reject the null hypothesis of no causality from one-month to three-month RV at the 1% level for both specifications. However, as shown in panel B, the test for the null hypothesis of no causality from the three-month to one-month RV cannot be rejected for any specification. Hence, we can conclude that there is a unidirectional Granger causality running from the one-month to the three-month RV. The results of the Granger causality tests confirm that the RVs of nearby contracts contain additional information when forecasting the RVs of distant maturity contracts, whereas the converse is not true.

**Table 4** Granger causality tests

| Panel A | $RV^{(3)}_{d,t+1d}$ | | $\ln RV^{(3)}_{d,t+1d}$ |
|---|---|---|---|
| $RV^{(1)}_{d,t}, RV^{(1)}_{w,t}, RV^{(1)}_{m,t}$ | 20.423<br>(0.000) | $\ln RV^{(1)}_{d,t}, \ln RV^{(1)}_{w,t}, \ln RV^{(1)}_{m,t}$ | 23.674<br>(0.000) |
| **Panel B** | $RV^{(1)}_{d,t+1d}$ | | $\ln RV^{(1)}_{d,t+1d}$ |
| $RV^{(3)}_{d,t}, RV^{(3)}_{w,t}, RV^{(3)}_{m,t}$ | 0.123<br>(0.947) | $\ln RV^{(3)}_{d,t}, \ln RV^{(3)}_{w,t}, \ln RV^{(3)}_{m,t}$ | 1.125<br>(0.338) |

*Notes.* This table shows the results of the Granger causality tests between the RVs of front contracts and three-month contracts. Specifically, the first column reports the F-statistics for the joint significance tests of the coefficients of daily, weekly, and monthly RV based on the estimated model (7) for panel A and (8) for panel B. The p-values based on the F-distribution are reported in parentheses.

The findings so far show that the daily RVs backed out from the prices of nearby contracts contains incremental information in forecasting the subsequent daily RV of distant maturity contracts, relative to the RV of the distant maturity contracts. When added to the standard HAR model, the daily RV of nearby contracts completely subsumes the information content of the daily RV of the distant maturity contracts. The adjusted $R^2$ also improves markedly. On the contrary, the RV of distant maturity contracts possesses little additional information when forecasting the RV of nearby contracts. The results of the Granger causality tests confirm that the RVs of nearby contracts contain additional information when forecasting the RVs of distant maturity contracts, but that the converse is not true. The findings support the volatility spillover effects among contracts with different maturities, and the direction of the volatility spillover is from nearby to distant maturity contracts.

## 5. Out-of-Sample Evaluation

To further explore the gain in forecast accuracy using our forecasting model which considers the volatility spillover effect along the crude oil forward curve, we compare the out-of-sample performance of different predictive models. A rolling window method is used to obtain the forecast series. Specifically, we use an initial window consisting of 450 daily observations to estimate the first set of coefficients and obtain the first out-of-sample forecast value. Thereafter, the estimating sample rolls by adding a new observation and dropping the first observation in the previous window. The forecasting models we use for comparison are listed below.

$$RV^{(3)}_{d,t+1d} = c + g_d RV^{(3)}_{d,t} + g_w RV^{(3)}_{w,t} + g_m RV^{(3)}_{m,t} + e_{t+1d} \tag{11}$$

$$RV^{(3)}_{d,t+1d} = c + g_d RV^{(3)}_{d,t} + g_w RV^{(3)}_{w,t} + g_m RV^{(3)}_{m,t} + b_d RV^{(1)}_{d,t} + e_{t+1d} \tag{12}$$

$$RV^{(3)}_{d,t+1d} = c + g_d RV^{(3)}_{d,t} + g_w RV^{(3)}_{w,t} + g_m RV^{(3)}_{m,t} + b_d RV^{(1)}_{d,t} + b_w RV^{(1)}_{w,t} + b_m RV^{(1)}_{m,t} + e_{t+1d} \tag{13}$$

$$RV^{(1)}_{d,t+1d} = c + g_d RV^{(1)}_{d,t} + g_w RV^{(1)}_{w,t} + g_m RV^{(1)}_{m,t} + e_{t+1d} \tag{14}$$

$$RV^{(1)}_{d,t+1d} = c + g_d RV^{(1)}_{d,t} + g_w RV^{(1)}_{w,t} + g_m RV^{(1)}_{m,t} + b_d RV^{(3)}_{d,t} + e_{t+1d} \tag{15}$$

$$RV^{(1)}_{d,t+1d} = c + g_d RV^{(1)}_{d,t} + g_w RV^{(1)}_{w,t} + g_m RV^{(1)}_{m,t} + b_d RV^{(3)}_{d,t} + b_w RV^{(3)}_{w,t} + b_m RV^{(3)}_{m,t} + e_{t+1d} \tag{16}$$

The root mean squared errors (RMSE) and mean absolute errors (MAE) are used as evaluation measures and the results are reported in Table 5. Specifically, columns (1)–(3) in panel A report the results for models (11)–(13) and columns (4)–(6) in panel B are for models (14)–(16). The values reported in panels A and B are the ratios of the evaluation measures relative to columns (1) and (4), respectively.

**Table 5** Out-of-sample forecast results

| | Panel A | | | Panel B | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| RMSE | 1.0000 | **0.9786** | 0.9822 | **1.0000** | 1.0011 | 1.0045 |
| MAE | 1.0000 | **0.9861** | 0.9900 | **1.0000** | 1.0011 | 1.0071 |

*Notes.* This table reports the measures to evaluate the out-of-sample forecasting performance of different predictive models. The evaluation measures are the root mean squared errors (RMSE) and the mean absolute errors (MAE). Columns (1)–(3) in panel A report the results for models (11)–(13) and columns (4)–(6) in panel B are for models (14)–(16). The values reported in panels A and B are the ratios relative to columns (1) and (4), respectively. The smallest value in each row is marked in bold.

The results in panel A show that the RV of the front contract possesses additional information when forecasting the subsequent RV of three-month contracts. The ratios in columns (2) and (3) are all less than one. The model using the daily RV of the front contract as an additional regressor performs the best in forecasting the RV of three-month contracts, indicating that the daily RV of front contracts contributes the most to improving forecast accuracy. However, the RV of three-month contract does not help in forecasting the RV of the front month contract, as the ratios in columns (5) and (6) are all larger than one.

## 6. Announcement Day Effect

The U.S. Energy Information Administration (EIA) releases the crude oil inventory data after 10:30 a.m. every Wednesday. We examine the announcement effect of the inventory data on the direction and strength of the volatility spillover along the forward curve by adding an interaction term for the announcement day dummy and the previous spillover term. The forecasting models are as follows, where $D(t+1d = Wednesday) = 1$.

$$RV^{(3)}_{d,t+1d} = c + g_d RV^{(3)}_{d,t} + g_w RV^{(3)}_{w,t} + g_m RV^{(3)}_{m,t} + b_1 RV^{(1)}_{d,t} + b_2 D \times RV^{(1)}_{d,t} + e_{t+1d}$$

$$RV^{(1)}_{d,t+1d} = c + g_d RV^{(1)}_{d,t} + g_w RV^{(1)}_{w,t} + g_m RV^{(1)}_{m,t} + b_1 RV^{(3)}_{d,t} + b_2 D \times RV^{(3)}_{d,t} + e_{t+1d}$$

We also consider the impact of newly released inventory data on the level of crude oil volatility. Announcement day dummies are added to the model as intercepts to detect whether volatility on the announcement day is significantly higher than on other trading days. The forecasting models used here are listed as follows, and again $D(t+1d = Wednesday) = 1$.

$$RV^{(3)}_{d,t+1d} = c + D + g_d RV^{(3)}_{d,t} + g_w RV^{(3)}_{w,t} + g_m RV^{(3)}_{m,t} + b_d RV^{(1)}_{d,t} + e_{t+1d}$$

$$RV^{(3)}_{d,t+1d} = c + D + g_d RV^{(3)}_{d,t} + g_w RV^{(3)}_{w,t} + g_m RV^{(3)}_{m,t} + b_d RV^{(1)}_{d,t} + b_w RV^{(1)}_{w,t} + b_m RV^{(1)}_{m,t} + e_{t+1d}$$

$$RV^{(1)}_{d,t+1d} = c + D + g_d RV^{(1)}_{d,t} + g_w RV^{(1)}_{w,t} + g_m RV^{(1)}_{m,t} + b_d RV^{(3)}_{d,t} + e_{t+1d}$$

$$RV^{(1)}_{d,t+1d} = c + D + g_d RV^{(1)}_{d,t} + g_w RV^{(1)}_{w,t} + g_m RV^{(1)}_{m,t} + b_d RV^{(3)}_{d,t} + b_w RV^{(3)}_{w,t} + b_m RV^{(3)}_{m,t} + e_{t+1d}$$

**Table 6** Announcement day effects on three-month contracts

| $RV^{(3)}_{d,t+1d}$ | | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| C | 0.001 | 0.001 | 0.001 |
| | (4.329) | (3.232) | (3.054) |
| $RV^{(3)}_{d,t}$ | 0.005 | 0.005 | 0.042 |
| | (0.140) | (0.140) | (1.326) |
| $RV^{(3)}_{w,t}$ | 0.315 | 0.328 | 0.141 |
| | (5.689) | (5.701) | (1.103) |
| $RV^{(3)}_{m,t}$ | 0.222 | 0.221 | 0.334 |
| | (4.299) | (4.253) | (2.167) |
| $RV^{(1)}_{d,t}$ | 0.333 | 0.346 | 0.297 |
| | (6.990) | (7.216) | (6.404) |
| $RV^{(1)}_{w,t}$ | | | 0.210 |
| | | | (1.718) |
| $RV^{(1)}_{m,t}$ | | | -0.128 |
| | | | (-0.872) |
| D | | 0.001 | 0.001 |
| | | (5.333) | (5.310) |
| $D \times RV^{(1)}_{d,t}$ | 0.132 | | |
| | (5.311) | | |
| Adj. $R^2$ | 0.623 | 0.617 | 0.617 |

*Notes.* This table reports the estimated announcement-day effect of inventory data on the realized volatility of three-month contracts and on the volatility spillover from front to three-month contracts. The data sample is from January 2010 to March 2016, and includes 1594 daily observations. The t-statistics reported in parentheses are based on the standard errors computed after the Newey-West correction for the serial correlation of order 20. The last line of the table reports the adjusted $R^2$.

**Table 7** Announcement day effect on front contracts

| | (1) | (2) | (3) |
|---|---|---|---|
| C | 0.001 | 0.000 | 0.000 |
| | (2.279) | (1.028) | (1.330) |
| $RV^{(1)}_{d,t}$ | 0.318 | 0.323 | 0.309 |
| | (7.007) | (7.044) | (6.998) |
| $RV^{(1)}_{w,t}$ | 0.366 | 0.381 | 0.419 |
| | (6.592) | (6.577) | (4.725) |
| $RV^{(1)}_{m,t}$ | 0.228 | 0.225 | 0.255 |
| | (4.953) | (4.872) | (1.871) |

| | | | |
|---|---|---|---|
| $RV_{d,t}^{(3)}$ | 0.019 | 0.029 | 0.044 |
| | (0.659) | (1.022) | (1.436) |
| $RV_{w,t}^{(3)}$ | | | -0.042 |
| | | | (-0.533) |
| $RV_{m,t}^{(3)}$ | | | -0.036 |
| | | | (-0.257) |
| D | | 0.002 | 0.002 |
| | | (6.296) | (6.291) |
| $D \times RV_{d,t}^{(3)}$ | 0.148 | | |
| | (5.468) | | |
| Adj. $R^2$ | 0.708 | 0.703 | 0.703 |

*Notes.* This table reports the estimated inventory data announcement-day effect on the realized volatility of front contracts and on the volatility spillover from three-month to front contracts. The data sample is from January 2010 to March 2016, and includes 1594 daily observations. The t-statistics reported in parentheses are based on the standard errors computed after Newey-West correction for serial correlation of order 20. The last line of the table reports the adjusted $R^2$.

Tables 6 and 7 report the influence of the crude oil inventory announcement on the direction and strength of volatility spillover along the forward curve and on the magnitude of the RV. The RV on the announcement day, for both front and three-month contracts, is higher than on other trading days, as indicated by the positive and significant intercept dummies in columns (2) and (3) in both tables. More importantly, the volatility spillover between crude oil front and three-month contracts is bi-directional on the announcement day. This may be caused by the incorporation of new information in the released inventory data and the resulting heavier trading over contracts.

To formally confirm the bi-directional spillover effects on the announcement day, we report the results of the Granger causality tests in Table 8. The Granger causality tests are based on the following forecasting models, where the daily, weekly, and monthly spillover terms and the corresponding interaction terms with the announcement day dummy are all included.

$$RV_{d,t+1d}^{(3)} = c + g_d RV_{d,t}^{(3)} + g_w RV_{w,t}^{(3)} + g_m RV_{m,t}^{(3)} + b_d RV_{d,t}^{(1)} + b_w RV_{w,t}^{(1)} + b_m RV_{m,t}^{(1)}$$
$$+ b_1 D \times RV_{d,t}^{(1)} + b_2 D \times RV_{w,t}^{(1)} + b_3 D \times RV_{m,t}^{(1)} + e_{t+1d}$$

$$RV_{d,t+1d}^{(1)} = c + g_d RV_{d,t}^{(1)} + g_w RV_{w,t}^{(1)} + g_m RV_{m,t}^{(1)} + b_d RV_{d,t}^{(3)} + b_w RV_{w,t}^{(3)} + b_m RV_{m,t}^{(3)}$$
$$+ b_1 D \times RV_{d,t}^{(3)} + b_2 D \times RV_{w,t}^{(3)} + b_3 D \times RV_{m,t}^{(3)} + e_{t+1d}$$

**Table 8** Granger causality tests for volatility spillover on announcement day

| | |
|---|---|
| $RV^{(3)}_{d,t+1d}$ | |
| $RV^{(1)}_{d,t}, RV^{(1)}_{w,t}, RV^{(1)}_{m,t},$<br>$D \times RV^{(1)}_{d,t}, D \times RV^{(1)}_{w,t}, D \times RV^{(1)}_{m,t}$ | 20.998<br>(0.000) |
| $RV^{(1)}_{d,t+1d}$ | |
| $RV^{(3)}_{d,t}, RV^{(3)}_{w,t}, RV^{(3)}_{m,t},$<br>$D \times RV^{(3)}_{d,t}, D \times RV^{(3)}_{w,t}, D \times RV^{(3)}_{m,t}$ | 13.745<br>(0.000) |

*Notes.* This table shows the results of the Granger causality tests for volatility spillover on the announcement day. Specifically, it reports the F-statistics for the joint significance tests of the coefficients of daily, weekly, and monthly RV and their corresponding interaction terms with the announcement-day dummy. The p-values based on the F-distribution are reported in parentheses.

The results in Table 8 show that the null hypotheses are rejected in both directions, which strongly supports bi-directional volatility spillovers between crude oil front contracts and three-month contracts on announcement days. The results indicate that the inventory announcement days are more information intense than other trading days.

## 7. Robustness Check

To test whether our results are sensitive to the frequency of the RV, we turn to a setting using weekly RV. The weekly RV is an average of the daily RVs within a week.

$$RV_w = \frac{1}{5}(RV_d + RV_{d-1} + RV_{d-2} + RV_{d-3} + RV_{d-4})$$

The simplest specification to test the volatility spillover effect among weekly RVs is the AR (1) model using the RV of contracts with a different maturity as an additional term. We use the AR (1) framework to test the additional information possessed by the volatilities of contracts with a different maturity in the previous week. We also adopt an AR (3) framework to explore the information contained in the previous month, by adding three lags of weekly RV of contracts with a different maturity. In addition to the settings using the RV levels, we also include the logarithmic equations for comparison. The model specifications are listed below.

$$RV^{(3)}_w = c + b_1 RV^{(3)}_{w-1} + g_1 RV^{(1)}_{w-1} + e_w \quad (17)$$

$$RV_{w}^{(1)} = c + b_{1}RV_{w-1}^{(1)} + g_{1}RV_{w-1}^{(3)} + e_{w} \tag{18}$$

$$RV_{w}^{(3)} = c + b_{1}RV_{w-1}^{(3)} + b_{2}RV_{w-2}^{(3)} + b_{3}RV_{w-3}^{(3)} + g_{1}RV_{w-1}^{(1)} + g_{2}RV_{w-2}^{(1)} + g_{3}RV_{w-3}^{(1)} + e_{w} \tag{19}$$

$$RV_{w}^{(1)} = c + b_{1}RV_{w-1}^{(1)} + b_{2}RV_{w-2}^{(1)} + b_{3}RV_{w-3}^{(1)} + g_{1}RV_{w-1}^{(3)} + g_{2}RV_{w-2}^{(3)} + g_{3}RV_{w-3}^{(3)} + e_{w} \tag{20}$$

$$\ln RV_{w}^{(3)} = c + b_{1}\ln RV_{w-1}^{(3)} + g_{1}\ln RV_{w-1}^{(1)} + e_{w} \tag{21}$$

$$\ln RV_{w}^{(1)} = c + b_{1}\ln RV_{w-1}^{(1)} + g_{1}\ln RV_{w-1}^{(3)} + e_{w} \tag{22}$$

$$\ln RV_{w}^{(3)} = c + b_{1}\ln RV_{w-1}^{(3)} + b_{2}\ln RV_{w-2}^{(3)} + b_{3}\ln RV_{w-3}^{(3)} + g_{1}\ln RV_{w-1}^{(1)} + g_{2}\ln RV_{w-2}^{(1)} + g_{3}\ln RV_{w-3}^{(1)} + e_{w} \tag{23}$$

$$\ln RV_{w}^{(1)} = c + b_{1}\ln RV_{w-1}^{(1)} + b_{2}\ln RV_{w-2}^{(1)} + b_{3}\ln RV_{w-3}^{(1)} + g_{1}\ln RV_{w-1}^{(3)} + g_{2}\ln RV_{w-2}^{(3)} + g_{3}\ln RV_{w-3}^{(3)} + e_{w} \tag{24}$$

Tables 9 and 10 report the results using AR models on the weekly RVs. The results are in line with those using the HAR framework to forecast the daily RVs. The first lag of the weekly RV of the front contracts possesses additional information in forecasting the subsequent weekly RVs of three-month contracts. Including the weekly RV of front contracts in the forecasting model also significantly improves the model fitness, as shown by the larger adjusted R-squared. The second and the third lags of the weekly RV of the front contracts are not significant, indicating that the latest information contained in the front contract is useful, but the predictive power of the RVs of the front contracts is not long-lasting. Again, the RV of the three-month contract possesses little additional forecasting power. The results for the logarithmic settings are very similar to those of the level equations.

**Table 9** Spillover effects for three-month contracts using weekly RV

| | $RV_w^{(3)}$ | | | | | $\ln RV_w^{(3)}$ | | | |
|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | | (5) | (6) | (7) | (8) |
| C | 0.002 | 0.003 | 0.001 | 0.002 | C | -0.627 | -0.688 | -0.356 | -0.479 |
| | (4.314) | (5.213) | (3.403) | (3.937) | | (-4.650) | (-5.100) | (-3.453) | (-3.904) |
| $RV_{w-1}^{(3)}$ | 0.827 | 0.195 | 0.590 | 0.166 | $\ln RV_{w-1}^{(3)}$ | 0.859 | 0.241 | 0.558 | 0.159 |
| | (23.373) | (1.682) | (8.227) | (1.467) | | (28.217) | (2.357) | (8.098) | (1.680) |
| $RV_{w-2}^{(3)}$ | | | 0.154 | 0.089 | $\ln RV_{w-2}^{(3)}$ | | | 0.167 | 0.094 |
| | | | (2.006) | (0.736) | | | | (2.515) | (1.458) |
| $RV_{w-3}^{(3)}$ | | | 0.147 | 0.110 | $\ln RV_{w-3}^{(3)}$ | | | 0.194 | 0.101 |
| | | | (2.960) | (1.108) | | | | (4.167) | (1.743) |
| $RV_{w-1}^{(1)}$ | | 0.587 | | 0.430 | $\ln RV_{w-1}^{(1)}$ | | 0.606 | | 0.443 |
| | | (5.757) | | (3.963) | | | (6.068) | | (4.637) |
| $RV_{w-2}^{(1)}$ | | | | 0.037 | $\ln RV_{w-2}^{(1)}$ | | | | 0.023 |
| | | | | (0.386) | | | | | (0.345) |
| $RV_{w-3}^{(1)}$ | | | | 0.007 | $\ln RV_{w-3}^{(1)}$ | | | | 0.074 |
| | | | | (0.073) | | | | | (1.140) |
| Adj. $R^2$ | 0.683 | 0.702 | 0.706 | 0.714 | Adj. $R^2$ | 0.735 | 0.760 | 0.765 | 0.776 |

*Notes.* This table reports the estimation results of the spillover effects for three-month contracts using weekly RV data. Panel A reports the results for models using the weekly RV levels, and panel B is for the logarithmic settings. The light crude oil futures data cover the period from January 2010 to March 2016. The t-statistics reported in parentheses are based on the standard errors computed with the Newey-West correction for the serial correlation of order 20. The last row of the table reports the adjusted $R^2$.

**Table 10** Spillover effects for front contracts using weekly RV

| | $RV^{(1)}_{w}$ | | | | | $\ln RV^{(1)}_{w}$ | | | |
|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | | (5) | (6) | (7) | (8) |
| C | 0.002 | 0.002 | 0.001 | 0.001 | C | -0.488 | -0.449 | -0.293 | -0.250 |
| | (3.534) | (3.237) | (3.166) | (2.362) | | (-3.870) | (-3.169) | (-3.204) | (-1.910) |
| $RV^{(1)}_{w-1}$ | 0.866 | 0.980 | 0.639 | 0.728 | $\ln RV^{(1)}_{w-1}$ | 0.890 | 0.795 | 0.627 | 0.597 |
| | (25.129) | (10.354) | (8.242) | (6.719) | | (30.919) | (10.903) | (10.455) | (8.418) |
| $RV^{(1)}_{w-2}$ | | | 0.139 | 0.181 | $\ln RV^{(1)}_{w-2}$ | | | 0.128 | 0.116 |
| | | | (2.134) | (1.872) | | | | (2.186) | (1.480) |
| $RV^{(1)}_{w-3}$ | | | 0.133 | 0.081 | $\ln RV^{(1)}_{w-3}$ | | | 0.179 | 0.108 |
| | | | (2.457) | (0.773) | | | | (3.206) | (1.343) |
| $RV^{(3)}_{w-1}$ | | -0.129 | | -0.099 | $\ln RV^{(3)}_{w-1}$ | | 0.103 | | 0.032 |
| | | (-1.080) | | (-1.035) | | | (1.192) | | (0.436) |
| $RV^{(3)}_{w-2}$ | | | | -0.046 | $\ln RV^{(3)}_{w-2}$ | | | | 0.011 |
| | | | | (-0.399) | | | | | (0.138) |
| $RV^{(3)}_{w-3}$ | | | | 0.055 | $\ln RV^{(3)}_{w-3}$ | | | | 0.080 |
| | | | | (0.538) | | | | | (1.058) |
| Adj. $R^2$ | 0.747 | 0.747 | 0.763 | 0.761 | Adj. $R^2$ | 0.789 | 0.789 | 0.807 | 0.806 |

*Notes.* This table reports the estimation results of the spillover effects for front contracts using the weekly RV data. Panel A reports the results for models using the weekly RV levels, and panel B is for the logarithmic settings. The light crude oil futures data is from January 2010 to March 2016. The t-statistics reported in parentheses are based on the standard errors computed with the Newey-West correction for the serial correlation of order 20. The last row of the table reports the adjusted $R^2$.

## 8. Conclusion

In this paper, we study the volatility spillover effect along the crude oil forward curve. Using the high-frequency prices of futures contracts with different maturities, we assess the additional power of the RV of nearby contracts for forecasting the RV of distant contracts. To achieve this, we include the lagged RV of contracts with a different maturity as additional forecasting variables in the HAR model (Corsi, 2009).

We find that the daily RVs of nearby contracts have a stronger power for forecasting the daily RVs of distant contracts relative to the lagged daily RVs of the latter. Specifically, when added to the standard HAR model, the RV of front contracts completely subsumes the information content of the RV of three-month contracts, indicating that the one-month futures market is more informative than the three-month futures market. The forecasting performance also improves significantly after including the RV of the front contracts in the model. Conversely, the RVs of three-month contracts possess little additional information in forecasting the RVs of front contracts.

The results of the Granger causality tests confirm that the RVs of nearby contracts contain important information when forecasting the RVs of distant contracts, even after controlling for the lagged RV of the latter. However, the converse is not true; in spite of the frequency of the RVs, the RV of distant contracts has little effect in forecasting the RV of nearby contracts. These findings support the volatility spillover effect among contracts along the crude oil forward curve, and the direction of the volatility spillover is from nearby to distant maturities contracts.

The out-of-sample results also provide supportive evidence for the volatility spillover from front to three-month contracts. The models having the lagged RV of front contracts as additional regressors beat the standard HAR model for the three-month RV. The stronger forecasting power comes mainly from the lagged daily RV of the front contracts.

The crude oil inventory data is released every Wednesday by the EIA. We have shown empirically that the inventory announcements have a significant announcement-day effect on both the spillover effect and the magnitude of volatility. On the announcement day, the volatility spillover between the front and three-month contracts becomes bi-directional, and the RVs become significantly larger for both front and three-month contracts.

Overall, our findings contribute to the volatility spillover literature, and shed light on the price discovery process of crude oil futures and information transmission among contracts with different maturities. We show that there is a unidirectional volatility spillover along the crude oil forward curve from nearby to distant contracts, indicating that the volatility of nearby contracts generally contains ex ante information on the volatility of distant maturities contracts. The prices of nearby contracts are more informative due to the higher trading volume, and thus play a leading role in the price discovery process. Clearly, these findings are important for risk management and other financial applications involving volatility forecasting.

## Appendix

**A.1.** Percentages of missing values before and after interpolation

| | Before Interpolation | After Interpolation |
|---|---|---|
| One-month contract | 0.003% | - |
| Two-month contract | 0.071% | 0.027% |
| Three-month contract | 1.251% | 0.046% |

*Notes.* The percentages are of missing values before and after interpolation for 5-min price data. The dataset includes one-month, two-month, and three-month crude oil prices from January 2010 to March 2016. The prices of the one-month crude oil contracts are not interpolated.

## References


Adämmer, P., Bohl, M.T., Gross C. (2015). Price discovery in thinly traded futures markets: How thin is too thin? [J]. Journal of Futures Markets, 36(9): 851–869.

Andersen, T.G., Bollerslev, T. (1998). Answering the skeptics: Yes, standard volatility models do provide accurate forecasts. International Economic Review 39: 885–905.

Andersen, T.G., Bollerslev, T., Diebold, F. X. (2007). Roughing it up: Including jump components in the measurement, modeling, and forecasting of return volatility. Review of Economics & Statistics, 89(4): 701–720.

Badshah, I.U., Frijns, B., Tourani-Rad, A. (2013). Contemporaneous spill-over among equity, gold, and exchange rate implied volatility indices. Futures Markets, 33(6): 555–572.

Barndorff-Nielsen, O.E., Shephard, N. (2007). Variation, jumps and high frequency data in financial econometrics. In R. Blundell, T. Persson, W.K. Newey, (Eds), Advances in Economics and Econometrics: Theory and Applications, Ninth World Congress, Econometric Society Monographs, Cambridge University Press, pp. 328–372.

Black, F. (1976). The pricing of commodity contracts. Journal of Financial Economics, 3(1): 167–179.

Chan, K., Chan, K.C., Karolyi, G.A., (1991). Intraday volatility in the stock index and stock index futures markets. The Review of Financial Studies, 4: 657–684.

Chang C.L., Mcaleer, M., Tansuchat, R. (2010). Analyzing and forecasting volatility spillovers, asymmetries and hedging in major oil markets. Energy Economics, 32(6): 1445–1455.

Corsi, F., (2009). A simple approximate long memory of realized volatility. Journal of Financial Econometrics 7: 174–196.

Diebold, F.X., Yilmaz, K. (2009). Measuring financial asset return and volatility spillovers, with application to global equity markets. The Economic Journal, 119(534): 158–171.

Diebold, F.X., Yilmaz, K. (2012). Better to give than to receive: Predictive directional measurement of volatility spillovers. International Journal of Forecasting, 28(1): 57–66.

Ito, T., Engle, R. F., Lin, W. L. (1990). Where does the meteor shower come from? The role of stochastic policy coordination. National Bureau of Economic Research (No. w3504).

Ewing, B.T., Malik, F., Ozfidan, O. (2002). Volatility transmission in the oil and natural gas markets. Energy Economics, 24(6): 525–538.

Karali, B., Ramirez, O. A. (2014). Macro determinants of volatility and volatility spillover in energy markets, Energy Economics, 46: 413–421

Koopman, S.J., Jungbacker, B., Hol, E. (2005). Forecasting daily variability of the S&P 100 Stock Index using historical, realised and implied volatility measures. Journal of Empirical Finance, 12: 445–475.

Martens, M., Van Dijk, D., De Pooter, M. (2004). “Modeling and forecasting S&P 500 volatility: Long-memory, structural breaks and nonlinearity.” Manuscript, Erasmus University Rotterdam.

Nazlioglu, S., Erdem, C., Soytas U. (2013). Volatility spillover between oil and agricultural commodity markets. Energy Economics, 36(3): 658–665.

Pilipovic, D., (2007). Energy Risk: Valuing and Managing Energy Derivatives, second ed. McGraw-Hill.

Souček, M., Todorova, N. (2014). Realized volatility transmission: The role of jumps and leverage effects. Economics Letters, 122(2): 111–115.

Tomek, W.G. (1980). Price behavior on a declining terminal market. American Journal of Agricultural Economics, 62(3): 434–444.

Working, H. (1948). Theory of the inverse carrying charge in futures markets. Journal of Farm Economics, 30: 1–28.

Working, H. (1962). New concepts concerning futures markets and prices. American Economic Review, 52(3): 431–459.

Wu, F., Guan, Z., Myers, R.J. (2011). Volatility spillover effects and cross hedging in corn and crude oil futures. Journal of Futures Markets, 31(11): 1052–1075.