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Forecasting International REITs Volatility: The Role of Oil-Price Uncertainty

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Abstract

We forecast realized variance (RV) of Real Estate Investment Trusts (REITs) for ten leading markets and regions, derived from 5-minutes-interval intraday data, based on the information content of two alternative metrics of daily oil-price uncertainty. Based on the period of the analysis covering January 2008 to July 2020, and using variants of the popular MIDAS-RV model, augmented to include oil market uncertainties, captured by its RV (also derived from 5-minute intraday data) and implied volatility (i.e., the oil VIX), we report evidence of significant statistical and economic gains in the forecasting performance. The result is robust to the size of the forecasting samples, including that of the COVID-19 period, jump risks, lag-length, nonlinearities, and asymmetric effects, and forecast horizon. Our results have important implications for investors and policymakers.

JEL Classifications: C22, C53, G15, Q02.

Keywords: REITs; International data; Realized volatility; Oil-Price Uncertainty, Forecasting

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1. Introduction

Real Estate Investment Trusts (REITs), associated with asset allocation, risk reduction, and diversification, have grown substantially during the last decade as an investment vehicle. According to recent figures, the total market capitalization stands at over US $1.9 trillion involving 40 countries, with the United States (US) as the leader among the REITs markets, given a market capitalization of US of over $1.15 trillion (European Public Real Estate Association (EPRA), 2020).[1] The success in attracting such a large scale of investment capital is mainly because REITs are accessible to all investors irrespective of portfolio size (Akinsomi et al., 2016). Naturally, accurate forecasting of REITs volatility is an important issue for investors, given that volatility, as a measure of risk, plays a critical role in portfolio diversification, derivatives pricing, hedging and financial risk management. Furthermore, REITs returns do not suffer from measurement error and high transaction costs compared to other real estate investments and provide a perfect high-frequency proxy for the overall real estate market, since REITs earn most of their income from investments in real estate being exchange-traded funds, and also because trading occurs as common stocks (Marfatia et al., 2017). Given these properties, and the fact that the Global Financial Crisis (GFC) had its roots in the collapse and the resulting uncertainty in the global real estate sector, forecastability of volatility of a relatively homogenous REITs sector, which is possible at a high-frequency unlike the heterogeneous housing market, is an important issue for policymakers too in allowing them to design appropriate policies to circumvent the potential negative impact of uncertainty in the REITs sector on the real economy (Marfatia et al., 2021).

Given the current emphasis[2] that intraday data leads to more precise estimates and

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[1] See: https://prodapp.epra.com/media/EPRA_Total_Markets_Table_-_Q4-2020_1611762538108.pdf for more details.

[2] 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 (2008), Bredin et al. (2007), Lee and Pai (2010), Zhou and Kang (2011), and Pavlova et al. (2014)).

forecasts for the volatility of the REITs returns (see, for example, Zhou (2017), Odusami (2021a, 2021b), Bonato et al. (2021a, b, forthcoming)), we contribute to this burgeoning line of research by predicting the realized variance (RV) of the US and other developed and developing REITs markets, where we estimate RV by using 5-minute-interval intraday data for the period from January 2008 to July 2020, based on a modified version of the mixed data sampling (MIDAS)-RV model, following the recent contributions to the high-frequency data literature by Ma et al. (2019, 2020, 2021), Wang et al. (2020) and Liang et al. (2021). More specifically, we extend the basic MIDAS-RV model to incorporate information on daily oil-price volatility, also captured by its RV (derived from 5-minute intraday data as well) or its implied volatility (IV), and examine the forecasting power of these metrics capturing oil market uncertainty (Wang et al., 2018; Liang et al., 2020; Wang et al., 2020) in extensive out-of-sample testing procedures. Given that the ultimate test of any predictive model, in terms of the econometric methodologies and predictors employed, is its out-of-sample performance (Campbell, 2008), we focus on the predictive analysis from an out-of-sample perspective.

Note that measuring the volatility of both REITs and oil markets using RV, which in our case is captured by the sum of squared intraday returns over a day (Andersen and Bollerslev, 1998), provides an observable and unconditional metric of volatility, which is otherwise a latent process. Conventionally, the time-varying volatility is modeled, and the fit assessed using various GARCH models (as has been primarily done thus far for REITs), under which the conditional variance is a deterministic function of model parameters and past data. Alternatively, modeling of asset price variance has also considered stochastic volatility (SV) models, where the volatility is a latent variable that follows a stochastic process (see Chan and Grant (2016) for a detailed review related to the oil market in this regard). Irrespective of whether we use GARCH or SV models, the underlying estimate of volatility is not model-free as in the case of RV. At the same time, the benchmark MIDAS-RV model can capture well-established long-memory and multi-scaling properties (Bollerslev et al., 2018) of the volatility of financial assets (REITs), despite having a simplistic structure. In this regard, the key feature of the MIDAS-RV model is that it uses volatilities from different time resolutions to forecast the realized REITs-price volatility. The model, thereby, captures the main idea motivating the heterogeneous market hypothesis (HMH), which states that different classes of market participants populate asset (REITs) markets and differ in their sensitivity to information flows at different time horizons. For example, speculators are very sensitive to short-term investment horizons, whereas investors are more concerned with long-term investment horizons.

Our decision to introduce metrics of oil volatility into the MIDAS-RV model of REITs emanates from two recent studies by Nazlioglu et al. (2016, 2020). Nazlioglu et al. (2016) examined the role of oil price and volatility on the first and second-moments of six REITs categories of the US: Residential, Hotel, Healthcare, Retail, Mortgage, and Warehouse/Industrial REITs. The results showed bi-directional volatility transmission between the oil market and all the REITs. In the same vein, following the econometric framework of Nazlioglu et al. (2016), Nazlioglu et al. (2020) provided an international dimension by analyzing price and volatility transmissions between nineteen REITs and the oil markets. Their REITs data represented a variety of countries at different stages of their development. Oil prices are primarily found to predict REITs prices in mature REITs markets, but the feedback from REITs to oil prices is weak. From the perspective of volatility, strong evidence of bidirectional transmission in the majority of the markets is observed. In sum, these studies showed significant impact of oil price and volatility on the corresponding first- and second-moments of US and international REITs (and also indicated of possible feedbacks).

Theoretically, the effect of oil-price volatility on the second-moments of REITs can be explained based on the seminal work of Schwert's (1989) discounted cash flow model, where the price of an asset is the sum of the discounted expected cash flows. Given this, the volatility of the price of an asset depends on the volatility (or dispersion) of expectations about future cash flows and discount rates. Therefore, time variation in asset market volatility is linked to the time varying degree of uncertainty regarding future discount factors and expected cash flows. Since both interest rates and expected cash flows depend on the state (health) of the economy, then it is plausible that a change in the level of uncertainty about future macroeconomic conditions would cause a proportional change in the asset (REITs) returns volatility, as outlined in Schwert (1989). According to this, if some macroeconomic series could provide information regarding the dispersion of expectations (or uncertainty) about future cash flows or discount rates, then these series could be determinants of the time variation in REITs market volatility. Now since, rising oil-price uncertainty, capturing volatility, results in growing uncertainty about discount factors via increasing uncertainty about real interest rates and expected inflation, and future cash flows, consequently, the second-moment of oil price is expected to predict rising volatility in the REITs market.

To the best of our knowledge, our study is the first attempt to forecast the RV of international REITs returns based on oil RV or its implied volatility. At this juncture, we must point out that there are some studies involving US REITs intraday data that relies on comparing the predictive performance of the popular Heterogeneous Autoregressive (HAR)-RV model, introduced by Corsi (2009), with squared returns or various forms of GARCH models (Zhou, 2017), or carrying out in-sample analyses based on macroeconomic and financial predictors (Odusami, 2021a). Our paper is more in line with the recent works of Bonato et al., (2021a, b, forthcoming), and Odusami (2021b), which involve augmented HAR-RV models. Bonato et al., (2021a), examined the forecasting power of a daily newspaper-based index of uncertainty associated with infectious diseases (EMVID) for RV of US REITs via the HAR-RV model. The authors showed that the EMVID index improves the forecast accuracy of RV of REITs at short-, medium-, and long-run horizons in a statistically significant manner, with the result being robust to the inclusion of additional controls (leverage, realized jumps, skewness, and kurtosis) capturing extreme market movements, and also carries over to 10 sub-sectors of the US REITs market. While Bonato et al. (2021b), used an international dataset on intraday data covering nine leading markets and regions of REITs to study out-of-sample predictive value of realized skewness and realized kurtosis for RV over and above realized jumps. They found that realized skewness and realized kurtosis significantly improve forecasting performance at a daily, weekly, and monthly forecast horizon and that their contribution to forecasting performance outweighs in terms of significance the contribution of realized jumps. In this regard, we must discuss the work of Odusami (2021b), which highlighted the vital role of jump risk in forecasting accuracies of RVs of the index- and firm-level US REITs data in terms of generating one-step ahead daily Value-at-Risk (VaR).

Finally, more related to our current work on the oil market-REITs nexus, Bonato et al. (forthcoming) examined, using aggregate and sectoral US REITs data, the predictive power of disentangled oil-price shocks for RV. Out-of-sample tests showed the significant predictive value of demand and financial-market-risk shocks for RV at short-, medium-, and long-forecast-horizons. The results carried over for a shorter sub-sample period that excluded the recent phase of exceptionally intense oil-market turbulence due to the outbreak of the COVID-19 pandemic, and for an extended benchmark model that featured realized higher-order moments (i.e., realized skewness and realized kurtosis), realized jumps, and a leverage effect as control variables.

Our paper, thus adds to the few existing studies associated with the forecasting of REITs RV based on extended HAR-RV models, primarily involving the US, by incorporating the role of oil market uncertainty in predicting the future path of the volatility of international REITs market, derived from intraday data as well, i.e., our work provides an international dimension while analyzing the effect of alternative proxies of oil market volatilities. From an econometric perspective, instead of relying on the HAR-RV model as has been done thus far in the literature, we employ the MIDAS-RV framework in our forecasting exercise. Note that the HAR-RV model evolved from the MIDAS-RV model and is a special form of the latter, i.e., the MIDAS-version is the more general in the class of RV models (Bollerslev et al., 2018). Given this, the MIDAS-RV tends to better capture the HMH than the HAR-RV, resulting in it exhibiting superior forecasting performance in practical applications (Ghysels and Sohn, 2009; Santos and Ziegelmann, 2014; Ma et al., 2019). Furthermore, our paper, while providing both statistical and economic evaluation of the role of oil market uncertainties for forecasting RV of the international REITs, account for market conditions, jump risks (importance of which has been highlighted in the literature discussed above and in particular by Odusami (2021b)), and nonlinearities (depicted by Nazlioglu et al. (2016, 2020)) via asymmetric effects of the measures of oil market volatility, as well as regime-switching in extended variants of the MIDAS-RV model.

The remainder of the paper is organized as follows: Section 2 outlines the methodologies, while Section 3 presents the data. Section 4 is devoted to our various econometric results, with a wide-array of robustness checks involving model specifications, forecast horizons, and data samples, including an analysis associated with the outbreak of the COVID-19 pandemic. Section 5 concludes the paper.

2. Methodologies

2.1 Realized measure of volatility

The superior ex post variance, realized variance (RV), is commonly used as proxy for risk in financial markets such as stock market, crude oil futures market and among others due to it contains less noise and is easy to implement (Andersen and Bollerslev, 1998). For a specific day t, this ex post measure of variance is given by:

$$\mathrm{RV}_t = \sum_{j=1}^{M} r_{t,j}^2, \quad (1)$$

where $M = 1/\Delta$, and Δ is the sampling rate; $r_{t,j}$ represents the j^{th} intraday return of day t. According to the arguments of Andersen et al. (2007), the distribution of RV generated from Equation (1) is leptokurtic. To this end, we employ the natural logarithm of RV in the forecasting process, the distribution of which is approximately Gaussian.

2.2 Predictive regressions

We implement the mixed data sampling (MIDAS) regression to generate the one-day-ahead forecast. The superior performance of MIDAS framework has been recorded in growing number of studies associated with volatility forecasting (Bollerslev et al., 2018; Ma et al., 2019, 2020, 2021; Wang et al., 2020; Liang et al., 2021). The standard benchmark model to predict international REITs volatility, i.e., realized variance, at the horizon of a trading day is the following MIDAS-RV model:

Model 1: MIDAS-RV[3]

$$\mathrm{RV}_{t,t+1} = \beta_0 + \beta_{\mathrm{RV}} \sum_{k=1}^{k^{max}} \omega_k \mathrm{RV}_{t-k-1,t-k} + \varepsilon_{t,t+1}, \tag{2}$$

where $\mathrm{RV}_{t-k,t-k-1}$ represents the lags of RV and subscripts $t-k-1$ to $t-k$ denote the time horizon (or frequency) that we used to generate $\mathrm{RV}_{t-k,t-k-1}$. We set the $k^{max} = 40$ and ω_k denotes the respective weights for different frequency components. Along the lines of Ghysels et al. (2006, 2007), the weight function is measured by following beta function:

$$b\left(k, \theta_1^{\mathrm{RV}}, \theta_2^{\mathrm{RV}}\right) = f\left(\frac{k}{k^{max}}, \theta_1, \theta_2\right) / \sum_{i=1}^{k^{max}} \mathrm{f}\left(\frac{k}{k^{max}}, \theta_1, \theta_2\right), \tag{3}$$

where $f(x,y,z) = x^{y-1}(1-x)^{z-1}/\beta(y,z)$ and $\beta(y,z)$ is evaluated by $\beta(y,z) = \Gamma(y)\Gamma(z)/\Gamma(y+z)$.

The goal of our study is to examine the role of crude oil volatility in forecasting international REITs volatility, hence, we extend the benchmark MIDAS-RV by incorporating RV of oil (ORV) or implied volatility of oil (OIV) as a predictor, to give us the following augmented-MIDAS-RVs:

Model 2: MIDAS-RV-ORV

$$\mathrm{RV}_{t,t+1} = \beta_0 + \beta_{\mathrm{RV}} \sum_{k=1}^{k^{max}} \omega_k \mathrm{RV}_{t-k-1,t-k} + \beta_{\mathrm{ORV}} \sum_{k=1}^{k^{max}} \omega_k \mathrm{ORV}_{t-k-1,t-k} + \varepsilon_{t,t+1}. \tag{4}$$

Model 3: MIDAS-RV-OIV

$$\mathrm{RV}_{t,t+1} = \beta_0 + \beta_{\mathrm{RV}} \sum_{k=1}^{k^{max}} \omega_k \mathrm{RV}_{t-k-1,t-k} + \beta_{\mathrm{OIV}} \sum_{k=1}^{k^{max}} \omega_k \mathrm{OIV}_{t-k-1,t-k} + \varepsilon_{t,t+1}. \tag{5}$$

2.3 Forecast evaluation

Along the lines of Welch and Goyal (2008), Rapach et al., (2010) and Wang et al., (2018), we employ the out-of-sample R^2 test to assess the forecasting quality, which basically evaluates the percent reduction of mean squared predictive error (MSPE) of the extended model ($\mathrm{MSPE}_{\mathrm{model}}$) relative to the MSPE of benchmark ($\mathrm{MSPE}_{\mathrm{bench}}$).

[3] The MIDAS approach comprises of two modeling issues simultaneously. The first is the specification of "smooth" distributed lag polynomials for representing the dynamic dependencies. While the second deals with the use of data sampled at different frequencies, and the choice of sampling-frequency for the predictor variables. In this study, we mainly focus on the first aspect of the MIDAS approach. The reader is referred to Section 3.5 of Bollerslev et al. (2018) for further details on these issues.

The R_{OOS}^2 is defined as,

$$R_{oos}^2 = 1 - \frac{\text{MSPE}_{\text{model}}}{\text{MSPE}_{\text{bench}}}\ , \tag{6}$$

where $\text{MSPE}_i = \frac{1}{T-M}\sum_{t=M+1}^{T}(\text{RV}_t - \widehat{\text{RV}}_{t,i})^2$ ($i = \text{model}, \text{bench}$), T and M are the lengths of the full-sample and the estimation window period. Furthermore, for assessing whether heterogeneous predictive performance exists across different models, we consider the MSPE-adjusted statistic of Clark and West (2007). Intuitively, a competing model is superior to the benchmark if the R_{OOS}^2 value is positive owing to the lower MSPE from the competing model.

Besides statistical evaluation, economic gain from the predictor is of vital important to investors. Therefore, we also look at economic value analysis, which allows us to compare the economic gains from each predictive regression. A mean-variance method is used to compare the difference of economic value obtained from all models that we consider, whereby the investor allocates her/his wealth to REITs or a risk-free asset. According to Bollerslev et al. (2018), expected utility obtained by averaging the corresponding realized expressions over the out-of-sample forecasts of RV can be written as follows[4]:

$$\overline{U}\left(\widehat{\text{RV}}_{t+1}\right) = \frac{1}{q}\sum_{t=m+1}^{m+q-1}\frac{\text{SR}^2}{\gamma}\left(\frac{\sqrt{\text{RV}_{t+1}}}{\sqrt{\widehat{\text{RV}}_{t+1}}} - \frac{1}{2}\frac{\text{RV}_{t+1}}{\widehat{\text{RV}}_{t+1}}\right), \tag{7}$$

where γ and SR are risk aversion coefficient and the Sharpe ratio. Along the lines of Bollerslev et al. (2018) and Liang et al. (2020), we set the annualized Sharpe ratio SR equal to 0.40, and the coefficient of relative risk aversion as $\gamma = 2$.

3. Data description

3.1 REITs data

We use 5-minute-interval intraday data on the REITs indexes over a 24 hour trading day to construct daily measure of RV, outlined in equation (1). Besides the FTSE Nareit All REITs (FNAR) Index for the US, which is the most prominent REITs market, we also investigate the role of oil uncertainty (the data for which we discuss below) on the REITs markets covering other developed and developing countries and regions (for

[4] More technical details about this economic analysis can be found in Bollerslev et al. (2018).

which intraday data is available) namely, the FTSE Nareit Developed Asia (EGAS) Index, FTSE Nareit North America Asia (EGNA) Index, FTSE Nareit Australia (ELAU) Index, FTSE Nareit Hong Kong (ELHK) Index, FTSE Nareit Japan (ELJP) Index, FTSE Nareit UK (ELUK) Index, FTSE Nareit Developed Markets (ENGL) Index, FTSE Nareit Eurozone (EPEU) Index, FTSE Nareit Emerging Markets (FENEI) Index. The price data for all these indexes, in a continuous format, are obtained from Bloomberg terminal.

3.2 Oil data

Our oil-based dataset consists of realized variance of crude oil futures (ORV) and implied volatility of crude oil futures (OIV). For ORV, the 5-minute intraday data of the front-month West Texas Intermediate (WTI) oil futures is derived from the NYMEX-CME. Such data frequency as a rule of thumb can offer a balance between market microstructure noise and predictive improvement (Liu et al., 2015). And, we also use the measure of implied volatility of crude oil futures based on the Crude Oil Volatility index (OVX) of the Chicago Board of Options Exchange (CBOE), as a predictor capturing oil market volatility, in an attempt to ensure robustness of our findings. The OVX is an annualized index that measures the market's expectation of 30-day volatility of crude oil prices. The index is available from the FRED database of the Federal Reserve Bank of St. Louis at: https://fred.stlouisfed.org/series/OVXCLS.

Table 1 reports the descriptive statistics of the series of international REITs volatility, ORV and OIV. Obviously, all the series show significantly right-skewed and leptokurtic. Moreover, the results of Jarque-Bera statistic test demonstrate all the series are non-normally distributed, while they are stationary at the 1% significance level from Augmented Dickey-Fuller (ADF) test.

Insert Table 1 here

4. Empirical results

4.1 Primary results

To generate our volatility forecasts at the horizon of one trading day, we consider the rolling window method. Although our ten international REITs indexes have different start and end dates, we set the first 50% observations as the estimation period and the last 50% observations as the out-of-sample forecasting sample.

Recall that, the primary objective of our study is to use oil-market uncertainties (ORV and OIV) to predict the realized volatility of international REITs indexes. Table 2 presents the out-of-sample R^2 test statistics and economic value analysis. The column named Out-of-sample R^2 test of Table 2 provides the $R^2_{OOS}(\%)$, the MSPE-adjusted statistics and the corresponding p-values of including with ORV or OIV relative to the benchmark (MIDAS-RV model). We first focus on the forecasting performance of ORV. The values of $R^2_{OOS}(\%)$ suggest that the forecasting model with ORV can lead to a reduction of MSPE between 3.447% and 9.799% for volatility forecasts of the 10 international REITs indexes that we consider. The p-values of MSPE-adjust statistic indicate that ORV can significantly improve the forecast accuracy of REITs volatility. Similar results are also obtained with the OIV. Specifically, the MIDAS-RV-OIV model can produce a reduction of MSPE between 0.348% and 9.065% over the forecasting period, with the p-values of the MSPE-adjusted test statistic being significant (except for the ENGL index) as well.

"Portfolio Exercise" column of Table 2 shows the results of the economic value analysis. Obviously, the percent realized utility of extending model with ORV and OIV are higher relative to the benchmark model for all international REITs indices. The results suggest the investors are willing to pay additional fee to access the models with information on ORV or OIV rather than simply using the benchmark (MIDAS-RV) model when dealing with one-day-ahead RV forecasting of the REITs markets. In other words, ORV or OIV can help the investor achieve higher realized utility from an economic point of view.

Insert Table 2 here

Overall, the results based on statistical and economic evaluation, suggests that ORV or OIV can successfully produce statistical and economic gains for the investors including REITs in their portfolios.

4.2 Robustness

4.2.1 Alternative forecasting window

Rossi and Inoue (2012) suggest that the choice of window size plays an important role forecasting results. In light of this, we consider different window sizes, which involves including the last 70% and 60% of observations as out-of-sample period. Table 3 and Table 4 reports the evaluation results associated with the out-of-sample R^2 test, and also the associated economic value analyses. The results provide strong empirical evidence that the extending the MIDAS-RV model with ORV and OIV outperforms the benchmark model, which is consistent with the previous findings with a 50% split, and confirm that our results are robust to forecasting-sample periods.

Insert Table 3 here

Insert Table 4 here

In the context of the size of the out-of-sample periods, we also decided to closely analyze the forecasting ability of the models during the COVID-19 pandemic outbreak, which has resulted in an unprecedented shock to real economic activities, financial market and public lives (Baker et al., 2020). This section investigates the forecasting performance of ORV or OIV during the COVID-19 period, which following the work of Ji et al. (2020), we set to cover from 1 January 2020 to 1 July 2020, during which oil market witnessed heightened variability. Table 5 reports the forecasting performance of ORV and OIV for this period. Several interesting findings emerge. First, the values of R^2_{OOS} provide evidence that ORV and OIV continue to reduce the MSPE for the volatility of the 10 international REITs indexes, in line with our previous findings. Second, we find that oil implied volatility is superior in forecasting international REITs volatility than oil realized volatility for most cases, as the R^2_{OOS} values of the predictive regression model with OIV are greater than those with ORV. One possible reason of this observation is possibly due to the fact that that implied volatility is associated with the future 30-days market expectations.

Insert Table 5 here

4.2.2 Alternative $\boldsymbol{k^{max}}$

Recall that previous sections consider $\boldsymbol{k^{max}} = 40$. In this subsection, we reinvestigate the forecasting ability from oil volatility to REITs volatility by considering different $\boldsymbol{k^{max}}$, as another robustness test. Panels A and Panel B of Table 6 reports the statistical evaluation results by considering $\boldsymbol{k^{max}} = 20$ and $\boldsymbol{k^{max}} = 60$, respectively. Indeed, we find that the ORV or OIV can significantly reduce the MSPEs for forecasting volatility of the REITs considered. The results provide strong evidence that our findings are robust to different $\boldsymbol{k^{max}}$.

Insert Table 6 here

4.2.3 Controlling jump risk

Several studies have indicated the important role of jump risk in affecting volatility of REITs markets, as indicated in the introduction.[5] To further highlight the forecasting ability of oil volatility, we extend the predictive regressions by considering jump components, following Andersen et al. (2007). The benchmark predictive regression with jump risk is defined as:

Model 4: MIDAS-RV-CJ

$$\mathrm{RV}_{t,t+1} = \beta_0 + \beta_{\mathrm{CRV}} \sum_{k=1}^{k^{max}} \omega_k \mathrm{CRV}_{t-k-1,t-k} + \beta_{\mathrm{CJ}} \sum_{k=1}^{k^{max}} \omega_k \mathrm{CJ}_{t-k-1,t-k} + \varepsilon_{t,t+1}, \quad (8)$$

where CRV represents the continuous sample path and CJ denotes the significant jump size[6]. Then we extend Model 4 with ORV or OIV to reinvestigate the role of oil volatility information, over and above jump risks, in forecasting REITs volatility, as

[5] In this regard, Li et al. (2015) showed the existence of jump dynamics in international REITs markets, and He et al. (2020) found the jump risk can transmit from US to Asian REITs markets.

[6] More technical details regarding significant jump size can be found by the work of Andersen et al., (2007).

follows:

Model 5: MIDAS-CJ-ORV

$$\mathrm{RV}_{t,t+1} = \beta_0 + \beta_{\mathrm{CRV}} \sum_{k=1}^{k^{max}} \omega_k \mathrm{CRV}_{t-k-1,t-k} + \beta_{\mathrm{CJ}} \sum_{k=1}^{k^{max}} \omega_k \mathrm{CJ}_{t-k-1,t-k}$$

$$+\beta_{\mathrm{ORV}} \sum_{k=1}^{k^{max}} \omega_k \mathrm{ORV}_{t-k-1,t-k} + \varepsilon_{t,t+1}. \quad (8)$$

Model 6: MIDAS-CJ-OIV

$$\mathrm{RV}_{t,t+1} = \beta_0 + \beta_{\mathrm{CRV}} \sum_{k=1}^{k^{max}} \omega_k \mathrm{CRV}_{t-k-1,t-k} + \beta_{\mathrm{CJ}} \sum_{k=1}^{k^{max}} \omega_k \mathrm{CJ}_{t-k-1,t-k}$$

$$+\beta_{\mathrm{ORV}} \sum_{k=1}^{k^{max}} \omega_k \mathrm{OIV}_{t-k-1,t-k} + \varepsilon_{t,t+1}. \quad (9)$$

Table 7 reports the evaluation results of the forecasting model with jump risk. The value of $R^2_{\mathrm{OOS}}(\%)$ is larger than zero for all international REITs indexes included in our study, with the *p*-values suggesting that the improvement of forecasting accuracy is statistically significant. In other words, our current findings are robust to jump risks.

Insert Table 7 here

4.2.4 The nonlinear oil-REITs volatility relationship

4.2.4.1 Regime-Switching

Given the evidence that the nexus between oil and REITs volatilities are nonlinear (Nazlioglu et al., 2016, 2020), we re-conduct our analysis using the two-stage Markov switching model, as outlined by Ma et al. (2017), Wang et al. (2018) and Wang et al. (2020) as follows:

Model 7: MRS-MIDAS-ORV

$$\mathrm{RV}_{t,t+1} = \beta_0 + \beta_{\mathrm{RV},S_t} \sum_{k=1}^{k^{max}} \omega_k \mathrm{RV}_{t-k-1,t-k}$$

$$+\beta_{\mathrm{ORV},S_t} \sum_{k=1}^{k^{max}} \omega_k \mathrm{ORV}_{t-k-1,t-k} + \varepsilon_{t,t+1}, \quad (10)$$

Model 8: MRS-MIDAS-OIV

$$\mathrm{RV}_{t,t+1} = \beta_0 + \beta_{\mathrm{RV},S_t} \sum_{k=1}^{k^{max}} \omega_k \mathrm{RV}_{t-k-1,t-k}$$

$$+\beta_{\mathrm{OIV},S_t}\sum_{k=1}^{k^{max}}\omega_k \mathrm{OIV}_{t-k-1,t-k}+\varepsilon_{t,t+1}, \tag{11}$$

Note that S_t=0 and S_t=1 indicates the low- and high-volatility regimes, respectively. We compare the forecasting performance of MRS-MIDAS-ORV (MRS-MIDAS-OIV) model with benchmark of MIDAS-ORV (MIDAS-OIV). Table 8 shows the forecasting results from the predictive regressions with and without regime-switching. Clearly, the MRS-MIDAS-ORV can further help to improve the accuracy of volatility forecasting for 8 out of 10 international REITs indexes including EGAS, EGNA, ELAU, ELJP, ELUK, EPEU, FENEI and FNAR. Similarly, the MRS-MIDAS-OIV model can outperform the benchmark for 7 out of 10 international REITs indexes including EGNA, ELAU, ELJP, ELUK, EPEU, FENEI and FNAR. The empirical results provide strong evidence that regime switching can further improve the accuracy of volatility forecasting for most cases of international REITs indexes.

Insert Table 8 here

To delve into this issue further, we divide the volatility forecasts over the out-of-sample period into high- and low-volatility level by median value of actual volatility for each REITs index. Table 9 presents the results of out-of-sample R^2 test during high, i.e., above-median and low, i.e., below-median, volatility levels. We find very strong evidence of forecasting ability from ORV and OIV for REITs volatility during the high-volatility regime, with weaker results under the low-volatility conditions.

Insert Table 9 here

These results suggest that investors in the REITs market are more sensitive to oil market uncertainty when volatility in the REITs sector is already high, i.e., agents are more worried about risk spillovers when the current volatility is in its higher rather than lower state, and hence aim to utilize the information content of oil uncertainty during this phase of the market to gauge whether the future risk is going to increase further or not to possibly assist in their investment decision and portfolio allocation. Similar concerns do not seem to arise at the lower-state of REITs volatility, even though increases in oil-price uncertainty is perceived as bad news, given that the underlying risk in international REITs is low, possibly due to initial low-levels of volatility in the oil market itself. This finding is also important from the perspective of policymakers who closely aim to monitor the volatility in the real estate sector following the GFC. Now policy authorities would know that future volatility in REITs is likely to increase further due to hikes in oil price uncertainty, particularly when the current uncertainty in the real estate market is already high, and in turn would require expansionary monetary policy to diffuse the risks in the market and in turn prevent a deep recession.

4.2.4.2 Asymmetric effect

While the role of oil uncertainty on the forecastability of the REITs market conditional on its state is an important issue, an equally pertinent question for both investors and policymakers is whether there is a role of asymmetry associated with positive or negative oil price movements in the resulting volatility process while forecasting REITs RV? For ORV, we construct "good" and "bad" volatility following the work of Patton and Sheppard (2015) as follows:

$$\text{"Good" ORV} = \sum_{j=1}^{\frac{1}{\Delta}} r_{(t-1)+j*\Delta}^{2} I\left(r_{(t-1)+j*\Delta} > 0\right), \tag{12}$$

$$\text{"Bad" ORV} = \sum_{j=1}^{\frac{1}{\Delta}} r_{(t-1)+j*\Delta}^{2} I\left(r_{(t-1)+j*\Delta} < 0\right), \tag{13}$$

For OIV, we consider an indicator of OIV on positive oil returns day as "Good" OIV ("Good" OIV $= \mathrm{OI}V_t * I(r_t \geq 0)$), and an indicator of OIV on negative returns day as "Bad" OIV ("Bad" OIV $= \mathrm{OIV}_t * I(r_t < 0)$. Then we extend the benchmark model with "Good" ORV, "Bad" ORV, "Good" OIV ot "Bad" OIV to examine the asymmetric effect of oil volatility in forecasting international REITs RV.

Table 10 reports the evaluation results with "good" and "bad" oil volatility. We first look at "good" and "bad" ORV. The value of R_{OOS}^2 is roughly equivalent when we construct regression models with "good" or "bad" ORV. We find no evidence that decomposing the ORV into "good" and "bad" components can further improve the forecasting accuracy. However, the forecasting performance of "Bad" OIV is a bit weaker, as the R_{OOS}^2 of regression model with "Bad" OIV is negative for 4 of the 10 REITs indexes. The R_{OOS}^2 value of "Good" OIV and "Bad" OIV suggests the regression model with "Good" OIV can outperform "Bad" OIV. This provides some evidence in terms of implied volatility, that increases in oil market uncertainty resulting from increases in oil price and/or returns, has a stronger predictive content than when volatility results from oil price and/or returns declines.

Insert Table 10 here

Note that, even though we define oil volatility associated with oil returns hikes as good volatility, considering the issue from the perspective of the oil trader, oil price increases (due to supply, oil-specific-consumption and precautionary demand) are generally viewed as bad news for the overall economy, unless it is due to a growing global economy (Demirer et al., 2020). Given this, oil uncertainty associated with positive oil returns is likely to affect REITs volatility relatively more, via the leverage effect that has been shown to be strongly present in international REITs markets (Tsai, 2013; Kawaguchi et al., 2017), than when increases in oil price volatility occurs due to oil price decreases, i.e., good news.

4.2.5 Forecasting performance at longer horizons

After ensuring that our results are robust to the size of the forecasting window, jump risks, and lag-length, as well as nonlinearities and asymmetric effects, we turn to the fact that investors not only focus on volatility forecasts at a-day-ahead, but also at longer horizons. To further investigate the forecasting performance of ORV or OIV for, we replace the left-hand side of Model 1, 2 and 3 by $\mathrm{RV}_{t+h,t+1}$, and consider the forecasting horizons of 5, 10 and 22 trading days i.e., h = 5, 10 and 22. Table 11 reports the forecasting results of the predictive regression models at longer horizons. We first look at out-of-sample R^2 test, to find that the results suggest both ORV and OIV can improve the accuracy of volatility forecasting for most international REITs index at the forecasting horizons of 5, 10 and 22 days. The results of the economic value analysis are also consistent with our previous findings for one-step-ahead, as they show that oil volatility can offer additional realized utility relative to the regressions without the information on oil uncertainty.

Insert Table 11 here

5. Summary and concluding remarks

Existing in-sample evidence indicate that causal effects from oil market uncertainty onto REITs market volatilities are exceptionally strong. Given that in-sample evidence does not necessarily translate into out-of-sample gains, in this paper we forecast realized variance (RV) of international REITs, derived from 5-minutes-interval intraday data. Based on the period of the analysis covering January, 2008 to July, 2020, and using variants of the popular MIDAS-RV model, augmented to include oil market uncertainty captured by its RV (ORV; derived from 5-minute intraday data) and implied volatility (OIV; obtained from oil VIX), we report evidence of significant statistical and economic gains in the forecasting performance emanating from these two metrics relative to the benchmark that excludes these predictors. The result is robust to the size of the forecasting samples, including that of the COVID-19 period, jump risks, lag-length, nonlinearities and asymmetric effects, and forecast horizon.

Given the tremendous growth of REITs as an asset class globally and, hence, the importance of accurate volatility forecasts as inputs for optimal asset-allocation decisions our findings suggest that incorporating ORV or OIV, in volatility forecasting models can help to improve the design of portfolios that include REITs across various investment horizons and countries, especially when the existing volatility in the REITs markets is high, and the oil uncertainty emanates from oil price increases. Further, with the future path of REITs volatility providing a high-frequency measure of uncertainty in the housing sector for which only low-frequency data is traditionally available, would allow policymakers to design timely responses to circumvent the negative influence on the real economy, given that the real estate sector is known to lead macroeconomic variables (Segnon et al., 2021). More specifically, policymakers need to be aware that oil market uncertainty spillover to the real estate sector particularly strongly at their respective higher ends, and can intensify the deepening of the recession that might have originated from oil uncertainty (Bernanke, 1983).

As part of future research, it would be is interesting to extend our study to sectoral REITs, as different REITs sectors are heterogeneously sensitive to the oil market. Moreover, given the evidence of bi-directional causality in the volatility processes of oil and the REITs markets, an analysis of REITs of which economies and sectors can accurately forecast oil market volatility would also be an important area to delve into, especially given the financialization of the oil market post-2008 (Bonato, 2019).

References

Akinsomi, O., Aye, G. C., Babalos, V., Economou, F., & Gupta, R. (2016). Real estate returns predictability revisited: novel evidence from the US REITs market. Empirical Economics, 51(3), 1165-1190.

Andersen, T. G., & Bollerslev, T. (1998). Answering the skeptics: Yes, standard volatility models do provide accurate forecasts. International economic review, 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. The review of economics and statistics, 89(4), 701-720.

Baker, S. R., Bloom, N., Davis, S. J., Kost, K. J., Sammon, M. C., & Viratyosin, T. (2020). The unprecedented stock market impact of COVID-19. The Review of Asset Pricing Studies, 10(4), 742–758.

Bernanke, B.S. (1983). Irreversibility, uncertainty, and cyclical investment. The Quarterly Journal of Economics, 98 (1), 85–106.

Bollerslev, T., Hood, B., Huss, J., & Pedersen, L. H. (2018). Risk everywhere: Modeling and managing volatility. The Review of Financial Studies, 31(7), 2729-2773.

Bonato, M. (2019). Realized correlations, betas and volatility spillover in the agricultural commodity market: What has changed? Journal of International Financial Markets, Institutions and Money 62, 184−202.

Bonato, M., Çepni, O., Gupta, R., and Pierdzioch, C. (Forthcoming). Do Oil-Price Shocks Predict the Realized Variance of U.S. REITs? Energy Economics.

Bonato, M., Çepni, O., Gupta, R., & Pierdzioch, C. (2021b).. Forecasting Realized Volatility of International REITs: The Role of Realized Skewness and Realized Kurtosis. Journal of Forecasting. DOI: https://doi.org/10.1002/for.2813.

Bonato, M., Çepni, O., Gupta, R., & Pierdzioch, C. (2021a). Uncertainty due to infectious diseases and forecastability of the realized variance of United States real estate investment trusts: A note. International Review of Finance. DOI:

https://doi.org/10.1111/irfi.12357.

Bredin, D., O'Reilly, G., & Stevenson, S. (2007). Monetary shocks and REIT returns. Journal of Real Estate Finance and Economics, 35, 315-331.

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

Chan, J. C., & Grant, A. L. (2016). Modeling energy price dynamics: GARCH versus stochastic volatility. Energy Economics, 54, 182-189.

Clark, T. E., & West, K. D. (2007). Approximately normal tests for equal predictive accuracy in nested models. Journal of econometrics, 138(1), 291-311.

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

Cotter, J., & Stevenson, S. (2008). Modeling long memory in REITs. Real Estate Economics, 36(3), 533-554.

Demirer, R., Gupta, R., Pierdioch, C., & Shahzad, S.J.H. (2020). The predictive power of oil price shocks on realized volatility of oil: A note? Resources Policy, 69, 101856.

Devaney, M. (2001). Time-varying risk premia for real estate investment trusts: a GARCH-M model. Quarterly Review of Economics and Finance, 41, 335-346.

Ghysels, E., Santa-Clara, P., & Valkanov, R. (2006). Predicting volatility: getting the most out of return data sampled at different frequencies. Journal of Econometrics, 131(1-2), 59-95.

Ghysels, E., Sinko, A., & Valkanov, R. (2007). MIDAS regressions: Further results and new directions. Econometric reviews, 26(1), 53-90.

Ghysels, E., & Sohn, B. (2009). Which power variation predicts volatility well?. Journal of Empirical Finance, 16(4), 686-700.

He, C. W., Chang, K. L., & Wang, Y. J. (2020). Does the jump risk in the US market matter for Japan and Hong Kong? An investigation on the REIT market. Finance Research Letters, 34, 101238.

Ji, Q., Zhang, D., & Zhao, Y. (2020). Searching for safe-haven assets during the

COVID-19 pandemic. International Review of Financial Analysis, 71, 101526.

Kawaguchi, Y., Sa-Aadu, J., & Shilling, J.D. (2017). REIT Stock Price Volatility and the Effects of Leverage. Real Estate Economics, 45(2), 452-477.

Lee, Y-H., & Pai, T-Y. (2010). REIT volatility prediction for skew-GED distribution of the GARCH model. Expert Systems with Applications, 37, 4737-4741.

Li, J., Li, G., & Zhou, Y. (2015). Do securitized real estate markets jump? International evidence. Pacific-Basin Finance Journal, 31, 13-35.

Liu, L. Y., Patton, A. J., & Sheppard, K. (2015). Does anything beat 5-minute RV? A comparison of realized measures across multiple asset classes. Journal of Econometrics, 187(1), 293-311.

Liang, C., Liao, Y., Ma, F., & Zhu, B. (2021). United States Oil Fund volatility prediction: the roles of leverage effect and jumps. Empirical Economics, 1-24.

Liang, C., Wei, Y., & Zhang, Y. (2020). Is implied volatility more informative for forecasting realized volatility: An international perspective. Journal of Forecasting, 39(8), 1253-1276.

Ma, F., Wahab, M. I. M., Huang, D., & Xu, W. (2017). Forecasting the realized volatility of the oil futures market: A regime switching approach. Energy Economics, 67, 136-145.

Ma, F., Liang, C., Ma, Y., & Wahab, M. I. M. (2020). Cryptocurrency volatility forecasting: A Markov regime-switching MIDAS approach. Journal of Forecasting, 39(8), 1277-1290.

Ma, F., Liang, C., Zeng, Q., & Li, H. (2021). Jumps and oil futures volatility forecasting: a new insight. Quantitative Finance, 21(5), 853-863.

Ma, F., Liao, Y., Zhang, Y., & Cao, Y. (2019). Harnessing jump component for crude oil volatility forecasting in the presence of extreme shocks. Journal of Empirical Finance, 52, 40-55.

Marfatia, H. A., Gupta, R., & Cakan, E. (2017). The international REIT's time-varying response to the US monetary policy and macroeconomic surprises. The North American Journal of Economics and Finance, 42, 640-653.

Marfatia, H.A., Gupta, R., and Lesame, K. (2021). Dynamic Impact of Unconventional Monetary Policy on International REITs. Journal of Risk and Financial Management 14(9), 429.

Nazlioglu, S., Gupta, R., Gormus, A., & Soytas, U. (2020). Price and volatility linkages between international REITs and oil markets. Energy Economics, 88, 104779.

Nazlioglu, S., Gormus, N. A., & Soytas, U. (2016). Oil prices and real estate investment trusts (REITs): Gradual-shift causality and volatility transmission analysis. Energy Economics, 60, 168-175.

Odusami, B.O. (2021b). Forecasting the Value-at-Risk of REITs using realized volatility jump models. The North American Journal of Economics and Finance, 58, 101426

Odusami, B.O. (2021a). Volatility jumps and their determinants in REIT returns. Journal of Economics and Business, 113, 105943.

Patton, A. J., & Sheppard, K. (2015). Good volatility, bad volatility: Signed jumps and the persistence of volatility. Review of Economics and Statistics, 97(3), 683-697.

Pavlova, I., Cho, J. H., Parhizgari, A. M., & Hardin III, W. G. (2014). Long memory in REIT volatility and changes in the unconditional mean: a modified FIGARCH approach. Journal of Property Research, 31(4), 315-332.

Rapach, D. E., Strauss, J. K., & Zhou, G. (2010). Out-of-sample equity premium prediction: Combination forecasts and links to the real economy. The Review of Financial Studies, 23(2), 821-862.

Rossi, B., & Inoue, A. (2012). Out-of-sample forecast tests robust to the choice of window size. Journal of Business & Economic Statistics, 30(3), 432-453.

Santos, D. G., & Ziegelmann, F. A. (2014). Volatility forecasting via MIDAS, HAR and their combination: An empirical comparative study for IBOVESPA. Journal of Forecasting, 33(4), 284-299.

Schwert, G.W. (1989). Why does stock market volatility change over time?. Journal of Finance, 44(5), 1115-1153.

Segnon, M., Gupta, R., Lesame, K., & Wohar, M. E. (2021). High-frequency volatility forecasting of US housing markets. The Journal of Real Estate Finance and Economics, 62(2), 283-317.

Stevenson, S. (2002). An examination of volatility spillovers in REIT returns. Journal of Real Estate Portfolio Management, 8, 229-238.

Tsai, I-C. (2013). Volatility clustering, leverage, size, or contagion effects: The fluctuations of Asian real estate investment trust returns. Journal of Asian Economics, 27, 18-32.

Wang, J., Huang, Y., Ma, F., & Chevallier, J. (2020). Does high-frequency crude oil futures data contain useful information for predicting volatility in the US stock market? New evidence. Energy Economics, 91, 104897.

Wang, Y., Wei, Y., Wu, C., & Yin, L. (2018). Oil and the short-term predictability of stock return volatility. Journal of Empirical Finance, 47, 90-104.

Welch, I., & Goyal, A. (2008). A comprehensive look at the empirical performance of equity premium prediction. The Review of Financial Studies, 21(4), 1455-1508.

Zhou, J. (2017). Forecasting REIT volatility with high-frequency data: a comparison of alternative methods. Applied Economics, 49(26), 2590-2605.

Zhou, J., & Kang, Z. (2011). A comparison of alternative forecast models of REIT volatility. The Journal of Real Estate Finance and Economics, 42(3), 275-294.

Tables

Table 1

Descriptive statistics.

Variable	Full sample period	Mean	Std.dev	Skewness	Kurtosis	Jarque-Bera	ADF
EGAS	2008.01.17-2020.07.01	0.798	1.548	6.947	69.003	628822.605 ***	-23.974 ***
EGNA	2008.01.24-2020.07.01	2.554	5.771	5.465	41.949	239924.411 ***	-20.594 ***
ELAU	2008.02.06-2020.07.01	1.451	3.195	8.626	123.666	1930066.123 ***	-20.590 ***
ELHK	2008.01.28-2020.07.01	1.921	5.110	8.857	106.577	1476613.364 ***	-34.890 ***
ELJP	2008.01.23-2020.07.01	1.969	6.692	25.219	899.512	96318528.057 ***	-42.614 ***
ELUK	2008.01.23-2020.07.01	1.401	13.716	51.082	2730.881	945659780.218 ***	-53.907 ***
ENGL	2008.01.09-2020.07.01	0.920	2.172	14.847	394.457	20114070.816 ***	-34.305 ***
EPEU	2008.03.25-2020.07.01	0.718	1.226	8.090	99.214	1276664.313 ***	-17.526 ***
FENEI	2011.05.02-2020.07.01	0.923	1.261	13.300	302.662	8835141.252 ***	-28.458 ***
FNAR	2008.09.19-2020.07.01	1.914	5.448	6.440	57.042	419502.299 ***	-18.602 ***
ORV	2008.01.09-2020.07.01	6.515	61.939	48.427	2534.791	827112398.390 ***	-42.765 ***
OIV	2008.01.09-2020.07.01	38.362	19.939	4.301	33.491	153698.468 ***	-6.698 ***

Notes: This table reports the descriptive statistics of RV of 10 international REITs index and oil volatility (ORV and OIV). Columns show variable, abbreviation, observation, mean, standard deviation (Std.dev), skewness, kurtosis, Jarque-Bera test and Augmented Dickey-Fuller test (ADF). *** denote rejection of null hypothesis at the 1% level of significance.

Table 2
Forecasting performance.

REITs index	Out-of-sample R^2 test						Portfolio Exercise (%)		
	Oil Realized Volatility (ORV)			Oil Implied Volatility (OIV)					
	R^2_{OOS}(%)	MSPE-Adj.	p-value	R^2_{OOS}(%)	MSPE-Adj.	p-value	Bench	ORV	OIV
EGAS	5.656	2.122	0.017	5.744	2.724	0.003	3.586	3.623	3.611
EGNA	4.539	2.592	0.005	3.387	2.819	0.002	3.260	3.304	3.309
ELAU	6.946	2.477	0.007	6.945	2.673	0.004	3.575	3.598	3.589
ELHK	8.745	5.442	0.000	5.887	5.674	0.000	3.697	3.867	3.745
ELJP	6.934	2.493	0.006	9.065	2.545	0.005	3.256	3.285	3.271
ELUK	9.799	2.373	0.009	6.305	2.724	0.003	3.669	3.677	3.677
ENGL	3.447	2.410	0.008	0.348	0.802	0.211	3.603	3.632	3.629
EPEU	6.910	2.417	0.008	5.125	2.525	0.006	3.666	3.682	3.689
FENEI	7.560	2.438	0.007	3.486	2.211	0.014	3.579	3.614	3.589
FNAR	6.161	2.265	0.012	5.962	2.546	0.005	3.626	3.639	3.640

Notes: The table represents the out-of-sample performance. The forecasting window covers at last 50% observations for 10 REITs index, respectively.

Table 3
Forecasting performance with alternative forecasting window.

Equity index	Out-of-sample R^2						Portfolio Exercise		
	Oil Realized Volatility (ORV)			Oil Implied Volatility (OIV)					
	R^2_{OOS}(%)	MSPE-Adj.	*p*-value	R^2_{OOS}(%)	MSPE-Adj.	*p*-value	Bench	ORV	OIV
EGAS	-0.106	0.750	0.227	5.713	2.432	0.008	3.587	3.606	3.605
EGNA	5.020	2.404	0.008	8.072	2.797	0.003	3.307	3.338	3.329
ELAU	3.745	1.885	0.030	7.986	2.215	0.013	3.623	3.642	3.638
ELHK	5.650	4.279	0.000	7.477	3.911	0.000	1.035	1.925	1.506
ELJP	1.471	2.146	0.016	4.501	2.935	0.002	3.271	3.282	3.285
ELUK	11.239	2.193	0.014	9.931	2.385	0.009	3.699	3.705	3.702
ENGL	3.344	2.570	0.005	3.209	2.612	0.004	3.537	3.542	3.536
EPEU	3.673	1.969	0.024	4.337	1.505	0.066	3.706	3.722	3.719
FENEI	2.658	1.732	0.042	4.876	2.407	0.008	3.579	3.582	3.595
FNAR	7.836	1.790	0.037	8.502	1.823	0.034	3.612	3.613	3.610

Notes: The table represents the out-of-sample performance with alternative forecasting window. The forecasting window covers at last 60% observations for 10 REITs index, respectively.

Table 4

Forecasting performance with alternative forecasting window.

REITs index	Out-of-sample R^2 test						Portfolio Exercise (%)		
	Oil Realized Volatility (ORV)			Oil Implied Volatility (OIV)					
	R^2_{OOS}(%)	MSPE-Adj.	*p*-value	R^2_{OOS}(%)	MSPE-Adj.	*p*-value	Bench	ORV	OIV
EGAS	4.360	1.881	0.030	7.000	2.463	0.007	3.582	3.606	3.600
EGNA	5.987	2.694	0.004	6.455	3.052	0.001	3.272	3.304	3.295
ELAU	6.118	2.254	0.012	8.119	2.527	0.006	3.598	3.617	3.610
ELHK	9.199	4.522	0.000	8.978	4.316	0.000	3.620	3.076	3.831
ELJP	2.899	1.942	0.026	7.317	2.338	0.010	3.287	3.308	3.301
ELUK	11.239	2.193	0.014	9.931	2.385	0.009	3.699	3.705	3.702
ENGL	3.344	2.570	0.005	3.209	2.612	0.004	3.537	3.542	3.536
EPEU	7.130	2.260	0.012	8.435	2.190	0.014	3.695	3.709	3.710
FENEI	5.624	2.178	0.015	-0.657	0.546	0.293	3.551	3.565	3.553
FNAR	8.355	2.152	0.016	8.057	2.301	0.011	3.627	3.637	3.636

Notes: The table represents the out-of-sample performance with alternative forecasting window. The forecasting window covers at last 40% observations for 10 REITs index, respectively.

Table 5

Forecasting performance during COVID-19 period.

Equity index	Oil Realized Volatility (ORV)			Oil Implied Volatility (OIV)		
	R^2_{OOS}(%)	MSPE-Adj.	p-value	R^2_{OOS}(%)	MSPE-Adj.	p-value
EGAS	4.315	1.503	0.066	5.481	1.816	0.035
EGNA	3.095	1.815	0.035	5.609	2.194	0.014
ELAU	4.369	1.783	0.037	5.611	2.103	0.018
ELHK	-0.866	3.070	0.001	13.677	3.336	0.000
ELJP	4.231	1.543	0.061	6.462	1.741	0.041
ELUK	7.372	1.412	0.079	5.518	1.189	0.117
ENGL	-0.417	0.690	0.245	4.063	1.986	0.024
EPEU	3.592	1.935	0.027	7.329	1.853	0.032
FENEI	7.487	2.252	0.012	5.390	2.262	0.012
FNAR	-5.026	-1.878	0.970	5.168	1.501	0.067

Notes: The table represents the out-of-sample performance during COVID-19 period.

Table 6

Forecasting performance with alternative k^{max}.

Equity index	Oil Realized Volatility (ORV)			Oil Implied Volatility (OIV)		
	R^2_{OOS}(%)	MSPE-Adj.	p-value	R^2_{OOS}(%)	MSPE-Adj.	p-value
Panel A: $k^{max} = 20$						
EGAS	4.678	1.960	0.025	7.079	2.509	0.006
EGNA	6.505	2.767	0.003	6.767	3.097	0.001
ELAU	6.542	2.315	0.010	8.392	2.547	0.005
ELHK	9.568	4.556	0.000	9.244	4.359	0.000
ELJP	1.127	1.912	0.028	2.779	2.242	0.012
ELUK	11.918	2.285	0.011	10.394	2.443	0.007
ENGL	4.080	2.708	0.003	3.888	2.711	0.003
EPEU	7.747	2.288	0.011	8.494	2.138	0.016
FENEI	6.473	2.452	0.007	4.229	2.297	0.011
FNAR	8.702	2.161	0.015	8.638	2.371	0.009
Panel B: $k^{max} = 60$						
EGAS	3.829	1.817	0.035	6.317	2.416	0.008
EGNA	5.824	2.646	0.004	6.215	3.009	0.001
ELAU	6.245	2.318	0.010	8.405	2.594	0.005
ELHK	9.669	4.546	0.000	9.085	4.354	0.000
ELJP	2.773	1.928	0.027	7.208	2.322	0.010
ELUK	10.850	2.157	0.015	9.539	2.320	0.010
ENGL	2.899	2.463	0.007	2.815	2.513	0.006
EPEU	6.201	2.228	0.013	7.421	2.118	0.017
FENEI	5.609	2.150	0.016	-3.723	-2.281	0.989
FNAR	8.806	2.125	0.017	7.802	2.228	0.013

Notes: The table represents the out-of-sample performance with alternative k^{max}. The forecasting window covers at last 50% observations for 10 REITs index, respectively.

Table 7
Forecasting performance controlling jump risk.

REITs index	Out-of-sample R^2 test					
	Oil Realized Volatility (ORV)			Oil Implied Volatility (OIV)		
	R^2_{OOS}(%)	MSPE-Adj.	p-value	R^2_{OOS}(%)	MSPE-Adj.	p-value
EGAS	4.365	1.615	0.053	3.497	1.887	0.030
EGNA	9.124	2.576	0.005	6.220	2.777	0.003
ELAU	3.722	1.533	0.063	3.614	2.143	0.016
ELHK	7.819	3.932	0.000	7.780	3.818	0.000
ELJP	3.042	1.944	0.026	4.889	2.180	0.015
ELUK	11.776	2.321	0.010	7.843	2.814	0.002
ENGL	17.143	1.496	0.067	12.975	1.357	0.087
EPEU	8.894	2.595	0.005	6.156	2.682	0.004
FENEI	3.197	1.592	0.056	6.795	0.741	0.229
FNAR	7.626	2.114	0.017	5.941	2.374	0.009

Notes: The table represents the out-of-sample performance controlling jump risk. The forecasting window covers at last 50% observations for 10 REITs index, respectively.

Table 8

Forecasting performance with regime switching models.

REITs index	MIDAS-ORV vs. MRS-MIDAS-ORV			MIDAS-OIV vs. MRS-MIDAS-OIV		
	R^2_{OOS}(%)	MSPE-Adj.	*p*-value	R^2_{OOS}(%)	MSPE-Adj.	*p*-value
EGAS	5.110	2.542	0.006	-0.331	0.712	0.238
EGNA	0.434	1.430	0.076	1.143	2.759	0.003
ELAU	9.760	1.963	0.025	5.168	1.884	0.030
ELHK	-2.732	0.432	0.333	-2.265	0.280	0.390
ELJP	0.548	1.869	0.031	3.981	1.332	0.091
ELUK	16.520	2.034	0.021	6.700	1.526	0.064
ENGL	-0.952	-1.856	0.968	-0.791	-1.762	0.961
EPEU	18.425	2.015	0.022	19.065	1.865	0.031
FENEI	1.000	1.921	0.027	0.819	1.393	0.082
FNAR	5.943	1.580	0.057	9.774	1.822	0.034

Notes: The table represents the out-of-sample performance with regime switching. The forecasting window covers at last 50% observations for 10 REITs index, respectively.

Table 9

Forecasting performance with high and low volatility level.

REITs index	Oil Realized Volatility (ORV)			Oil Implied Volatility (OIV)		
	R^2_{OOS}(%)	MSPE-Adj.	p-value	R^2_{OOS}(%)	MSPE-Adj.	p-value
Panel A: High Volatility Level						
EGAS	4.425	1.887	0.030	7.070	2.469	0.007
EGNA	6.966	2.938	0.002	6.734	3.132	0.001
ELAU	6.185	2.262	0.012	8.228	2.517	0.006
ELHK	10.327	4.579	0.000	9.618	4.313	0.000
ELJP	0.998	1.820	0.034	2.798	2.249	0.012
ELUK	11.357	2.195	0.014	10.046	2.388	0.008
ENGL	3.959	2.906	0.002	3.400	2.711	0.003
EPEU	7.281	2.273	0.012	8.543	2.189	0.014
FENEI	5.939	2.225	0.013	-0.537	0.574	0.283
FNAR	8.466	2.143	0.016	8.164	2.300	0.011
Panel B: Low Volatility Level						
EGAS	-5.046	-0.752	0.774	-3.054	-0.745	0.772
EGNA	-71.327	-1.001	0.841	-15.314	-1.017	0.845
ELAU	-0.374	1.033	0.151	0.520	1.337	0.091
ELHK	-70.022	-0.625	0.734	-36.623	0.601	0.274
ELJP	0.896	2.007	0.022	1.170	4.029	0.000
ELUK	-1.557	0.537	0.296	-2.705	-0.094	0.537
ENGL	-48.739	-0.977	0.836	-12.898	-1.044	0.852
EPEU	-5.459	-0.820	0.794	-1.081	0.982	0.163
FENEI	-12.248	-1.527	0.937	-8.315	-1.950	0.974
FNAR	1.230	2.541	0.006	-2.008	-0.017	0.507

Notes: The table reports the evaluation results during high and low volatility level. The forecasting window covers at last 50% observations for 10 REITs index, respectively.

Table 10

Forecasting performance with 'good' and 'bad' oil volatility.

Equity index	ORV				OIV			
	"Good" ORV		"Bad" ORV		"Good" OIV		"Bad" OIV	
	R^2_{OOS}(%)	p-value	R^2_{OOS}(%)	p-value	R^2_{OOS}(%)	p-value	R^2_{OOS}(%)	p-value
EGAS	3.873	0.030	4.167	0.029	2.097	0.086	0.682	0.229
EGNA	6.522	0.004	4.606	0.004	0.226	0.252	-1.275	0.679
ELAU	6.187	0.012	5.733	0.013	1.228	0.106	-0.384	0.547
ELHK	8.371	0.000	8.900	0.000	3.234	0.001	0.502	0.021
ELJP	3.865	0.021	4.718	0.015	3.025	0.022	-0.537	0.389
ELUK	10.279	0.013	10.055	0.014	3.205	0.015	1.719	0.066
ENGL	3.171	0.010	2.687	0.004	1.417	0.063	1.346	0.083
EPEU	7.326	0.021	5.847	0.003	0.724	0.127	-1.126	0.531
FENEI	6.141	0.023	6.716	0.027	5.962	0.009	1.261	0.031
FNAR	7.714	0.029	6.141	0.010	-0.585	0.591	0.027	0.417

Notes: The table represents the out-of-sample performance with "Good" and "Bad" volatility. The forecasting window covers at last 50% observations for 10 REITs index, respectively.

Table 11

Forecasting performance for longer horizons.

REITs index	Oil Realized Volatility (ORV)			Oil Implied Volatility (OIV)			Portfolio Exercise		
	R^2_{OOS}(%)	MSPE-Adj.	*p*-value	R^2_{OOS}(%)	MSPE-Adj.	*p*-value	Bench	ORV	OIV
Panel A: $h = 5$									
EGAS	8.113	2.777	0.003	11.581	2.857	0.002	3.697	3.719	3.734
EGNA	6.348	3.616	0.000	11.510	3.987	0.000	3.574	3.585	3.609
ELAU	1.557	2.822	0.002	9.091	3.037	0.001	3.733	3.761	3.763
ELHK	5.942	4.810	0.000	10.164	4.510	0.000	3.595	3.682	3.661
ELJP	1.067	2.074	0.019	2.394	2.700	0.003	3.494	3.528	3.532
ELUK	5.769	2.061	0.020	5.085	1.897	0.029	3.784	3.790	3.791
ENGL	2.598	3.006	0.001	2.990	3.002	0.001	3.324	3.299	3.336
EPEU	6.464	2.552	0.005	4.613	1.896	0.029	3.794	3.801	3.812
FENEI	-3.647	0.337	0.368	0.926	1.687	0.046	3.780	3.782	3.787
FNAR	4.666	2.526	0.006	7.318	2.510	0.006	3.650	3.657	3.667
Panel B: $h = 10$									
EGAS	4.691	2.539	0.006	6.864	2.731	0.003	3.650	3.662	3.715
EGNA	5.566	4.409	0.000	9.883	4.706	0.000	3.525	3.529	3.570
ELAU	4.177	4.128	0.000	10.494	3.919	0.000	3.665	3.707	3.715
ELHK	7.604	5.655	0.000	11.357	5.155	0.000	3.651	3.741	3.723
ELJP	1.370	2.079	0.019	2.055	2.777	0.003	3.434	3.489	3.512
ELUK	3.883	2.228	0.013	1.977	1.799	0.036	3.738	3.751	3.755
ENGL	-0.263	-0.777	0.781	2.668	3.275	0.001	3.354	3.318	3.376
EPEU	4.322	2.560	0.005	1.912	1.295	0.098	3.776	3.778	3.794
FENEI	-0.567	0.737	0.231	0.134	1.320	0.093	3.769	3.766	3.771
FNAR	2.425	2.475	0.007	3.663	2.329	0.010	3.535	3.547	3.558

Panel C: *h* = 22									
EGAS	2.187	3.139	0.001	0.958	3.025	0.001	3.343	3.359	3.505
EGNA	3.694	5.452	0.000	8.255	5.119	0.000	3.247	3.253	3.338
ELAU	10.728	5.747	0.000	14.023	4.933	0.000	3.304	3.388	3.431
ELHK	17.435	7.516	0.000	13.269	7.197	0.000	3.678	3.754	3.738
ELJP	2.122	2.571	0.005	1.077	2.744	0.003	2.807	2.908	3.038
ELUK	2.824	3.218	0.001	-0.526	2.280	0.011	3.563	3.582	3.598
ENGL	-0.860	-2.233	0.987	2.473	4.222	0.000	3.082	2.993	3.155
EPEU	0.252	5.596	0.000	-4.935	-0.416	0.661	3.590	3.584	3.616
FENEI	-2.038	0.906	0.182	-1.417	1.584	0.057	3.779	3.768	3.768
FNAR	2.949	3.517	0.000	2.690	3.133	0.001	2.898	2.910	2.987

Notes: The table represents the out-of-sample performance for longer horizon. The forecasting window covers at last 50% observations for 10 REITs index, respectively.