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Uncertainty due to infectious diseases and forecastability of the realized variance of United States real estate investment trusts: A note

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Abstract

We examine the forecasting power of a daily newspaper-based index of uncertainty associated with infectious diseases (EMVID) for real estate investment trusts (REITs) realized market variance of the United States (US) via the heterogeneous autoregressive realized volatility (HAR-RV) model. Our results show that the EMVID index improves the forecast accuracy of realized variance 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. Our results have important portfolio implications for investors during the current period of unprecedented levels of uncertainty resulting from the outbreak of COVID-19.

KEYWORDS

forecasting, infectious diseases, realized variance, REITs, uncertainty

JEL CLASSIFICATION

C22; C53; G10

1 | INTRODUCTION

The COVID-19 outbreak, which started off as a regional crisis in China, before swelling to an unprecedented health crisis on a global scale, is the first pandemic in the 21st century, and can be regarded as a catastrophe for the human race (Gupta et al., 2021). On the economic front, the lockdown instituted to contain the spread of the virus triggered the worst economic downturn since the "Great Depression" (Gupta et al., 2020). In parallel, financial markets plummeted to their lowest levels since the Global Financial Crisis (GFC) of 2007–2009 (Zhang et al., 2020), due to substantial and unprecedented spike in uncertainty (Bouri et al., 2020). In this regard, the securitized real estate markets, that is, real estate investment trusts (REITs), which is considered an important asset class globally and particularly in the United States (US), have also not been spared with a loss of nearly 30% worldwide and 32% in the US (Akinsomi, 2020).

REITs have witnessed tremendous growth in the US since the early 1990s. 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 US, with stock-exchange listed REITs holding ~2 trillion US dollars in assets, and US-listed REITs having an equity market capitalization of more than 1 trillion US dollars. The success in attracting such a massive scale of investment capital is mainly because REITs are accessible to all investors irrespective of portfolio size. Further, with REITs being exchange-traded funds that earn most of their income from investments in real estate, REITs have been the epicenter of research interest (particularly since the Global Financial Crisis, which had its roots in the collapse of the US real estate sector) as their returns do not suffer from measurement error and high transaction costs compared to other real estate investments, and provide a very good high-frequency proxy for the real estate market, since REITs shares trade as common stocks (Marfatia et al., 2017). Understandably, accurate forecasting of REITs variance is an important issue for academics, policymakers, and investors, given that variance, as a measure of risk, plays a critical role in portfolio diversification, derivatives pricing, hedging, and financial risk management. Against this backdrop, the objective of our paper is to assess, for the first time,[1] the ability of historical uncertainty related to infectious diseases of various types (such as MERS, SARS, Ebola, H5N1, H1N1, and of course the Coronavirus) in predicting the future path of REITs realized variance.

In this regard, a necessary first step is to quantify uncertainty related to infectious diseases in a way that would act as suitable input into a statistical model for predicting REITs variance. In this regard, we use the recently developed newspaper-based index of Baker et al. (2020), which tracks daily equity market volatility (EMV), in particular the movements in the Chicago Board Options Exchange (CBOE)'s Volatility Index (VIX), due to infectious diseases. Given the current emphasis[2] that intraday data leads to more precise estimates and forecasts for daily return variance of the REITs (Odusami, 2020; Zhou, 2017, 2020a, 2020b), we contribute to this burgeoning line of research, by forecasting the realized variance (*RV*) of US REITs returns, computed from 5-min-interval intraday data, 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 EMV due to infectious diseases (EMVID) and examine its forecasting power over the period September 2008 to August 2020.

At this stage, it is important to highlight the fact that the main channel through which we expect the EMVID index to affect REITs *RV* is through the "leverage effect," which is a dominant feature of REITs returns (Kawaguchi et al., 2017). This effect implies that the negative impact on REITs returns in the wake of "bad news" associated with an increase in financial uncertainty due to the outbreak of infectious diseases would translate into higher REITs volatility. Furthermore, the REITs sector is also likely to be affected by volatility spillovers from other financial sectors following an EMVID shock, given the strong interconnectedness of financial markets, including REITs markets (Tiwari et al., 2020). We organize the remainder of our paper as follows: Section 2 outlines the data and the methodology, Section 3 presents the results, and Section 4 concludes.

2 | DATA AND METHODOLOGY

2.1 | Data

We use intraday data on the FTSE Nareit All REITs Index (FNAR)[3] over a 24 h trading day to construct daily measures of realized variance (*RV*), the corresponding good (*RVG*) and bad (*RVB*) variants, and the other covariates, that is, leverage (*LEV*) based on days which register negative values of daily returns (and zero else; returns being computed as the end of the day price difference [logs, close to close]), realized jumps (*JUMPS*), realized skewness (*RSK*), realized kurtosis (*RKU*), which we use as additional controls. The usage of *LEV*, *JUMPS*, *RSK*, and *RKU* in the model is important, as it will highlight the robust forecasting role, if any, of the infectious diseases-related uncertainty, over and above these variables capturing extreme behavior of the REITs market. In this regard, it should also be noted that we include the variable *LEV* in our analysis because it allows the incremental "leverage effect" due to EMVID shocks to be isolated. Besides the FNAR index, given that COVID-19 may have a differential impact on REITs sectors,[4] as an additional analysis, we also investigate the role of uncertainty due to infectious diseases for sectoral REITs namely, 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, in a continuous format, are obtained from Bloomberg.

The daily measure of uncertainty due to infectious diseases (EMVID) is publicly available from: http://policyuncertainty.com/infectious_EMV.html, and is developed by Baker et al., (2020), with index being newspaper-based infectious disease EMV tracker, available at the daily frequency from January, 1985 till recent days. To construct the EMVID, Baker et al., (2020) specify four sets of terms namely, E: economic, economy, financial; M: "stock market," equity, equities, "Standard and Poors"; V: volatility, volatile, uncertain, uncertainty, risk, risky; ID: epidemic, pandemic, virus, flu, disease, coronavirus, mers, sars, ebola, H5N1, H1N1, and then obtain daily counts of newspaper articles that contain at least one term in each of E, M, V, and ID across ~3000 US newspapers. After this, the raw EMVID counts is scaled by the count of all articles in the same day, and finally, the authors multiplicatively rescale the resulting series to match the level of the VIX, by using the overall EMV index, and then scaling the EMVID index to reflect the ratio of the EMVID articles to total EMV articles. Based on data availability of the two variables under consideration, our analysis covers (after removal of weekends, public holidays, etc.) the sample period September 19, 2008–August 13, 2020. Figure 1 plots our data.

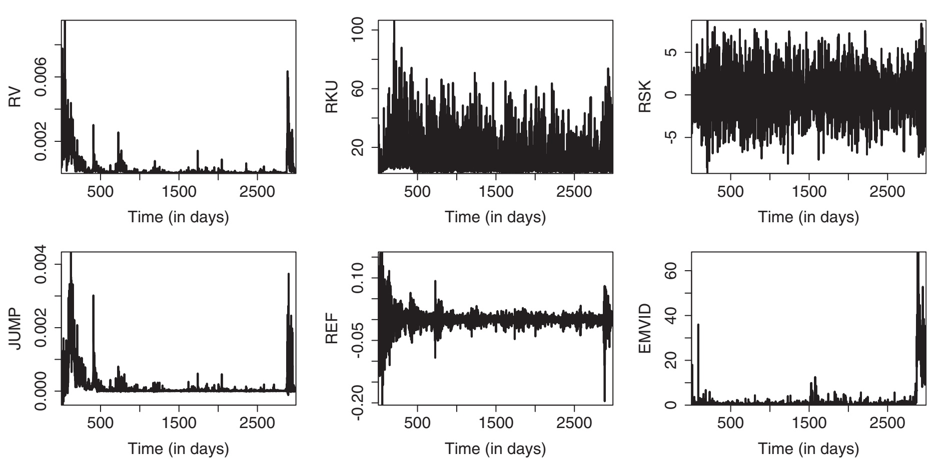

FIGURE 1 The data. RV, realized variance; RKU, realized kurtosis; RSK, realized skewness; JUMP, realized jumps; RET, daily returns; EMVID, Infectious diseases

2.2 | Methodology and higher-moments

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

$$RV_{t+h} = \beta_0 + \beta_d RV_t + \beta_w RV_{w,t} + \beta_m RV_{m,t} + \varepsilon_{t+h} \tag{1}$$

where the index h denotes the forecast horizon, and (for $h > 1$) RV_{t+h} denotes the average realized variance over the h-days forecast horizon, with $h = 1$, 5, and 22 in our context. In addition, $RV_{w,t}$ is the average RV from day $t-5$ to day $t-1$, while $RV_{m,t}$ denotes the average RV from day $t-22$ to day $t-1$.

In addition, we also investigate an extended version of the HAR-RV model in Equation (1) by incorporating *LEV*, *JUMPS*, *RSK*, and *RKU* as follows:

$$RV_{t+h} = \beta_0 + \beta_d RV_t + \beta_w RV_{w,t} + \beta_m RV_{m,t} + \beta_1 LEV_t + \beta_2 JUMPS_t + \beta_3 RSK_t + \beta_4 RKU_t + \varepsilon_{t+h} \tag{2}$$

To capture the role of uncertainty due to infectious diseases, the models in the above two equations are modified to include the EMVID index as follows:

$$RV_{t+h} = \beta_0 + \beta_d RV_t + \beta_w RV_{w,t} + \beta_m RV_{m,t} + \theta EMVID_t + \varepsilon_{t+h} \tag{3}$$

and,

$$RV_{t+h} = \beta_0 + \beta_d RV_t + \beta_w RV_{w,t} + \beta_m RV_{m,t} + \beta_1 LEV_t + \beta_2 JUMPS_t + \beta_3 RSK_t + \beta_4 RKU_t + \theta EMVID_t + \varepsilon_{t+h} \tag{4}$$

In this regard, it must be pointed out that we use the classical estimator of RV, that is, the sum of squared intraday returns (Andersen & Bollerslev, 1998), expressed as

$$RV_t = \sum_{i=1}^{M} r_{t,i}^2 \tag{5}$$

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

Upward ("good," *RVG*) and downward ("bad," *RVB*) realized variance (semi-variance) can serve as measures of downside and upside risk, and capture the sign asymmetry in the price process. Thus, we also forecast *RVG* and *RVB* based on the information content of the EMVID, by replacing RV ($RVG + RVB$) in the above equation by *RVG* and *RVB* in turn. In line with Barndorff-Nielsen et al. (2010), we compute bad and good realized semi-variance as:

$$RVG_t = \sum_{i=1}^{M} r_{t,i}^2 \; \mathbf{1}_{[(r_{t,i}) > 0]}, \tag{6}$$

$$RVB_t = \sum_{i=1}^{M} r_{t,i}^2 \; \mathbf{1}_{[(r_{t,i}) < 0]}. \tag{7}$$

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

$$\lim_{M\to\infty} RV_t = \int_{t-1}^{t} \sigma^2(s)ds + \sum_{j=1}^{N_t} k_{t,j}^2, \tag{8}$$

where N_t is the number of jumps within day t and $k_{t,j}$ is the jump size. This specification suggests 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 of Barndorff-Nielsen and Shephard (2004, 2006) further show that:

$$\lim_{M\to\infty} BV_t = \int_{t-1}^{t} \sigma^2(s)ds, \tag{9}$$

where BV_t is the realized bipolar variation defined as:

$$BV_t = \mu_1^{-2}\left(\frac{M}{M-1}\right)\sum_{i=2}^{M} | r_{t,i-1}||r_{i,t} | = \frac{\pi}{2}\sum_{i=2}^{M} | r_{t,i-1}||r_{i,t} | , \tag{10}$$

and

$$\mu_a = E(|Z|^a), Z \sim N(0,1), a > 0. \tag{11}$$

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

$$J_t = RV_t - BV_t. \tag{12}$$

In order to test the significance of the jumps, we adopt the following formal test estimator proposed by Barndorff-Nielsen and Shephard (2006):

$$JT_t = \frac{RV_t - BV_t}{(v_{bb} - v_{qq})\frac{1}{N}QP_t}, \tag{13}$$

where QP_t is the Tri-Power Quarticity defined as:

$$TP_t = M\frac{M}{M-2}\left(\frac{\Gamma(0.5)}{2^{2/3}\Gamma(7/6)}\right)\sum_{i=3}^{M} |r_{t,i}|^{4/3}|r_{t,i-1}|^{4/3}|r_{t,i-2}|^{4/3}, \tag{14}$$

which converges to

$$TP_t \to \int_{t-1}^{t} \sigma^4(s)ds, \tag{15}$$

even in the presence of jumps. $v_{bb} = \left(\frac{\pi}{2}\right) + \pi - 3$ 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 (12), the jump contribution to RV_t is either positive or null. Therefore, in order to avoid having negative empirical contributions, we follow Zhou and Zhu (2012) and re-define the jump measure as

$$RJ_t = max(RV_t - BV_t; 0). \tag{16}$$

Finally, we compute *RSK RKU* as measures of the higher-moments of the daily REITs returns distribution. 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. Given the intraday returns and realized variance, *RSK* on day *t* is

$$RSK_t = \frac{\sqrt{M}\sum_{i=1}^{M} r_{(i,t)^3}}{RV_t^{3/2}}, \tag{17}$$

while, *RKU* on day *t* is given by

$$RKU_t = \frac{M\sum_{i=1}^{M} r_{(i,t)^4}}{RV_t^2}. \tag{18}$$

The scaling of *RSK* and *RKU* by $(M)^{1/2}$ and *M*, respectively, makes sure that their magnitudes correspond to daily skewness and kurtosis.

3 | EMPIRICAL RESULTS

Table 1 summarizes the results (*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 rolling-estimation windows (250, 500, 1000, 1500, and 200 observations). We study three different forecast horizons ($h = 1, 5, 22$), corresponding to daily, weekly, and monthly forecasts. We construct the data matrix such that the number of forecasts is the same for all forecast horizons. In addition, we present results for the realized standard variance and also for the realized downward ("bad") variance, and the realized upward ("good") variance.

Panel A of Table 1 depicts the results that we obtain when we compare the baseline HAR-RV model with the HAR-RV model that features infectious diseases as an additional predictor. The results demonstrate that infectious diseases improve the overall forecast performance of the HAR-RV model at all three forecast horizons being studied, where two results for realized bad volatility are insignificant at the 10% level of significance.

Panel B of Table 1 depicts the results that we obtain when we study an extended model that includes, in addition to the standard predictors of the baseline HAR-RV model, measures of realized skewness, realized kurtosis, realized jumps, and a leverage effect. While, as one would have expected, a few test results turn out to be insignificant, the key message to take home is unchanged: Infectious diseases help to forecast realized (standard, bad, and good) realized variance.

Panel C of Table 1 depicts the test results for a HAR-RV model estimated on realized volatility (that is, the square root of realized variance). In this model, we use the square root of infectious diseases as a predictor. We present results for this model because Figure 1 shows periods of relatively high realized variance and infectious diseases at the beginning and the end of our sample period. The test results again witness that infectious diseases help to predict realized volatility and its bad and good variants.

In Table 2, we dig a bit deeper and present results for sectoral data for the baseline model (and realized standard volatility). The results for the sectoral data corroborate the results for the overall market. Extending the standard HAR-RV model to include data on infectious diseases as an additional predictor helps to improve the overall forecast performance of the model in terms of the MSPE.

In Table 3, we report for the baseline model results for a pre-COVID-19 subsample period and a COVID-19 subsample period. The results of the subsample analysis demonstrate that the case for using infectious diseases as an additional predictor forecasting REITs realized volatility has strengthened during the recent pandemic. While we

TABLE 1 Out-of-sample tests

Panel A: Baseline model															
Forecast horizon	$h=1$	$h=5$	$h=22$	$h=1$	$h=5$	$h=22$	$h=1$	$h=5$	$h=22$	$h=1$	$h=5$	$h=22$	$h=1$	$h=5$	$h=22$
Window length	250	250	250	500	500	500	1000	1000	1000	1500	1500	1500	2000	2000	2000
Realized standard variance	0.0385	0.0553	0.0229	0.0273	0.0517	0.029	0.0151	0.0336	0.0198	0.0117	0.0216	0.0113	0.0105	0.0158	0.0067
Realized bad variance	–	0.0667	0.0386	–	0.0912	0.0579	0.0453	0.0343	0.0247	0.0305	0.0219	0.014	0.0285	0.0169	0.008
Realized good variance	0.0372	0.0123	0.0091	0.0252	0.0084	0.0064	0.0132	0.0058	0.0032	0.0072	0.0047	9e-04	0.0059	0.0046	0.0007
Panel B: Extended model															
Forecast horizon	$h=1$	$h=5$	$h=22$	$h=1$	$h=5$	$h=22$	$h=1$	$h=5$	$h=22$	$h=1$	$h=5$	$h=22$	$h=1$	$h=5$	$h=22$
Window length	250	250	250	500	500	500	1000	1000	1000	1500	1500	1500	2000	2000	2000
Realized standard variance	–	0.0354	0.0316	0.0423	0.0116	0.0159	0.0259	0.0106	0.0126	0.0194	0.0074	0.0067	0.0193	0.0065	0.0042
Realized bad variance	–	0.0627	0.0291	0.0689	0.0339	0.0312	0.021	0.0213	0.0174	0.0188	0.0167	0.0141	0.0192	0.0129	0.0131
Realized good variance	–	0.0199	0.0263	–	0.0057	0.0149	–	0.0036	0.0124	–	0.0032	0.0035	0.0818	0.0033	0.0019
Panel C: Realized volatility															
Forecast horizon	$h=1$	$h=5$	$h=22$	$h=1$	$h=5$	$h=22$	$h=1$	$h=5$	$h=22$	$h=1$	$h=5$	$h=22$	$h=1$	$h=5$	$h=22$
Window length	250	250	250	500	500	500	1000	1000	1000	1500	1500	1500	2000	2000	2000
Realized standard variance	0.0141	0.0058	0.006	0.0103	0.0063	0.0081	0.0093	0.0292	0.0608	0.0118	0.055	0.0814	0.0226	–	–
Realized bad variance	0.0202	0.0188	0.0128	0.0176	0.0088	0.0063	0.0171	0.0336	0.0352	0.0211	0.0655	0.0515	0.03	0.0933	0.0715
Realized good variance	0.0072	0.0067	0.006	0.0063	0.0081	0.0061	0.0077	0.015	0.0248	0.0078	0.0258	0.0461	0.0148	0.0556	0.0831

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 lengths of the rolling-estimation window used to compute forecasts. The HAR-RV model without EMVID is the benchmark model, and the HAR-RV extended to include EMVID is the rival model. The alternative hypothesis is that the rival model has a smaller MSPE than the benchmark model. The extended models include realized skewness, realized kurtosis, realized jumps, and a leverage effects as additional predictors. Realized volatility is defined as the square root of the realized standard variance. The model that is being used to forecast realized volatility features the square root of infectious diseases as a predictor. 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 *SE*.

TABLE 2 Out-of-sample tests for sectoral data

Forecast horizon	$h=1$	$h=5$	$h=22$	$h=1$	$h=5$	$h=22$	$h=1$	$h=5$	$h=22$	$h=1$	$h=5$	$h=22$	$h=1$	$h=5$	$h=22$
Window length	250	250	250	500	500	500	1000	1000	1000	1500	1500	1500	2000	2000	2000
FNAPT	0.0063	0.0113	0.0055	0.0053	0.0097	0.0078	0.0086	0.056	0.0633	0.0116	0.0865	0.0981	0.0252	–	–
FNCO	0.0132	0.006	0.0063	0.0109	0.0067	0.0089	0.0102	0.0308	0.0622	0.0121	0.0577	0.0818	0.0243	–	–
FNER	0.0132	0.0059	0.0067	0.0127	0.0073	0.0124	0.0107	0.0363	0.0738	0.0123	0.0662	0.0902	0.0267	–	–
FNHEA	0.0113	0.008	0.0081	0.0052	0.0054	0.0073	0.0069	0.0163	0.0411	0.0097	0.0319	0.0697	0.0166	0.0572	0.0968
FNIND	0.0045	0.0172	0.0124	0.0037	0.0114	0.0078	0.004	0.0218	0.0343	0.005	0.0597	0.0618	0.0308	–	–
FNMAL	0.0106	0.055	0.0501	0.0019	0.0117	0.0179	0.0022	0.0037	0.0124	0.0062	0.0124	0.0206	0.012	0.0416	0.0433
FNOFF	0.0055	0.0015	0.0035	0.006	0.0028	0.0087	0.0055	0.0198	0.0603	0.0081	0.0347	0.0741	0.0167	0.0713	–
FNRES	0.0055	0.0066	0.0043	0.0046	0.0076	0.009	0.0079	0.0563	0.0773	0.0119	0.0816	–	0.0266	–	–
FNRET	0.0135	0.004	0.0062	0.0112	0.0013	0.0049	0.0115	0.0072	0.0396	0.0157	0.0122	0.047	0.0221	0.0251	0.0694
FNSHO	0.0114	0.0022	0.0016	0.0098	0.0016	0.0025	0.0154	0.0088	0.0376	0.0203	0.0132	0.0453	0.0253	0.0239	0.0703

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 lengths of the rolling-estimation window used to compute forecasts. The HAR-RV model without EMVID is the benchmark model, and the HAR-RV extended to include EMVID is the rival model. The alternative hypothesis is that the rival model has a smaller MSPE than the benchmark model. The benchmark and the rival models are estimated on sectoral data for realized volatility. 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 3 The effect of the COVID-19 pandemic (out-of-sample tests)

Panel A: Before the COVID-19 pandemic															
Forecast horizon	$h=1$	$h=5$	$h=22$	$h=1$	$h=5$	$h=22$	$h=1$	$h=5$	$h=22$	$h=1$	$h=5$	$h=22$	$h=1$	$h=5$	$h=22$
Window length	250	250	250	500	500	500	1000	1000	1000	1500	1500	1500	2000	2000	2000
Realized variance	–	–	–	0.0993	–	0.0356	–	0.0413	0.0351	–	0.0704	–	–	–	–
Realized volatility	0.0272	–	0.0101	0.0097	0.0551	0.0545	0.0112	0.0597	0.0479	0.0663	–	–	–	–	–
Panel B: During the COVID-19 pandemic															
Forecast horizon	$h=1$	$h=5$	$h=22$	$h=1$	$h=5$	$h=22$	$h=1$	$h=5$	$h=22$	$h=1$	$h=5$	$h=22$	$h=1$	$h=5$	$h=22$
Window length	250	250	250	500	500	500	1000	1000	1000	1500	1500	1500	2000	2000	2000
Realized variance	0.0313	0.0270	0.0174	0.0234	0.0337	0.0241	0.0131	0.0192	0.0143	0.0102	0.0120	0.0066	0.0090	0.0101	0.0036
Realized volatility	0.0088	0.0014	0.0015	0.0090	0.0015	0.0015	0.0085	0.0216	0.0344	0.0108	0.0532	0.0565	0.0195	0.0960	0.0900

Note: This table reports results for the baseline model. Results for the period of time before the COVID-19 pandemic are obtained when 250 forecasts are deleted at the end of the sample period. Results for the period of time during the COVID-19 pandemic are obtained when only the 250 forecasts at the end of the sample period are being used. The results are (*p*-values) of the Clark-West test for an equal mean-squared prediction error (MSPE) for alternative forecast horizons and alternative lengths of the rolling-estimation window used to compute forecasts. The HAR-RV model without EMVID is the benchmark model, and the HAR-RV extended to include EMVID is the rival model. The alternative hypothesis is that the rival model has a smaller MSPE than the benchmark model. The extended models include realized skewness, realized kurtosis, realized jumps, and a leverage effects as additional predictors. Realized volatility is defined as the square root of the realized standard variance. The model that is being used to forecast realized volatility features the square root of infectious diseases as a predictor. 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 *SE*.

observe significant test results mainly for the short/intermediate rolling-window lengths before the pandemic, all test results are significant for the COVID-19 subsample period.[5]

4 | CONCLUSION

Given the recent turmoil in the financial markets due to the outbreak of the COVID-19 pandemic, this paper extends the literature on forecasting US REITs market variance, derived from intraday data, in a novel direction by exploring the predictive power of a daily newspaper-based metric of uncertainty associated with infectious diseases (EMVID). When the information from this index is included in a HAR-RV model, we find that the EMVID index significantly improves the forecasting performance of the benchmark HAR-RV model that does not include this index. The result is robust to the inclusion of leverage, realized jumps, realized skewness, and realized kurtosis, and also carries over to 10 sub-sectors as well.

Given the tremendous growth of REITs as an asset class, and hence, the importance of accurate variance forecasts in the computation of optimal investment positions, our findings suggest that incorporating uncertainty associated with infectious diseases in forecasting models can help to improve the design of portfolios that include REITs. As part of future research, it would be interesting to extend our study to international REITs markets.

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CONFLICT OF INTEREST

The authors declare no conflict of interest.

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ENDNOTES

[1] In-sample analyses of the impact of policy-related and financial market uncertainties can be found in the works of Ajmi et al. (2014), Sadhwani et al. (2019), and Odusami (2020).

[2] Earlier studies on modeling and forecasting of REITs volatility were primarily based on Generalized Autoregressive Conditional Heteroscedasticity (GARCH)-type models (see Lee and Pai (2010), Zhou and Kang (2011), and Pavlova et al. (2014), for detailed reviews of this literature).

[3] 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.

[4] See: https://www.reit.com/news/blog/market-commentary/outlook-reits-during-covid-19-crisis.

[5] Similarly, visual inspection of a graph (not reported, but available upon request) of the cumulated sum of squared forecast error clearly showed the strong contribution of infectious diseases to forecast accuracy during the recent pandemic.

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