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Do Oil-Price Shocks Predict the Realized Variance of U.S. REITs?

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Abstract

We examine, using aggregate and sectoral U.S. data for the period 2008−2020, the predictive power of disentangled oil-price shocks for Real Estate Investment Trusts (REITs) realized market variance via the heterogeneous auto-regressive realized variance (HAR-RV) model. In-sample tests show that demand and financial-market risk shocks contribute to a larger extent to the overall fit of the model than supply shocks, where the in-sample transmission of the impact of the shocks mainly operates through their significant effects on realized upward ("good") variance. Out-of-sample tests corroborate the significant predictive value of demand and risk shocks for realized variance and its upward counterpart at a short, medium, and long forecast horizon, for various recursive-estimation windows, for realized volatility (that is, the square root of realized variance), for a shorter sub-sample period that excludes the recent phase of exceptionally intense oil-market turbulence, and for an extended benchmark model that features realized higher-order moments, realized jumps, and a leverage effect as control variables.

JEL Classifications: C22, C53, G10, Q02.

Keywords: Oil price; Shocks, REITs; Realized variance; Forecasting

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1 Introduction

The securitized real estate market, i.e., Real Estate Investment Trusts (REITs), has witnessed tremendous growth in the United States (U.S.) since the early 1990s, with an extensive body of research shedding light on the benefits of REIT investments for portfolio management operating through asset allocation, risk reduction, and diversification channels, especially during periods of high economic uncertainty and intense financial-market turmoil (Chandrashekaran, 1999; Hudson-Wilson et al., 2003; Chun et al., 2004; Chen et al., 2005; Lee and Stevenson, 2005; Hung et al., 2008; Fugazza et al., 2009; Chaudhry et al., 2010; Huang and Zhong, 2013; Lu et al., 2013). According to the National Association of Real Estate Investment Trusts (NAREIT), REITs of all types collectively own more than 3 trillion US dollars in gross real estate assets across the U.S., with stock-exchange listed REITs holding approximately 2 trillion dollars in assets, and U.S. listed REITs having an equity market capitalization of more than 1 trillion dollars. The success in attracting investment capital at such a massive scale reflects that REITs are accessible to a broad audience of investors irrespective of portfolio size while, at the same time, offering diversification benefits relative to the conventional equity market. Moreover, with REITs being exchange-traded funds that earn their income mainly by investing in real estate, REITs have been studied extensively by academics and policy authorities (particularly since the Global Financial Crisis, which originated in the US real estate sector) because REITs returns do not suffer from measurement error and high transaction costs compared to other real estate investments. Furthermore, REITs are an excellent good high-frequency proxy for the real estate market, as REITs shares trade as common stocks (Akinsomi et al., 2016; Marfatia et al., 2017). Understandably, accurate forecasting of REITs returns variance is a key issue for researchers, policymakers, and investors, given that variance (and volatility, that is, the standard deviation of returns), as a measure of risk, plays a critical role in portfolio diversification, derivatives pricing, hedging and financial risk management.

Given the current emphasis[1] that intraday data leads to more precise estimates and forecasts for the volatility of the REIT returns (Zhou 2017, 2020a, 2020b; Odusami, 2020), we contribute to this burgeoning line of research by predicting the realized variance and volatility (RV) of U.S. REITs returns both at the aggregate and at the sectoral level, where we estimate RV by using 5-minute-interval intraday data for the period from September 2008 to August 2020, based on a modified version of the popular Heterogeneous Autoregressive (HAR) model introduced by Corsi (2009). More specifically, we extend the basic HAR-RV model to incorporate information on daily structural shocks (based on the work by Ready, 2018) associated with the demand and supply of the oil market, over and above innovations associated with financial-market risks, and examine the

[1]Earlier studies on modeling and forecasting of REITs volatility were primarily based on Generalized Autoregressive Conditional Heteroscedasticity (GARCH)-type models (see, for example, Devaney (2001), Stevenson (2002), Cotter and Stevenson (2006), Bredin et al. (2007), Lee and Pai (2010), Zhou and Kang (2011), and Pavlova et al. (2014)).

forecasting power of these shocks using both extensive in- and out-of-sample testing procedures.

Our decision to introduce oil shocks into the HAR-RV model emanates from a series of recent studies (Kang et al., 2017; Degiannakis et al., 2018; Degiannakis and Filis, 2019; Hailemariam et al., 2019; Gupta et al., 2020a; Sheng et al., 2020; Shahzad et al., forthcoming)[2] that demonstrate that oil shocks are a major driver of economic and financial uncertainty, where the shock transmission operates via direct and indirect channels associated with investment, inflation, production, and the size of the public sector. In general, the results of earlier empirical studies suggest that negative oil shocks tend to increase uncertainty and positive demand shock reduces the same. Given the role of REITs in mitigating risk and offering diversification benefits, following poor performance of the stock market during periods of heightened uncertainty (Chuliá et al., 2017; Gupta et al., 2020b) resulting from oil shocks, we hypothesize that demand and supply shocks originating in the oil market would help to predict REITs variance and volatility. Intuitively, because demand shocks in the oil market are likely to be associated with expansions of economic activity, REIT investments are likely to be substituted by investment in conventional risky assets, and this will reduce REITs returns and volatility due to less trading. The opposite might be true following supply shocks, resulting in contractions of the economy, and higher REIT returns due to increased demand for these assets (Huang and Lee, 2009), resulting in higher volatility from increased trading. Understandably, financial-market risks shocks are also expected to be associated with a rise in REITs volatility, emanating from higher trading, given the diversification qualities of REIT investments.[3]

At this stage, it is important to highlight that we study the role of oil shocks for predicting REITs variance and volatility rather than at the predictive value of movements of the oil price per se because of the possible differential impact of oil shocks as highlighted by Kilian's (2009) line of reasoning that "Not All Oil Shocks are Alike". In addition, using oil shocks instead of oil-price movements avoids the issue of endogeneity associated with the predictors, given the evidence of bidirectional causality between oil prices and REITs markets (Nazlioglu et al., 2016, 2020). To the best of our knowledge, our study is the first attempt to forecast the realized variance and volatility of REITs returns based on oil and financial-risks shocks, with existing studies on intraday data relying on comparing the predictive performance of the HAR-RV model with squared returns or various forms of GARCH models (Zhou, 2017, 2020a, 2020b), or carrying out in-sample analyses based on macroeconomic and financial predictors (Odusami, 2020). The results of our empirical study show that, as far as in-sample tests are concerned, oil demand and financial-market risk shocks contribute to a larger extent to the overall fit of the HAR-RV model than oil supply shocks.

[2]For some earlier studies in this regard, the reader can refer to Kang and Ratti (2013a, 2013b, 2015), and Antonakakis et al., (2014).

[3]In recent research, Bouri et al., (2020) show that oil demand and supply, and financial-risks shocks identified using the methodology proposed by Ready (2018), can predict oil-market volatility, and Nazlioglu et al. (2016, 2020) show that oil volatility causes REITs volatility due to portfolio-allocation decisions (Tiwari et al. 2018). A channel operating along this line of reasoning also could help explain why oil shocks affect REITs volatility.

Our results further suggest that the in-sample transmission of the impact of the shocks mainly operates through their significant effects on realized upward ("good") variance. Results of extensive out-of-sample tests confirm the significant predictive value of demand and financial-market risk shocks for REITS realized variance and volatility at a short, medium, and long forecast horizon, for various recursive-estimation windows, for a shorter sub-sample period that excludes the recent phase of exceptionally intense oil-market turbulence, and for an extended benchmark model that features realized higher-order moments, realized jumps, and a leverage effect as control variables.

We organize the remainder of our paper as follows. In Section 2, we describe our data and the methodology we use for our empirical study. In Section 3, we summarize our empirical results. In Section 4, we conclude.

2 Data and Methodology

2.1 Data

We use 5-minute-interval intraday data on the FTSE Nareit All REITs Index (FNAR) to conduct our empirical study.[4] The intraday data cover a 24-hour trading day and are ideally suited to construct daily measures of realized variance (RV). In addition, we construct the corresponding upward ("good", RVG) and downward ("bad", RVB) variances, and we use the intraday data to compute other covariates: leverage (LEV) based on days that register negative values of daily returns (and zero otherwise; returns being computed as the end of the day price difference, close to close), realized jumps ($JUMPS$), realized skewness (RSK), and realized kurtosis (RKU). The usage of LEV, $JUMPS$, RSK, and RKU helps to assess the robustness of the predictive value, if any, of the oil and financial-market-related shocks. Besides the FNAR index, given that oil-price movements may have a differential impact on REITs sectors (Nazlioglu et al., 2016), as an extension of our empirical study, we also investigate the role of oil supply, oil demand, and financial-market risk shocks on the following sectoral REITs: All Equity (FNER), Industrial (FNIND), Office (FNOFF), Retail (FNRET), Apartment (FNAPT), Residential (FNRES), Shopping (FNSHO), Health Care (FNHEA), Composite (FNCO), and Regional Malls (FNMAL). The price data, obtained from Bloomberg, is available in a continuous format.

Kilian (2009) and Kilian and Park (2009) note that, in order to get a more accurate assessment of oil-price effects on the economy as a whole and asset markets, it is important to account for the different sources of oil-price fluctuations by distinguishing between supply- and demand-related

[4]The FTSE Nareit All REITs Index is a market capitalization-weighted index that and includes all tax-qualified real estate investment trusts (REITs) that are listed on the New York Stock Exchange, the American Stock Exchange or the NASDAQ National Market List. The FTSE Nareit All REITs Index is not free float adjusted, and constituents are not required to meet minimum size and liquidity criteria.

shocks. Although the decomposition method proposed by Kilian (2009) has been widely used in the earlier literature, it tends to give too much weight to oil-specific demand shocks relative to supply shocks, and the applicability of the method is limited to monthly data only. The decomposition method recently introduced by Ready (2018) overcomes these limitations by computing supply- and demand-related shocks based on traded asset prices and, thereby, allows our analysis to be performed at a daily frequency. In order to compute oil demand and oil supply as well as financial-market risk shocks based on the decomposition method proposed by Ready (2018), we collect daily price data for the world integrated oil and gas producer index,[5] the nearest maturity NYMEX crude-light sweet oil-futures contract, and the Chicago Board Options Exchange (CBOE) volatility index (VIX). We derive the data from the Datastream database maintained by Thomson Reuters. Like 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 the VIX index, obtained as the residuals from an Autoregressive Moving Average (ARMA)(1,1) model estimated on data for the VIX index, to capture shocks related to changes in the market discount rate that tend to co-vary with attitudes towards risk.

– Please include Figure 1 about here. –

Based on data availability of the variables under consideration, our analysis covers the sample period 09/19/2008–08/13/2020. Figure 1 plots our data.

2.2 Methodology

2.2.1 Identification of Oil-Price Shocks

Based on the decomposition method described by Ready (2018), we define oil-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 index. The innovations to the VIX index, in turn, control for aggregate changes in market discount rates that affect stock returns of oil-producing companies, and are employed as a proxy for financial-market-risk shocks. Finally, we represent oil-supply shocks by the residual component of oil-price changes that is orthogonal to both oil-demand shocks and financial-market risk shocks. Formally, the decomposition methodology proposed by Ready (2018) can be represented in terms of the following matrix form:

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

where $X_t = [\Delta oil_t, R_t^{Prod}, \xi_{VIX,t}]'$ is a 3×1 vector, with Δoil_t = the change in the oil price in period t, R_t^{Prod} = the returns on the global stock index of oil-producing firms, and $\xi_{VIX,t}$ = the innovation

[5]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).

to the VIX index (derived, as mentioned in Section 2.1, by estimating an ARMA(1,1) model). The focus of our empirical analysis is on $Z_t = [s_t, d_t, v_t]'$, which is a 3×1 vector of oil-supply shocks (s_t), oil-demand shocks (d_t), and financial-market risk shocks (v_t). Finally, A is a 3×3 matrix of coefficients to be estimated that is given by

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

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

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

where $\Sigma_X =$ the covariance matrix of the variables in X_t, and σ_s^2, σ_d^2 and σ_v^2 are the variances of the oil-supply and oil-demand demand, and the financial-market-risk shocks. The condition formalized in Equation (3) is a renormalization of the standard orthogonalization commonly applied in order to identify structural shocks in a structural vector autoregressive model. It should be mentioned that the variance of oil-price shocks is not normalized to unity but, instead, that the sum of the three shocks, given the way they are computed, has to equal the total variation in the oil price. This approach to decompose oil-price fluctuations into shocks identifies an oil-supply shock as the part of oil-price fluctuations that cannot be explained by changes in global aggregate demand and changes in financial-market risk.[6]

2.2.2 Heterogeneous Autoregressive Realized Variance (HAR-RV) Model and Higher Moments

For our in-sample and out-of-sample forecasting analysis, we use variants of the widely-studied HAR-RV framework developed by Corsi (2009) to model and predict forecast the daily realized REITs variance. While the HAR-RV model apparently has a simple structure, it has become increasingly popular in the empirical-finance literature because it is able to capture long memory and multi-scaling behavior of financial-market and REITs volatility (Zhou, 2011, 2020a; Pavlova et al., 2014; Assaf, 2015). In our forecasting analysis, the benchmark HAR-RV model is given by

$$RV_{t+h} = \beta_0 + \beta_d RV_t + \beta_w RV_{w,t} + \beta_m RV_{m,t} + \epsilon_{t+h}, \tag{4}$$

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

where h = the forecast horizon, and (for $h > 1$) RV_{t+h} = the average realized variance over the h-days forecast horizon, where we study a short (daily, $h = 1$), a medium (weekly, $h = 5$), and a long (monthly, $h = 22$) forecast horizon. In addition, $RV_{w,t}$ is the average RV from day $t-5$ to day $t-1$, while $RV_{m,t}$ is the average RV from day $t-22$ to day $t-1$.

In addition, we study an extended version of the HAR-RV model in Equation (4) by incorporating LEV, $JUMPS$, RSK, and RKU as additional control variables. The extended HAR-RV model is given by

$$RV_{t+h} = \beta_0 + \beta_d RV_t + \beta_w RV_{w,t} + \beta_m RV_{m,t} + \beta_1 LEV_t + \beta_2 JUMPS_t + \beta_3 RSK_t + \beta_4 RKU_t + \epsilon_{t+h}. \quad (5)$$

In order to capture the role of oil-supply, oil-demand, and financial-market-risk shocks, we modify the HAR-RV models given in Equations (4) and (5) as follows:

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

and,

$$RV_{t+h} = \beta_0 + \beta_d RV_t + \beta_w RV_{w,t} + \beta_m RV_{m,t} + \beta_1 LEV_t + \beta_2 JUMPS_t + \beta_3 RSK_t + \beta_4 RKU_t + \theta' Q_t + \epsilon_{t+h}, \quad (7)$$

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

We use the classical estimator of RV, i.e., the sum of squared intraday returns (Andersen and Bollerslev, 1998), expressed as

$$RV_t = \sum_{i=1}^{M} r_{t,i}^2, \quad (8)$$

where $r_{t,i}$ is the intraday $M \times 1$ return vector and $i = 1, ..., M$ is the number of intraday returns.

Downward ("bad", RVB) and upward ("good", RVG) realized variance (that is, the semi-variances) serve as measures of downside and upside risk, and capture the sign asymmetry in the oil-price process. Thus, we also forecast RVG and RVB based on the information content of the oil-price and financial-market-risk shocks, by replacing RV (=$RVB + RVG$) in the above equation by RVB and RVG. In line with Barndorff-Nielsen et al. (2010), we compute bad and good realized semi-variance as

$$RVB_t = \sum_{i=1}^{T} r_{t,i}^2 \ \mathbf{1}_{[(r_{t,i})<0]}, \tag{9}$$

$$RVG_t = \sum_{i=1}^{T} r_{t,i}^2 \ \mathbf{1}_{[(r_{t,i})>0]}. \tag{10}$$

Odusami (2020) documents the presence of volatility jumps ($JUMPS$) in higher frequency REITs returns, to which we turn next, in addition to realized skewness, RSK, and realized kurtosis, RKU. Barndorff-Nielsen and Shephard (2004) derive the results that realized variance converges into permanent and discontinuous (jump) components as

$$\lim_{M\to\infty} RV_t = \int_{t-1}^{t} \sigma^2(s)ds + \sum_{j=1}^{N_t} k_{t,j}^2, \tag{11}$$

where N_t is the number of jumps within day t and $k_{t,j}$ is the jump size. This result implies that RV_t is a consistent estimator of the integrated variance $\int_{t-1}^{t} \sigma^2(s)ds$ plus the jump contribution. The asymptotic results derived by Barndorff-Nielsen and Shephard (2004, 2006) further show that

$$\lim_{M\to\infty} BV_t = \int_{t-1}^{t} \sigma^2(s)ds, \tag{12}$$

where BV_t is the realized bipolar variation defined as

$$BV_t = \mu_1^{-1} \left(\frac{N}{M-1}\right) \sum_{i=2}^{M} |r_{t,i-1}||r_{i,t}| = \frac{\pi}{2} \sum_{i=2}^{M} |r_{t,i-1}||r_{i,t}|, \tag{13}$$

where

$$\mu_a = E(|Z|^a), Z \sim N(0,1), a > 0. \tag{14}$$

Equipped with the continuous component of realized variance, a consistent estimator of the pure jump contribution can then be expressed as

$$J_t = RV_t - BV_t. \tag{15}$$

In order to test the significance of the jumps, we rely on a formal test estimator proposed by Brandorff-Nielsen and Shephard (2006) given by

$$JT_t = \frac{RV_t - BV_t}{(v_{bb} - v_{qq})\frac{1}{N}QP_t}, \tag{16}$$

where QP_t is the Tri-Power Quarticity:

$$TP_t = M_{\mu_{4/3}^{-3}} \left(\frac{M}{M-1} \right) \sum_{i=3}^{M} |r_{t,i-2}|^{4/3} |r_{t,i}|^{4/3}, \tag{17}$$

which converges to

$$TP_t \to \int_{t-1}^{t} \sigma^4(s) ds, \tag{18}$$

even in the presence of jumps. We use the notation $v_{bb} = \left(\frac{\pi}{2}\right) + \pi - 3$ and $v_{qq} = 2$. Note that for each t, $JT_t \sim N(0,1)$ as $M \to \infty$.

As can be seen in Equation (15), the jump contribution to RV_t is either positive or null. Therefore, so as to avoid obtaining negative empirical contributions, we redefine, like Zhou and Zhu (2012), the jump measure as

$$RJ_t = max(RV_t - BV_t; 0). \tag{19}$$

Finally, we compute the higher-moments of the daily REITs returns distribution, that is, RSK and RKU. Like Amaya et al. (2015), we consider RSK as a measure of the asymmetry of the daily REITs returns distribution, and RKU as a measure that accounts for extremes. We compute RSK on day t as

$$RSK_t = \frac{\sqrt{N} \sum_{i=1}^{N} r_{(i,t)^3}}{RV_t^{3/2}}, \tag{20}$$

and RKU on day t as

$$RKU_t = \frac{N \sum_{i=1}^{N} r_{(i,t)^4}}{RV_t^2}. \tag{21}$$

The scaling of RSK and RKU by $(N)^{1/2}$ and N ensures that magnitudes correspond to daily skewness and kurtosis.

3 Empirical Results

3.1 Full-Sample Results

Table 1 summarizes full-sample results for the realized variance of aggregate REITs returns. We present results for a short (daily), medium (weekly), and long (monthly) forecast horizons ($h = 1, 5, 22$) and eight different models: the classic HAR-RV model, versions of the HAR-RV model extended to include one of the shocks, versions of the HAR-RV models that feature combinations of two shocks, and a HAR-RV model that features simultaneously all shocks. As for the classic HAR-RV model, we find that realized variance and realized weekly variance are highly significant for the short and medium forecast horizons. For the long forecast horizon, only the coefficient estimated for realized variance turns out to be statistically significant. As expected, the HAR-RV model fits the data quite well, where the adjusted R^2 statistic takes on a value of about 0.78 for the medium forecast horizon, and about 0.72 and 0.73 for the short and long forecast horizons. Turning to the shocks, we find that oil-supply shocks and oil-demand shocks have significant explanatory power at all three forecast horizons, while the coefficients estimated for the financial-market-risk shocks are significant at the medium and long forecast horizons. In line with our intuition in terms of the differential impact of the shocks, the coefficient estimated for the oil-demand shocks have a negative sign, while the coefficients for the oil-supply and financial-market-risk shocks have a positive sign, with the latter being in line with the findings of Odusami (2020) associated with the VIX index.[7] We also observe that the estimation results for the adjusted R^2 statistic reveal that, when compared to the R^2 statistic estimated for the classic HAR-RV model without any shocks, the overall contribution of oil-supply shocks to the explanatory power of the estimated models is rather small. In contrast, adding oil-demand and/or financial-market risk shocks to the HAR-RV model leads to a noticeable increase in the adjusted R^2 statistic.

– Please include Table 1 about here. –

Table 2 summarizes the results for realized bad variance. As compared to realized variance, the estimated adjusted R^2 statistic of the estimated models is smaller, ranging from about 0.52 to 0.72. The classic HAR-RV again provides a satisfactory fit of the data, where the main sources of model fit are the realized variance and the realized weekly variance. In contrast to what we find for the standard realized variance, the contribution of the shocks to the overall fit of the model is small. At the short forecast horizon, not a single estimated shock coefficient is significant. The coefficients estimated for the financial-market-risk shocks are significant at the medium forecast horizon, and the coefficients estimated for the oil-supply shocks are mainly significant at the long forecast horizon (all coefficients have a positive sign). On balance, though, the shocks seem to have a rather moderate explanatory power for the realized bad variance.

– Please include Table 2 about here. –

The results for realized good variance summarized in Table 3 are more encouraging than those for realized bad variance, and highlight the importance of distinguishing between variance due to negative and positive returns. At all three forecast horizons, all estimated coefficients of all three shocks are statistically significant. Again in line with intuition, the coefficients estimated for oil-demand shocks are negative, while the coefficients estimated for oil-supply and financial-market-risk shocks are positive. Importantly, all shocks, but especially oil-demand and financial-market-risk shocks, have a noticeable effect on the estimated adjusted R^2 statistic of the models.

[7]Evidence of uncertainty spillovers due to financial market on to REITs volatility can also be found in the works of Ajmi et al. (2014), and Sadhwani et al. (2019).

The estimated adjusted R^2 statistic increases for the short (medium, long) forecast horizon from approximately 0.52 to roughly 0.59 (0.72 to 0.75, 0.74 to 0.76) when we move from the classic HAR-RV model to the HAR-RV model extended to include all three shocks.

– Please include Table 3 about here. –

Taken together, the full-sample results suggest that oil-demand and financial-market risk shocks should have a more substantial impact on the out-of-sample predictive ability of the model than oil-supply shocks, and that the contribution of oil-demand and financial-market-risk shocks to the predictive value of the model should be particularly strong in case of realized good variance. These results tie-up well with the intuition that REITs offer diversification benefits in relation to equity markets in the wake of expansions of economic activity and during periods of financial-market turmoil, and associated volatility (i.e., upside risk) due to higher trading.

3.2 Out-of-Sample Results

Table 4 shows that this is indeed the case based on the forecasting exercise, with the out-of-sample experiment aiming to provide more robust evidence of the predictive capacity of the shocks, given that Campbell (2008) notes that the ultimate test of any predictive model (in terms of the econometric methodologies and the predictors under consideration) is in its out-of-sample performance. We report in Table 4 the results of p-values of the Clark and West (2007) test for an equal out-of-sample mean-squared prediction error (MSPE). In order to compute out-of-sample forecasts, we use a recursive-estimation window, where we use various training periods (the first 250 observations, the first 500 observations, and so on) to initialize the recursive-estimation scheme. The classic HAR-RV model is the benchmark model, and the HAR-RV extended to include a shock or a combination of shocks is the rival model. The alternative hypothesis is that the rival model has a smaller MSPE than the benchmark HAR-RV model. We only depict in the table those p-values that are smaller than or equal to a marginal significance level of 10%, and drop insignificant results for better readability of the table. The test results can be summarized as follows. First, we observe several significant test results for the standard realized variance, and especially for the realized good variance. Second, the test results for the realized bad variance are always insignificant. Third, we obtain significant test results in the cases of oil-demand and financial-market-risk shocks, but not in the case of oil-supply shocks.

– Please include Tables 4 and 5 about here. –

Next, we present in Table 5 out-of-sample test results for realized volatility (that is, the square root of realized variance). Studying realized volatility is interesting because it plays an important role for asset pricing in general and the pricing of derivative securities in particular. In addition, studying the square root of realized variance is warranted as a robustness check given the clusters of large realizations of realized variance at the beginning and end of the sample period. The test results for realized volatility corroborate the results for the realized variance. Again, we find significant test results when considering oil-demand and financial-market-risk shocks, and when we study either realized volatility or realized good volatility.

– Please include Table 6 about here. –

As another forecasting experiment, we study the out-of-sample predictive value of the shocks for a somewhat shorter sample period. The motivation for this forecasting experiment is that Figure 1 clearly shows the occurrence of a cluster of relatively large shocks at the very end of the sample period. In order to account for these relatively large shocks, we drop 100 daily data at the end of the sample period and then implement the out-of-sample tests on the resulting somewhat shorter sample of forecasts. Table 6 gives the results. The results show that the evidence that the shocks help to improve forecasting performance in the case of realized bad variance strengthens, mainly in case of the financial-market-risk shock. For the standard realized variance and realized good variance, we obtain results that are qualitatively similar to the results we observe in Table 4.

– Please include Table 7 about here. –

In Table 7, we change the benchmark model. Specifically, we extend the classic HAR-RV model to include realized kurtosis, realized skewness, realized jumps, and a leverage effect (that equals returns when they are negative, and zero otherwise). We then add to this extended benchmark model the shocks and use the Clark-West test to study whether the shocks improve the predictive performance relative to the extended benchmark model, where we focus on the standard realized variance and volatility and the realized good variance and volatility. The test results show that the predictive value of oil-demand and financial-market-risk shocks becomes weaker than in the case of the core HAR-RV benchmark model, where this effect is more pronounced for the realized variance than for the realized volatility. However, for the realized good variance, and especially for the realized volatility, the oil-demand and financial-market-risk shocks continue to add predictive value to the model for several parameterizations of the forecast horizon and the training period.

– Please include Table 8 about here. –

Finally, we take in Table 8 a more disaggregated view by looking at various REIT subindices. We focus on realized (standard, bad, and good) volatility and the extended model, where we add all three shocks at the same time. We find that the shocks have predictive value for realized bad volatility in a few cases, but the overall picture is that the shocks mainly play a role for predictive accuracy in the case of standard realized volatility and especially in the case of realized good volatility.

4 Concluding Remarks

We have explored in our empirical research the predictive value of oil-demand, oil-supply, and financial-market-risk shocks for the realized variance and volatility of REITs returns derived from intraday data. Utilizing a recently proposed model to decompose oil-price fluctuations into supply and demand related shocks, we have examined the in-sample and out-of-sample predictive performance of various HAR-RV models by incorporating oil-price and financial-market-risk shocks as predictors in different combinations.

We have found in extensive in-sample analyses, using aggregate and sectoral U.S. data for the period 2008−2020, that oil-demand and financial-market risk shocks contribute to a larger extent to the overall fit of the HAR-RV model than oil-supply shocks. We also have found that the in-sample transmission of the impact of the shocks mainly operates through their significant effects on realized good variance. We then have moved on to a study of the contribution of the shocks to the predictive out-of-sample performance of the HAR-RV model. We have found that oil-demand and financial-market risk shocks significantly contribute out-of-sample performance in the cases of realized variance and realized good variance, where we have used extensive robustness checks to explore the sensitivity of our findings. For example, we have reported results for realized volatility instead of realized variance, for a shorter subsample period that excludes the recent phase of exceptionally intense oil-market turbulence, and for an extended HAR-RV benchmark model.

Given the tremendous growth of REITs as an asset class in the U.S. and, hence, the importance of accurate variance forecasts as inputs for optimal asset-allocation decisions, our findings suggest that incorporating oil-price and financial-market-risk shocks in forecasting models can help to improve the design of portfolios that include REITs across various investment horizons. As part of future research, it is interesting to extend our study to international REITs markets, and in the process distinguish between oil-exporting and oil-importing countries.

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Table 1: Full-Sample Results for Realized Variance

Panel A: $h = 1$

Model	Intercept	RV	RV_w	RV_m	Supply	Demand	Risk	Adj. R^2
HAR-RV	2.0997	7.6523	3.6356	1.4166	–	–	–	0.7191
p-value	0.0358	0.0000	0.0003	0.1567	–	–	–	–
HAR-RV-Supply	2.0928	7.6083	3.6823	1.4639	1.8119	–	–	0.7192
p-value	0.0364	0.0000	0.0002	0.1433	0.0701	–	–	–
HAR-RV-Demand	1.6577	7.5702	3.7787	1.5094	–	-2.4353	–	0.7227
p-value	0.0975	0.0000	0.0002	0.1313	–	0.0149	–	–
HAR-RV-Risk	2.4770	7.7823	3.9857	1.4430	–	–	1.2888	0.7212
p-value	0.0133	0.0000	0.0001	0.1491	–	–	0.1976	–
HAR-RV-Supply-Demand	1.6358	7.5267	3.8094	1.5690	2.4515	-2.4937	–	0.7230
p-value	0.1020	0.0000	0.0001	0.1167	0.0143	0.0127	–	–
HAR-RV-Supply-Risk	2.4724	7.3423	3.8818	1.5044	2.1189	–	1.2806	0.7213
p-value	0.0135	0.0000	0.0001	0.1326	0.0342	–	0.2004	–
HAR-RV-Demand-Risk	1.9572	7.3615	3.8982	1.5087	–	-2.1188	0.9248	0.7237
p-value	0.0504	0.0000	0.0001	0.1315	–	0.0342	0.3551	–
HAR-RV-Supply-Demand-Risk	1.9318	7.2827	3.9198	1.5671	2.5046	-2.1895	0.9363	0.7239
p-value	0.0535	0.0000	0.0001	0.1172	0.0123	0.0286	0.3492	–

Panel B: $h = 5$

Model	Intercept	RV	RV_w	RV_m	Supply	Demand	Risk	Adj. R^2
HAR-RV	1.6341	4.2593	2.9654	1.2139	–	–	–	0.7806
p-value	0.1023	0.0000	0.0030	0.2249	–	–	–	–
HAR-RV-Supply	1.6622	4.3802	2.8680	1.2412	2.7470	–	–	0.7810
p-value	0.0966	0.0000	0.0042	0.2146	0.0061	–	–	–
HAR-RV-Demand	1.6887	4.8437	3.3973	1.4229	–	-2.4996	–	0.7857
p-value	0.0914	0.0000	0.0007	0.1549	–	0.0125	–	–
HAR-RV-Risk	2.1878	5.4776	3.6723	1.4695	–	–	3.3556	0.7903
p-value	0.0288	0.0000	0.0002	0.1418	–	–	0.0008	–
HAR-RV-Supply-Demand	1.6531	4.9290	3.4039	1.4635	4.3362	-2.5940	–	0.7865
p-value	0.0984	0.0000	0.0007	0.1434	0.0000	0.0095	–	–
HAR-RV-Supply-Risk	2.2270	5.3685	3.7167	1.5493	4.3019	–	3.4439	0.7910
p-value	0.0260	0.0000	0.0002	0.1214	0.0000	–	0.0006	–
HAR-RV-Demand-Risk	2.1237	5.3605	3.7632	1.5325	–	-1.9505	3.1772	0.7926
p-value	0.0338	0.0000	0.0002	0.1255	–	0.0512	0.0015	–
HAR-RV-Supply-Demand-Risk	2.0570	5.6229	3.7045	1.5680	5.1616	-2.0823	3.1848	0.7936
p-value	0.0398	0.0000	0.0002	0.1170	0.0000	0.0374	0.0015	–

Panel B: $h = 22$

Model	Intercept	RV	RV_w	RV_m	Supply	Demand	Risk	Adj. R^2
HAR-RV	1.2753	3.6277	1.1828	1.3845	–	–	–	0.7277
p-value	0.2023	0.0003	0.2370	0.1663	–	–	–	–
HAR-RV-Supply	1.2919	3.6017	1.1916	1.4266	1.9701	–	–	0.7281
p-value	0.1965	0.0003	0.2335	0.1538	0.0489	–	–	–
HAR-RV-Demand	1.5187	4.2657	1.3523	1.5390	–	-1.8998	–	0.7307
p-value	0.1289	0.0000	0.1764	0.1239	–	0.0576	–	–
HAR-RV-Risk	1.6521	4.2655	1.4948	1.4737	–	–	2.2192	0.7350
p-value	0.0986	0.0000	0.1351	0.1407	–	–	0.0265	–
HAR-RV-Supply-Demand	1.5271	4.2939	1.3500	1.5948	2.7164	-2.0359	–	0.7314
p-value	0.1268	0.0000	0.1771	0.1109	0.0066	0.0418	–	–
HAR-RV-Supply-Risk	1.8981	4.6077	1.6347	1.6529	2.8078	–	2.4784	0.7357
p-value	0.0578	0.0000	0.1022	0.0985	0.0050	–	0.0133	–
HAR-RV-Demand-Risk	1.8744	4.9003	1.6411	1.6217	–	-1.8476	2.4296	0.7361
p-value	0.0610	0.0000	0.1009	0.1050	–	0.0648	0.0152	–
HAR-RV-Supply-Demand-Risk	1.8826	4.8457	1.6594	1.7066	3.0968	-1.9674	2.4646	0.7370
p-value	0.0599	0.0000	0.0971	0.0880	0.0020	0.0492	0.0138	–

For better readability of the estimation results, the table depicts the t-ratios of the estimated coefficients and the corresponding p-values (based on robust standard errors).

Table 2: Full-Sample Results for Bad Realized Variance

Panel A: $h = 1$

Model	Intercept	RV	RV_w	RV_m	Supply	Demand	Risk	Adj. R^2
HAR-RV	2.4486	1.8285	3.3687	1.5907	–	–	–	0.5225
p-value	0.0144	0.0676	0.0008	0.1118	–	–	–	–
HAR-RV-Supply	2.4746	1.7970	3.5310	1.6797	-0.0366	–	–	0.5224
p-value	0.0134	0.0724	0.0004	0.0931	0.9708	–	–	–
HAR-RV-Demand	2.4323	1.7218	3.4757	1.6822	–	-0.1832	–	0.5224
p-value	0.0151	0.0852	0.0005	0.0926	–	0.8546	–	–
HAR-RV-Risk	2.0727	2.0813	3.4466	1.5936	–	–	-0.9825	0.5244
p-value	0.0383	0.0375	0.0006	0.1111	–	–	0.3259	–
HAR-RV-Supply-Demand	2.4237	1.7110	3.4245	1.6519	-0.0134	-0.1823	–	0.5222
p-value	0.0154	0.0872	0.0006	0.0987	0.9893	0.8554	–	–
HAR-RV-Supply-Risk	2.0879	2.1301	3.5229	1.6270	-0.1955	–	-0.9878	0.5243
p-value	0.0369	0.0332	0.0004	0.1038	0.8450	–	0.3234	–
HAR-RV-Demand-Risk	1.9636	2.0661	3.4919	1.6632	–	-0.4282	-0.9876	0.5244
p-value	0.0497	0.0389	0.0005	0.0964	–	0.6685	0.3234	–
HAR-RV-Supply-Demand-Risk	1.9738	2.0791	3.4581	1.6323	-0.1520	-0.4259	-0.9977	0.5242
p-value	0.0485	0.0377	0.0006	0.1027	0.8792	0.6702	0.3185	–

Panel B: $h = 5$

Model	Intercept	RV	RV_w	RV_m	Supply	Demand	Risk	Adj. R^2
HAR-RV	1.9995	3.0513	2.7654	1.2531	–	–	–	0.7160
p-value	0.0456	0.0023	0.0057	0.2103	–	–	–	–
HAR-RV-Supply	2.0010	3.2320	2.8166	1.2920	1.1425	–	–	0.7162
p-value	0.0455	0.0012	0.0049	0.1965	0.2533	–	–	–
HAR-RV-Demand	2.0753	3.1980	2.8924	1.3233	–	-1.0375	–	0.7170
p-value	0.0380	0.0014	0.0039	0.1858	–	0.2996	–	–
HAR-RV-Risk	2.1862	3.0068	2.9447	1.3566	–	–	1.7118	0.7190
p-value	0.0289	0.0027	0.0033	0.1750	–	–	0.0870	–
HAR-RV-Supply-Demand	2.0015	3.2258	2.8215	1.3109	1.4205	-1.0637	–	0.7173
p-value	0.0454	0.0013	0.0048	0.1900	0.1556	0.2876	–	–
HAR-RV-Supply-Risk	2.1997	3.1145	3.0369	1.4268	1.4575	–	1.7145	0.7194
p-value	0.0279	0.0019	0.0024	0.1537	0.1451	–	0.0865	–
HAR-RV-Demand-Risk	2.2370	3.0473	3.0613	1.4291	–	-0.8913	1.7118	0.7196
p-value	0.0254	0.0023	0.0022	0.1531	–	0.3729	0.0870	–
HAR-RV-Supply-Demand-Risk	2.1574	2.8589	2.8802	1.3608	1.6578	-0.9076	1.7532	0.7200
p-value	0.0311	0.0043	0.0040	0.1737	0.0975	0.3642	0.0797	–

Panel B: $h = 22$

Model	Intercept	RV	RV_w	RV_m	Supply	Demand	Risk	Adj. R^2
HAR-RV	1.2179	2.9753	1.5361	1.6451	–	–	–	0.6754
p-value	0.2234	0.0030	0.1246	0.1000	–	–	–	–
HAR-RV-Supply	1.2955	3.1157	1.6224	1.6825	1.6938	–	–	0.6759
p-value	0.1952	0.0019	0.1048	0.0926	0.0904	–	–	–
HAR-RV-Demand	1.4283	3.4533	1.6828	1.6744	–	-0.9402	–	0.6762
p-value	0.1533	0.0006	0.0925	0.0942	–	0.3472	–	–
HAR-RV-Risk	1.5603	3.1174	1.8590	1.6432	–	–	1.3269	0.6790
p-value	0.1188	0.0018	0.0631	0.1004	–	–	0.1846	–
HAR-RV-Supply-Demand	1.3730	3.4091	1.6368	1.6898	1.9358	-1.0730	–	0.6768
p-value	0.1699	0.0007	0.1018	0.0912	0.0530	0.2834	–	–
HAR-RV-Supply-Risk	1.7334	3.3494	2.0801	1.9069	2.0965	–	1.4677	0.6797
p-value	0.0831	0.0008	0.0376	0.0566	0.0361	–	0.1423	–
HAR-RV-Demand-Risk	1.7551	2.9578	2.0682	1.8117	–	-0.9307	1.4326	0.6794
p-value	0.0794	0.0031	0.0387	0.0701	–	0.3521	0.1521	–
HAR-RV-Supply-Demand-Risk	1.7115	3.0028	2.0197	1.8166	2.1642	-1.0602	1.4610	0.6801
p-value	0.0871	0.0027	0.0435	0.0694	0.0305	0.2891	0.1441	–

For better readability of the estimation results, the table depicts the t-ratios of the estimated coefficients and the corresponding p-values (based on robust standard errors).

Table 3: Full-Sample Results for Good Realized Variance

Panel A: $h = 1$

Model	Intercept	RV	RV_w	RV_m	Supply	Demand	Risk	Adj. R^2
HAR-RV	1.9256	5.0087	1.7172	2.6002	–	–	–	0.5243
p-value	0.0542	0.0000	0.0860	0.0094	–	–	–	–
HAR-RV-Supply	1.9573	4.9742	1.7483	2.7946	2.1570	–	–	0.5247
p-value	0.0504	0.0000	0.0805	0.0052	0.0311	–	–	–
HAR-RV-Demand	1.0371	5.6795	1.6886	2.5918	–	-3.9071	–	0.5475
p-value	0.2998	0.0000	0.0914	0.0096	–	0.0001	–	–
HAR-RV-Risk	3.2153	5.7586	1.7115	2.5093	–	–	5.0405	0.5766
p-value	0.0013	0.0000	0.0871	0.0122	–	–	0.0000	–
HAR-RV-Supply-Demand	1.0503	5.6212	1.7090	2.8228	2.9846	-4.0267	–	0.5487
p-value	0.2936	0.0000	0.0876	0.0048	0.0029	0.0001	–	–
HAR-RV-Supply-Risk	3.1947	5.8052	1.6981	2.6430	3.4164	–	5.1113	0.5779
p-value	0.0014	0.0000	0.0896	0.0083	0.0006	–	0.0000	–
HAR-RV-Demand-Risk	2.1061	6.2971	1.6689	2.4819	–	-2.9528	4.6711	0.5869
p-value	0.0353	0.0000	0.0952	0.0131	–	0.0032	0	–
HAR-RV-Supply-Demand-Risk	2.1594	6.2355	1.6620	2.6653	3.1078	-3.1163	4.7447	0.5887
p-value	0.0309	0.0000	0.0966	0.0077	0.0019	0.0018	0.0000	–

Panel B: $h = 5$

Model	Intercept	RV	RV_w	RV_m	Supply	Demand	Risk	Adj. R^2
HAR-RV	1.2698	3.8861	1.6733	1.8057	–	–	–	0.7150
p-value	0.2043	0.0001	0.0944	0.0711	–	–	–	–
HAR-RV-Supply	1.2827	4.0116	1.5914	1.7859	2.388	–	–	0.7159
p-value	0.1997	0.0001	0.1116	0.0742	0.017	–	–	–
HAR-RV-Demand	1.3314	5.1687	1.8720	1.9243	–	-4.0949	–	0.7287
p-value	0.1832	0.0000	0.0613	0.0544	–	0.0000	–	–
HAR-RV-Risk	2.0159	5.6315	1.8221	1.8471	–	–	5.2214	0.7458
p-value	0.0439	0.0000	0.0685	0.0648	–	–	0.0000	–
HAR-RV-Supply-Demand	1.2884	5.2013	1.8456	1.9891	3.1501	-4.1440	–	0.7302
p-value	0.1977	0.0000	0.0651	0.0468	0.0016	0.0000	–	–
HAR-RV-Supply-Risk	2.1154	5.6630	1.8789	1.9636	3.0509	–	5.5538	0.7474
p-value	0.0345	0.0000	0.0604	0.0497	0.0023	–	0.0000	–
HAR-RV-Demand-Risk	1.8964	6.0176	2.0464	1.9439	–	-3.5891	5.1359	0.7519
p-value	0.0580	0.0000	0.0408	0.0520	–	0.0003	0.0000	–
HAR-RV-Supply-Demand-Risk	1.9792	6.0387	2.0581	2.0647	3.1290	-3.7451	5.4504	0.7540
p-value	0.0479	0.0000	0.0397	0.0390	0.0018	0.0002	0.0000	–

Panel B: $h = 22$

Model	Intercept	RV	RV_w	RV_m	Supply	Demand	Risk	Adj. R^2
HAR-RV	1.1024	3.5196	1.2075	1.6834	–	–	–	0.7364
p-value	0.2704	0.0004	0.2273	0.0924	–	–	–	–
HAR-RV-Supply	1.1221	3.4972	1.2349	1.7597	1.8835	–	–	0.7368
p-value	0.2619	0.0005	0.2170	0.0786	0.0597	–	–	–
HAR-RV-Demand	1.4952	4.5879	1.3610	1.9779	–	-2.5303	–	0.7443
p-value	0.1350	0.0000	0.1736	0.0480	–	0.0114	–	–
HAR-RV-Risk	1.9372	4.7147	1.4147	1.9354	–	–	4.0211	0.7563
p-value	0.0528	0.0000	0.1573	0.0530	–	–	0.0001	–
HAR-RV-Supply-Demand	1.5087	4.6403	1.3857	2.0967	3.2919	-2.6045	–	0.7451
p-value	0.1315	0.0000	0.1659	0.0361	0.0010	0.0092	–	–
HAR-RV-Supply-Risk	2.0105	5.0273	1.4611	2.0916	3.3002	–	4.2829	0.7573
p-value	0.0445	0.0000	0.1441	0.0366	0.0010	–	0.0000	–
HAR-RV-Demand-Risk	1.9067	4.9816	1.4774	2.0362	–	-2.8263	4.1719	0.7596
p-value	0.0567	0.0000	0.1397	0.0418	–	0.0047	0.0000	–
HAR-RV-Supply-Demand-Risk	1.7324	4.5020	1.4307	2.0334	3.4942	-2.6676	3.8420	0.7608
p-value	0.0833	0.0000	0.1526	0.0421	0.0005	0.0077	0.0000	–

For better readability of the estimation results, the table depicts the t-ratios of the estimated coefficients and the corresponding p-values (based on robust standard errors).

Table 4: Out-of-Sample Tests for Realized Variance

Panel A: Realized variance

Forecast horizon	$h=1$	$h=5$	$h=22$	$h=1$	$h=5$	$h=22$	$h=1$	$h=5$	$h=22$	$h=1$	$h=5$	$h=22$	$h=1$	$h=5$	$h=22$
Training period	250	250	250	500	500	500	1000	1000	1000	1500	1500	1500	2000	2000	2000
Supply	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
Demand	0.0200	0.0129	0.0583	0.0329	0.0216	0.0663	0.0862	0.0437	0.0854	0.0961	0.0465	0.0876	0.096	0.0485	0.0901
Risk	–	0.0039	0.0071	–	0.0159	0.0129	–	0.0446	0.0259	–	0.0504	0.0287	–	0.0671	0.0314
Risk + supply	–	0.0024	0.0042	–	0.0095	0.0074	–	0.0259	0.0143	–	0.0295	0.0157	–	0.0391	0.0175
Risk + demand	0.0615	0.0028	0.0078	–	0.0105	0.0130	–	0.0291	0.0245	–	0.0336	0.0268	–	0.0442	0.0297
Supply + demand	0.0240	0.0134	0.0548	0.0346	0.0200	0.0599	0.0729	0.0348	0.0721	0.0818	0.0363	0.0745	0.0845	0.0376	0.0757
Risk + supply + demand	0.0463	0.0016	0.0047	–	0.0057	0.0076	–	0.0161	0.0140	–	0.0184	0.0155	–	0.0236	0.0172

Panel B: Realized bad variance

Forecast horizon	$h=1$	$h=5$	$h=22$	$h=1$	$h=5$	$h=22$	$h=1$	$h=5$	$h=22$	$h=1$	$h=5$	$h=22$	$h=1$	$h=5$	$h=22$
Training period	250	250	250	500	500	500	1000	1000	1000	1500	1500	1500	2000	2000	2000
Supply	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
Demand	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
Risk	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
Risk + supply	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
Risk + demand	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
Supply + demand	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
Risk + supply + demand	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–

Panel C: Realized good variance

Forecast horizon	$h=1$	$h=5$	$h=22$	$h=1$	$h=5$	$h=22$	$h=1$	$h=5$	$h=22$	$h=1$	$h=5$	$h=22$	$h=1$	$h=5$	$h=22$
Training period	250	250	250	500	500	500	1000	1000	1000	1500	1500	1500	2000	2000	2000
Supply	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
Demand	0.0008	0.0048	0.0088	0.002	0.0098	0.0126	0.0080	0.0284	0.0222	0.0099	0.032	0.0243	0.0111	0.0359	0.0262
Risk	0.0070	0.0007	0.0009	0.0259	0.0054	0.0025	0.0976	0.0248	0.0074	–	0.0265	0.0074	–	0.0331	0.0075
Risk + supply	0.0038	0.0002	0.0003	0.0150	0.0016	0.0010	0.0605	0.0081	0.0031	0.0624	0.0089	0.0031	0.0676	0.0117	0.0032
Risk + demand	0.0026	0.0001	0.0002	0.0108	0.0011	0.0005	0.0512	0.0079	0.0021	0.0530	0.0089	0.0026	0.0572	0.0124	0.0034
Supply + demand	0.0029	0.0094	0.0125	0.0048	0.0148	0.0161	0.0111	0.0287	0.0241	0.0126	0.0307	0.0258	0.0134	0.0324	0.0273
Risk + demand	0.0012	0.0001	0.0001	0.0052	0.0006	0.0004	0.0254	0.0037	0.0015	0.0262	0.0044	0.0017	0.0280	0.0063	0.0021

Note: This table reports results (p-values) of the Clark-West test for an equal mean-squared prediction error (MSPE) for alternative forecast horizons and alternative training periods. The training periods are used to initialize estimation. Forecasts are computed using a recursive estimation window. The HAR-RV model without shocks is the benchmark model, and the HAR-RV extended to include the shock or the combination of shocks shown in the left column is the rival model. The alternative hypothesis is that the rival model has a smaller MSPE than the benchmark model. For better readability of the estimation results, the table only summarizes those p-values that are smaller than or equal to a marginal significance level of 10%. The p-values are based on robust standard errors.

Table 5: Out-of-Sample Tests for Realized Volatility

Panel A: Realized volatility

Forecast horizon	$h=1$	$h=5$	$h=22$	$h=1$	$h=5$	$h=22$	$h=1$	$h=5$	$h=22$	$h=1$	$h=5$	$h=22$	$h=1$	$h=5$	$h=22$
Training period	250	250	250	500	500	500	1000	1000	1000	1500	1500	1500	2000	2000	2000
Supply	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
Demand	0.0011	0.0015	0.0269	0.0027	0.0044	0.0343	0.0193	0.0156	0.0562	0.0373	0.0235	0.0682	0.0463	0.0348	0.0816
Rsk	0.0019	0.0000	0.0014	0.0155	0.0006	0.0036	–	0.0026	0.0111	–	0.0051	0.0154	–	0.0209	0.0258
Risk + supply	0.0009	0.0000	9e-04	0.0082	0.0003	0.0022	0.0620	0.0015	0.0070	0.0998	0.0028	0.0098	–	0.0114	0.0169
Risk + demand	0.0004	0.0000	0.0015	0.0039	0.0004	0.0035	0.0432	0.0019	0.0107	0.0742	0.0038	0.0149	–	0.0141	0.0245
Supply + demand	0.0025	0.0039	0.0281	0.0047	0.0083	0.034	0.0197	0.0211	0.0507	0.0358	0.0277	0.059	0.0456	0.0359	0.0685
Risk + supply + demand	0.0002	0.0000	0.0009	0.0018	3e-04	0.0022	0.0204	0.0014	0.0066	0.0391	0.0025	0.0092	0.0904	0.0080	0.0147

Panel B: Realized bad volatility

Forecast horizon	$h=1$	$h=5$	$h=22$	$h=1$	$h=5$	$h=22$	$h=1$	$h=5$	$h=22$	$h=1$	$h=5$	$h=22$	$h=1$	$h=5$	$h=22$
Training period	250	250	250	500	500	500	1000	1000	1000	1500	1500	1500	2000	2000	2000
Supply	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
Demand	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
Risk	–	0.0772	–	–	–	–	–	–	–	–	–	–	–	–	–
Risk + supply	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
Risk + demand	–	0.0979	–	–	–	–	–	–	–	–	–	–	–	–	–
Supply + demand	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
Risk + supply + demand	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–

Panel C: Realized good volatility

Forecast horizon	$h=1$	$h=5$	$h=22$	$h=1$	$h=5$	$h=22$	$h=1$	$h=5$	$h=22$	$h=1$	$h=5$	$h=22$	$h=1$	$h=5$	$h=22$
Training period	250	250	250	500	500	500	1000	1000	1000	1500	1500	1500	2000	2000	2000
Supply	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
Demand	0.0000	0.0000	0.0007	0.0000	0.0002	0.0017	0.0004	0.0032	0.0066	0.0014	0.007	0.0105	0.0033	0.0157	0.0153
Risk	0.0000	0.0000	0.0000	0.0004	0.0000	0.0000	0.0118	0.0005	0.0003	0.0165	0.0009	0.0006	0.0329	0.0046	0.0016
Risk + supply	0.0000	0.0000	0.0000	0.0002	0.0000	0.0000	0.0072	0.0002	0.0002	0.0102	0.0004	0.0004	0.0210	0.0021	0.0011
Risk + demand	0.0000	0.0000	0.0000	0.0001	0.0000	0.0000	0.0044	0.0001	0.0002	0.0070	0.0003	0.0005	0.0153	0.0020	0.0014
Supply + demand	0.0000	0.0001	0.0007	0.0001	0.0006	0.0015	0.0014	0.0047	0.0056	0.0033	0.0082	0.0089	0.0058	0.0149	0.0137
Risk + supply +demand	0.0000	0.0000	0.0000	0.0001	0.0000	0.0000	0.0022	0.0001	0.0001	0.0036	0.0002	0.0003	0.0080	0.0010	0.0008

Note: This table reports results (p-values) of the Clark-West test for an equal mean-squared prediction error (MSPE) for alternative forecast horizons and alternative training periods. The training periods are used to initialize estimation. Forecasts are computed using a recursive estimation window. The HAR-RV model without shocks is the benchmark model, and the HAR-RV extended to include the shock or the combination of shocks shown in the left column is the rival model. The alternative hypothesis is that the rival model has a smaller MSPE than the benchmark model. For better readability of the estimation results, the table only summarizes those p-values that are smaller than or equal to a marginal significance level of 10%. The p-values are based on robust standard errors.

Table 6: Out-of-Sample Tests for Realized Variance (Shorter Sample Period)

Panel A: Realized variance

Forecast horizon	$h=1$	$h=5$	$h=22$	$h=1$	$h=5$	$h=22$	$h=1$	$h=5$	$h=22$	$h=1$	$h=5$	$h=22$	$h=1$	$h=5$	$h=22$
Training period	250	250	250	500	500	500	1000	1000	1000	1500	1500	1500	2000	2000	2000
Supply	–	–	–	–	0.0646	–	–	–	–	–	–	–	0.0890	–	–
Demand	0.0023	0.0102	0.0148	0.0123	0.0630	0.0221	–	0.0404	–	–	–	–	–	–	–
Risk	0.0015	0.0018	0.0003	0.0245	0.0300	0.0040	0.0239	0.0003	0.0003	0.0322	0.0017	0.0049	0.0741	0.0169	0.0403
Risk + supply	0.0012	0.0017	0.0004	0.0224	0.0304	0.0041	0.0180	0.0003	0.0003	0.0256	0.0017	0.0050	0.0598	0.0174	0.0354
Risk + demand	0.0011	0.0014	0.0003	0.0194	0.0241	0.0031	0.0211	0.0002	0.0012	0.0351	0.0014	0.0116	0.0689	0.0159	0.0794
Supply + demand	0.0007	0.0092	0.0175	0.0054	0.0626	0.0235	–	0.0456	–	–	–	–	–	–	–
Risk + supply + demand	0.0008	0.0014	0.0003	0.0162	0.0236	0.0031	0.0143	0.0002	0.0012	0.0261	0.0015	0.0117	0.0493	0.0166	0.0667

Panel B: Realized bad variance

Forecast horizon	$h=1$	$h=5$	$h=22$	$h=1$	$h=5$	$h=22$	$h=1$	$h=5$	$h=22$	$h=1$	$h=5$	$h=22$	$h=1$	$h=5$	$h=22$
Training period	250	250	250	500	500	500	1000	1000	1000	1500	1500	1500	2000	2000	2000
Supply	–	0.0872	–	–	0.0463	–	–	–	–	–	–	–	–	–	–
Demand	–	–	–	–	–	–	–	–	–	–	–	–	0.0731	–	–
Risk	–	0.0289	0.0230	–	–	0.0551	–	0.0056	0.0135	–	0.0111	0.0380	–	0.0376	0.0871
Risk + supply	–	0.0299	0.0271	–	–	0.0606	–	0.0053	0.0127	–	0.0106	0.035	–	0.0367	0.0729
Risk + demand	–	0.0405	0.0238	–	–	0.0550	–	0.0055	0.0243	–	0.0110	0.0584	–	0.0376	–
Supply + demand	–	–	–	–	0.0811	–	–	–	–	–	–	–	0.0712	–	–
Risk + supply + demand	–	0.0419	0.0276	–	–	0.0592	–	0.0052	0.0240	–	0.0104	0.0557	–	0.0369	–

Panel C: Realized good variance

Forecast horizon	$h=1$	$h=5$	$h=22$	$h=1$	$h=5$	$h=22$	$h=1$	$h=5$	$h=22$	$h=1$	$h=5$	$h=22$	$h=1$	$h=5$	$h=22$
Training period	250	250	250	500	500	500	1000	1000	1000	1500	1500	1500	2000	2000	2000
Supply	–	0.0186	–	–	0.0272	–	–	–	–	–	0.0651	–	–	–	–
Demand	0.0000	0.0010	0.0001	0.0000	0.0083	0.0003	0.0025	0.0000	0.006	0.0873	0.0011	0.0476	–	0.0152	–
Risk	0.0002	0.0001	0.0000	0.0064	0.0054	0.0001	0.0000	0.0000	0.0000	0.0001	0.0001	0.0000	0.0055	0.0025	0.0061
Risk + supply	0.0002	0.0001	0.0000	0.0064	0.0051	0.0001	0.0000	0.0000	0.0000	0.0001	0.0001	0.0000	0.0050	0.0026	0.0054
Risk + demand	0.0002	0.0000	0.0000	0.0037	0.0009	0.0000	0.0000	0.0000	0.0000	0.0001	0.0000	0.0001	0.0037	0.0021	0.0191
Supply + demand	0.0000	0.0008	0.0001	0.0000	0.0078	0.0003	0.0019	0.0000	0.0065	0.0765	0.0012	0.0465	–	0.0178	–
Risk + supply + demand	0.0001	0.0000	0.0000	0.0035	0.0012	0.0000	0.0000	0.0000	0.0000	0.0001	0.0000	0.0001	0.0031	0.0024	0.0177

Note: This table reports results (p-values) of the Clark-West test for an equal mean-squared prediction error (MSPE) for alternative forecast horizons and alternative training periods. The training periods are used to initialize estimation. Forecasts are computed using a recursive estimation window. The HAR-RV model without shocks is the benchmark model, and the HAR-RV extended to include the shock or the combination of shocks shown in the left column is the rival model. The alternative hypothesis is that the rival model has a smaller MSPE than the benchmark model. For better readability of the estimation results, the table only summarizes those p-values that are smaller than or equal to a marginal significance level of 10%. The p-values are based on robust standard errors. In order to obtain the results for the shorter sample period, 100 daily observations at the end of the sample period werde deleted.

Table 7: Out-of-Sample Tests When an Extended Model is the Benchmark

Panel A: Realized variance

Forecast horizon Training period	$h=1$ 250	$h=5$ 250	$h=22$ 250	$h=1$ 500	$h=5$ 500	$h=22$ 500	$h=1$ 1000	$h=5$ 1000	$h=22$ 1000	$h=1$ 1500	$h=5$ 1500	$h=22$ 1500	$h=1$ 2000	$h=5$ 2000	$h=22$ 2000
Supply	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
Demand	–	0.0596	–	–	0.0803	–	–	–	–	–	–	–	–	–	–
Risk	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
Risk + supply	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
Risk + demand	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
Supply + demand	–	0.0619	–	–	0.0738	–	–	0.0884	–	–	0.0878	–	–	0.0864	–
Risk + supply + demand	–	0.085	0.0871	–	–	0.0986	–	–	0.0999	–	–	–	–	–	–

Panel B: Realized good variance

Forecast horizon Training period	$h=1$ 250	$h=5$ 250	$h=22$ 250	$h=1$ 500	$h=5$ 500	$h=22$ 500	$h=1$ 1000	$h=5$ 1000	$h=22$ 1000	$h=1$ 1500	$h=5$ 1500	$h=22$ 1500	$h=1$ 2000	$h=5$ 2000	$h=22$ 2000
Supply	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
Demand	0.0713	0.0652	0.0733	0.0626	0.0911	0.0882	0.0367	–	0.0872	0.0457	–	0.0913	0.0443	–	0.0957
Risk	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
Risk + supply	–	–	0.0998	–	–	0.0947	–	–	0.0892	–	–	0.094	–	–	0.0954
Risk + demand	–	–	0.0932	–	–	0.0953	–	–	0.0891	–	–	0.0974	–	–	–
Supply + demand	0.063	0.068	0.0781	0.0607	0.0763	0.0837	0.0519	0.0823	0.083	0.0551	0.0847	0.0845	0.0548	0.0859	0.0848
Risk + supply + demand	0.0601	0.0802	0.0545	0.0718	–	0.0548	0.0665	–	0.0521	0.0745	–	0.0551	0.0704	–	0.0559

Panel C: Realized volatility

Forecast horizon Training period	$h=1$ 250	$h=5$ 250	$h=22$ 250	$h=1$ 500	$h=5$ 500	$h=22$ 500	$h=1$ 1000	$h=5$ 1000	$h=22$ 1000	$h=1$ 1500	$h=5$ 1500	$h=22$ 1500	$h=1$ 2000	$h=5$ 2000	$h=22$ 2000
Supply	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
Demand	0.0458	0.0224	–	0.0541	0.037	–	0.0975	0.0605	–	–	0.0761	–	–	0.085	–
Risk	–	0.0743	0.0975	–	–	–	–	–	–	–	–	–	–	–	–
Risk + supply	–	0.0513	0.0717	–	–	0.0832	–	–	–	–	–	–	–	–	–
Risk + demand	–	0.0265	0.0708	–	0.0615	0.086	–	0.0713	–	–	0.0943	–	–	–	–
Supply + demand	0.0463	0.0366	–	0.0545	0.0491	–	0.0738	0.0677	–	–	0.078	–	–	0.0837	–
Risk + supply + demand	0.0532	0.0172	0.0426	–	0.0370	0.0508	–	0.0418	0.0611	–	0.0533	0.0675	–	0.0961	0.0814

Panel D: Realized good volatility

Forecast horizon Training period	$h=1$ 250	$h=5$ 250	$h=22$ 250	$h=1$ 500	$h=5$ 500	$h=22$ 500	$h=1$ 1000	$h=5$ 1000	$h=22$ 1000	$h=1$ 1500	$h=5$ 1500	$h=22$ 1500	$h=1$ 2000	$h=5$ 2000	$h=22$ 2000
Supply	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
Demand	0.0293	0.0102	0.0413	0.0168	0.0166	0.0538	0.0088	0.0280	0.0537	0.0291	0.0490	0.0668	0.0291	0.0751	0.0731
Risk	0.0157	0.0234	0.0447	0.0500	0.0530	0.0532	–	–	0.0739	–	–	0.0895	–	–	–
Risk + supply	0.0147	0.0194	0.0251	0.0322	0.0357	0.0290	0.0687	0.0575	0.0407	–	0.0764	0.0496	–	–	0.0697
Risk + demand	0.0024	0.0030	0.0194	0.0075	0.0078	0.0253	0.0296	0.0189	0.0330	0.0887	0.0428	0.0436	–	–	0.0603
Supply + demand	0.0684	0.0313	0.0365	0.0623	0.0375	0.0440	0.0549	0.0462	0.0453	0.0684	0.0571	0.0522	0.0692	0.0681	0.0577
Risk + supply + demand	0.0086	0.0072	0.0107	0.0155	0.0134	0.0134	0.0291	0.0227	0.0177	0.0504	0.0346	0.0228	0.0606	0.0686	0.0310

Note: This table reports results (p-values) of the Clark-West test for an equal mean-squared prediction error (MSPE) for alternative forecast horizons and alternative training periods. The training periods are used to initialize estimation. Forecasts are computed using a recursive estimation window. The HAR-RV model without shocks is the benchmark model, and the HAR-RV extended to include realized kurtosis, realized skewness, realized jumps, a leverage term (for negative returns), and the shock or the combination of shocks shown in the left column is the rival model. The alternative hypothesis is that the rival model has a smaller MSPE than the benchmark model. For better readability of the estimation results, the table only summarizes those p-values that are smaller than or equal to a marginal significance level of 10%. The p-values are based on robust standard errors.

Table 8: Out-of-Sample Tests for the Subindices

Panel A: Realized volatility

Forecast horizon	$h=1$	$h=5$	$h=22$	$h=1$	$h=5$	$h=22$	$h=1$	$h=5$	$h=22$	$h=1$	$h=5$	$h=22$	$h=1$	$h=5$	$h=22$
Training period	250	250	250	500	500	500	1000	1000	1000	1500	1500	1500	2000	2000	2000
FNAPT	–	0.0156	0.0285	–	0.0294	0.0368	–	0.0485	0.0567	–	0.0592	0.0634	–	0.094	0.0740
FNCO	0.0587	0.0177	0.0455	–	0.038	0.0539	–	0.0427	0.0636	–	0.0541	0.0694	–	0.0986	0.0837
FNER	0.0546	0.0147	0.0447	–	0.0326	0.0511	–	0.0356	0.0596	–	0.0471	0.0668	–	0.0887	0.0820
FNHEA	0.0969	0.0907	–	–	–	–	–	–	–	–	–	–	–	–	–
FNIND	–	0.0158	0.0783	–	0.0524	–	–	0.0481	0.095	–	0.0589	–	–	0.0882	–
FNMAL	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
FNOFF	–	0.0167	0.0426	–	0.0342	0.0578	–	0.0441	0.0751	–	0.0563	0.0856	–	0.0903	–
FNRES	0.0683	0.0094	0.0224	–	0.0188	0.0285	–	0.0328	0.0458	–	0.0445	0.0533	–	0.0760	0.0638
FNRET	0.0524	0.0779	0.0779	0.0795	0.0890	0.0776	–	0.0978	0.0866	–	–	0.0923	–	–	–
FNSHO	0.0730	0.0458	0.0694	0.0986	0.0657	0.0808	–	0.0734	0.0938	–	0.0806	0.0995	–	–	–

Panel B: Realized bad volatility

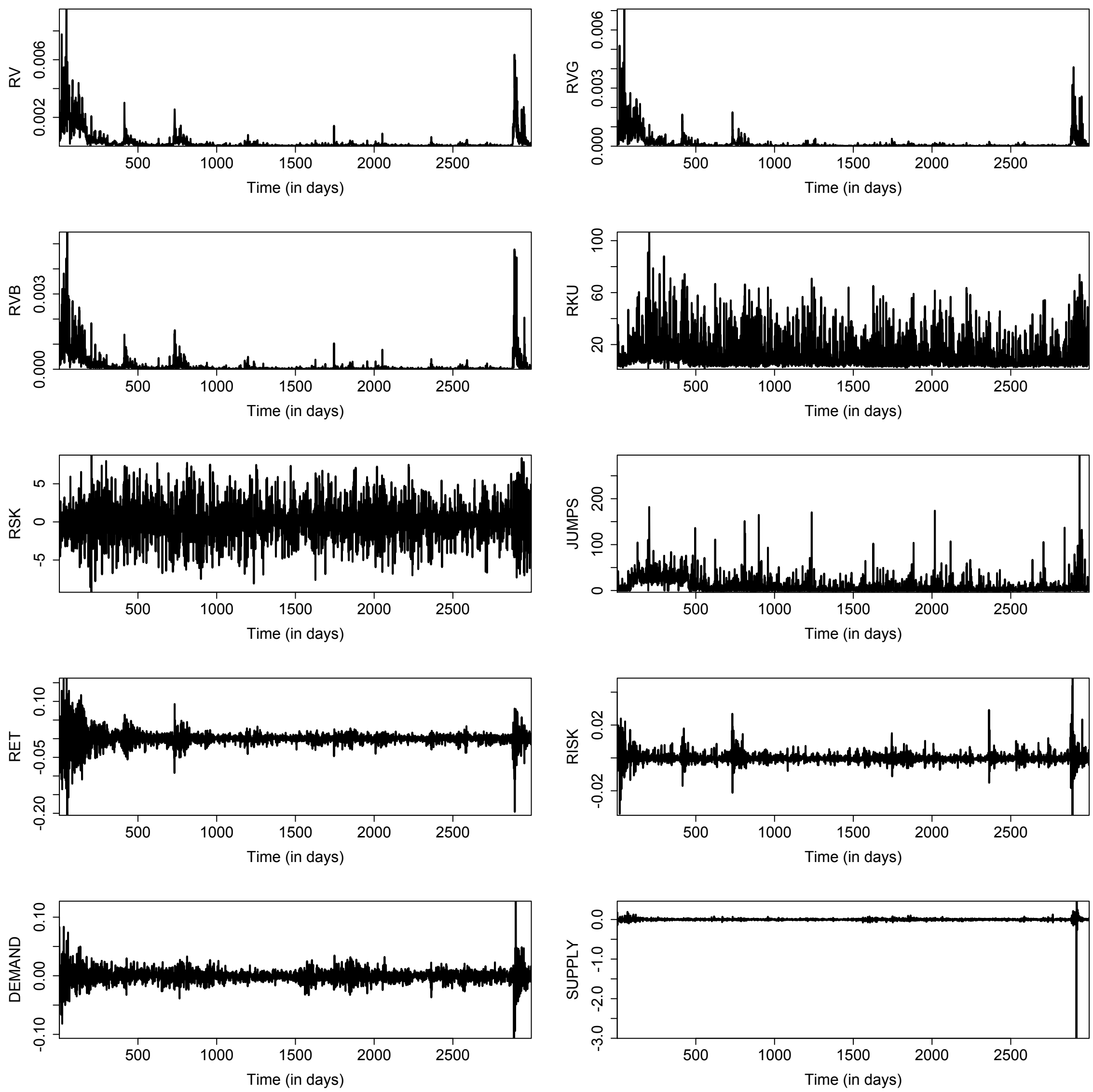
Forecast horizon	$h=1$	$h=5$	$h=22$	$h=1$	$h=5$	$h=22$	$h=1$	$h=5$	$h=22$	$h=1$	$h=5$	$h=22$	$h=1$	$h=5$	$h=22$
Training period	250	250	250	500	500	500	1000	1000	1000	1500	1500	1500	2000	2000	2000
FNAPT	0.0999	–	–	0.0551	–	–	0.0489	–	–	–	–	–	–	–	–
FNCO	0.0908	–	–	0.0437	–	–	0.0754	–	–	–	–	–	–	–	–
FNER	0.0628	–	–	0.0520	–	–	0.0866	–	–	–	–	–	–	–	–
FNHEA	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
FNIND	0.0330	–	–	0.0418	–	–	0.0676	–	–	0.0998	–	–	–	–	–
FNMAL	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
FNOFF	0.0571	–	–	0.0648	–	–	–	–	–	–	–	–	–	–	–
FNRES	–	–	–	0.0364	–	–	0.0496	–	–	–	–	–	–	–	–
FNRET	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
FNSHO	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–

Panel C: Realized good volatility

Forecast horizon	$h=1$	$h=5$	$h=22$	$h=1$	$h=5$	$h=22$	$h=1$	$h=5$	$h=22$	$h=1$	$h=5$	$h=22$	$h=1$	$h=5$	$h=22$
Training period	250	250	250	500	500	500	1000	1000	1000	1500	1500	1500	2000	2000	2000
FNAPT	0.0078	0.0033	0.0063	0.0126	0.0066	0.0081	0.0301	0.0187	0.0159	0.0567	0.0315	0.0222	0.0775	0.0703	0.0306
FNCO	0.0083	0.0071	0.0112	0.0152	0.0133	0.0140	0.0283	0.0225	0.0182	0.0504	0.0343	0.0231	0.0604	0.0687	0.0316
FNER	0.0056	0.0040	0.0106	0.0116	0.0081	0.0123	0.0248	0.0148	0.0157	0.0446	0.0248	0.0208	0.0550	0.0553	0.0290
FNHEA	0.0029	0.0276	0.0354	0.0046	0.0350	0.0319	0.0115	0.0541	0.0394	0.0279	0.0783	0.0500	0.0482	–	0.0718
FNIND	0.0770	0.0033	0.0337	0.0762	0.0120	0.0365	0.0151	0.0068	0.0257	0.0306	0.0132	0.0317	0.0305	0.0253	0.0378
FNMAL	0.0184	0.0632	0.0628	0.0293	0.0669	0.0520	0.0517	0.0798	0.0599	0.0678	0.0882	0.0669	0.0880	–	0.0761
FNOFF	0.0126	0.0082	0.0112	0.0178	0.0141	0.0147	0.0276	0.0244	0.0216	0.0511	0.0387	0.0303	0.0517	0.0648	0.0400
FNRES	0.0071	0.0023	0.0061	0.0113	0.0046	0.0074	0.0283	0.0139	0.0142	0.0620	0.0279	0.0210	0.0856	0.0668	0.0289
FNRET	0.0253	0.0506	0.0437	0.0348	0.0574	0.0422	0.0525	0.0714	0.0503	0.0720	0.0829	0.0589	0.0873	–	0.0748
FNSHO	0.0403	0.0458	0.0534	0.0458	0.0598	0.0621	0.0570	0.0742	0.0756	0.0718	0.0856	0.0881	0.0829	–	–

Note: This table reports results (p-values) of the Clark-West test for an equal mean-squared prediction error (MSPE) for alternative forecast horizons and alternative training periods. The training periods are used to initialize estimation. Forecasts are computed using a recursive estimation window. The HAR-RV model without shocks is the benchmark model, and the HAR-RV extended to include realized kurtosis, realized skewness, realized jumps, a leverage term (for negative returns), and the shock or the combination of shocks shown in the left column is the rival model. The alternative hypothesis is that the rival model has a smaller MSP) than the benchmark model. For better readability of the estimation results, the table only summarizes those p-values that are smaller than or equal to a marginal significance level of 10%. The p-values are based on robust standard errors.

Figure 1: The Data



RV = Realized variance. RVG = Realized good variance. RVB = Realized bad variance. RKU = Realized kurtosis. RSK = Realized skewness. JUMP = Realized jumps. RET = Daily returns. RISK = Financial-market-risk shock. DEMAND = Oil-demand shock. SUPPLY = Oil-supply shock.