Testing the Forecasting Power of Global Economic Conditions for the Volatility of International REITs using a GARCH-MIDAS Approach

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Abstract:

We examine the power of global economic conditions (GECON) in forecasting the daily return volatility of various international Real Estate Investment Trusts (REITs) indices. To this end, we use the GARCH-MIDAS framework due to the mixed frequencies of the variables under study and given its merit of circumventing the problems of information loss due to data aggregation and biases through data disaggregation. The results show evidence of forecast gains in the model that accommodates GECON, and significant in-sample forecastability where improvements in global economic conditions lower the risk associated with the international REITs particularly in the US and emerging markets. Further analysis shows the possibility of gaining higher returns on REITs by exploiting the information contents of GECON. A robustness analysis indicates that other measures of global economic conditions such as Global Weakness Index (GWI) and Global Intensity Index (GII) contain lower forecasting power than GECON but with significant improvements in their forecast outcomes when combined with the latter using the principal components analysis. Consequently, monitoring the global economic dynamics *via* GECON as well as other indices (GWI and GII) is crucial for optimal investment decisions.

Keywords: REITs volatility; global economic conditions; mixed data analysis; GARCH-MIDAS model; forecasting

JEL Codes: C32, C53, E32, R30

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1. Introduction

During the last decade, Real Estate Investment Trusts (REITs) have grown substantially as an investment instrument, driven by its accessibility to various investors irrespective of their portfolio size (Akinsomi et al., 2016) and its utility for asset allocation and risk reduction. According to the latest available figures covering the third quarter of 2021, the total market capitalization of REITs in 40 countries stands at over US $2.3 trillion, with the United States (US) being the dominant with a market capitalization of over $1.5 trillion (European Public Real Estate Association (EPRA), 2021).[1] Understandably, accurate forecasting of the volatility of REITs is an important issue for market players, since volatility (as a metric of risk) plays a crucial role in portfolio diversification, derivatives pricing, hedging and financial risk management (Granger and Poon, 2003). Moreover, REITs returns do not suffer from issues of measurement errors and high transaction costs compared to other real estate investments and, hence provides a perfect high-frequency proxy for the overall real estate market. This is particularly the case because, REITs earn most of their income from investments in real estate, being exchange-traded funds and also since trading occurs as common stocks (Marfatia et al., 2017). Given these characteristics, and the fact that the Global Financial Crisis (GFC) had its roots in the collapse of the US real estate sector, high-frequency forecastability of volatility of a relatively homogenous REITs sector, unlike the heterogeneous housing market, is of paramount importance to policymakers as well, given that it allows them to design appropriate policies to mitigate the potential negative impact of uncertainty in the REITs sector on the real economy (Marfatia et al., 2021).

In light of the importance of volatility modeling and predictability of the volatility of REITs, a large number of studies (see, for example, Devaney (2001), Stevenson (2002), Cotter and Stevenson (2008), Bredin et al. (2007), Lee and Pai (2010), Zhou and Kang (2011), Pavlova et al. (2014), among others) have relied on the univariate Generalized Autoregressive Conditional Heteroscedasticity (GARCH)-type models. At this stage, it must be pointed out that there is a recent literature on the role of economic activity, i.e., low frequency macroeconomic variables, on the volatility of stock markets (Asgharian, 2013; Engle et al., 2013; Conrad et al., 2014; Conrad and Loch, 2015). Given this, and motivated by the fact that REITs are similar in nature to equities (Nyakabawo et al., 2018), we aim to extend the existing line of research on forecasting REITs

[1] See: https://prodapp.epra.com/media/EPRA_Total_Markets_Table_-_Q3-2021-rev_1638350675348.pdf for more details.

volatility based on the information content of economic activity. For our purpose, we use the GARCH variant of mixed data sampling (MIDAS), i.e., the GARCH-MIDAS model. The GARCH-MIDAS avoids the loss of information that would have resulted by averaging the daily (realized) volatility to a lower monthly frequency (Das et al., 2019). In this regard, some recent papers have relied on intraday data to forecast volatility of the REITs returns at daily frequency (see, for example, Zhou (2017), Odusami (2021a, 2021b), Bonato et al. (2021a, b, forthcoming)). The main idea behind the GARCH-MIDAS model is that volatility is not just volatility, but that there are different components to volatility namely, one pertaining to short-term fluctuations and the other to a long-run component, with the latter likely to be (negatively) affected by economic activity as stressed by Engle and Lee (1999) and Engle and Rangel (2008), Rangel and Engle (2012).

Borrowing from the literature on stock markets outlined above, we can also conjecture a negative relationship between economic conditions and REITs market volatility. The underlying theoretical channel can be elaborated as follows. The present value model of asset prices (Shiller, 1981a, 1981b) can be used to show that asset market volatility, and hence REITs volatility, depends on the volatility of cash flows and the discount factor. Given that worsening of economic conditions (such as in crises periods) affects the volatility of variables that reflect future cash flows by generating economic uncertainty (Bernanke, 1983), and the discount factor (Schwert, 1989), one can hypothesize a negative relationship between economic conditions and REITs market volatility.

Against this backdrop, the objective of our analysis is to forecast daily REITs return volatility of not only the US, but also developed (excluding the US) and emerging blocs, based on a new monthly measure of global economic conditions, developed by Baumeister et al. (2020). This index covers conditions of not only real economic activity, commodity (excluding precious metals and energy) prices, financial indicators, transportation, uncertainty, expectations, weather, and energy market-related indicators. Hence, it essentially encapsulates the various measures that capture the economic conditions of the world economy (not just in the US), all of which have been severely affected recently by the COVID-19 pandemic, to forecast REITs market volatility, which too has also been deeply affected during the coronavirus outbreak (Akinsomi, 2020). Given that this global economic conditions index (GECON) is available at a monthly frequency, we rely on the GARCH-MIDAS model to help predict REITs volatility on a daily basis (to avoid loss of information). The decision to forecast volatility at a daily frequency is not only due to the underlying statistical need to provide more accurate measures of volatility (Ghysels et al., 2019),[2] but also because high-frequency forecasts are important for investors in terms of making timely portfolio decisions, given that daily volatility forecasts features prominently in the context of Value-at-Risk (VaR) estimates (Ghysels and Valkanov, 2012).

To the best of our knowledge, this study is the first attempt to forecast the daily volatility of REITs returns using a broad index of global economic conditions (GECON) based on a GARCH-MIDAS approach. Notably, our study compliments the recent work of Salisu et al., (2020, 2022a), which highlights the important predictive role of the GECON index for volatility of precious metals and energy-based commodities in a GARCH-MIDAS framework as well.

The remainder of the paper is organized as follows: Section 2 discusses the data, while Section 3 outlines the econometric framework; Section 4 presents the empirical results from the in-sample and out-sample predictive analyses, with Section 5 concluding the paper.

2. Data

The data used in this study covers real estate investment trusts (REITs) and global economic conditions (GECON).

Six different REITs indices are used at the daily frequency, namely the Financial Times Stock Exchange (FTSE) REITs for the US, the world, developed countries, emerging countries, world excluding the US, and developed countries excluding the US. All these REITs are denominated in US dollar. They are free-float adjusted, market capitalization-weighted indices designed to track the performance of listed real estate companies. The constituents of each REIT index are screened on liquidity, size, and revenue. The FTSE USA REIT measures the performance of the US REIT industry at both industry-wide level and sector-by-sector basis. It covers data centers, diversified, healthcare, industrial, industrial/office mixed, lodging/resorts, office, residential, retail, self-storage, and speciality. The FTSE World REIT measures the performance of listed real estate companies in both developed and emerging countries worldwide, covering 38 countries. The FTSE Developed REIT covers Australia, Austria, Belgium, Canada, Finland, France, Germany, Hong Kong, Ireland, Israel, Italy, Japan, Netherlands, New Zealand, Norway, Singapore, Spain, Sweden,

[2] Ghysels et al. (2019) compare the GARCH and RV methodologies by producing multiperiod-ahead forecasts and conclude that the MIDAS-based model yields the most precise forecasts of in-and out-of-sample volatility.

Switzerland, UK, USA. The FTSE Emerging REIT covers Brazil, Chile, China, Czech Republic, India, Indonesia, Kuwait, Malaysia, Mexico, Philippines, Russia, Saudi Arabia, South Africa, Taiwan, Thailand, Turkey, UAE. The daily REIT indices are obtained from the DataStream of Refinitiv. They have different start dates (see Table 1), as dictated by their data availability.

The GECON index is at the monthly frequency, obtained from Baumeister et al., (2020)[3]. It is derived by applying the expectation-maximization algorithm to 16 indicators associated with commodity prices, economic activity, financial indicators, transportation, uncertainty and expectation measures, weather, and energy-related indicators (Baumeister et al., 2020). Hence, it is an elaborate indicator of the global economic conditions pertaining to not only macroeconomic variables but financial and commodity markets as well as behavioural variables and climate-related risks. The start and end data of the GECON index is shown in Table 1. For robustness in the empirical section, we consider two variants of the measure of global economic conditions namely, Global Weakness Index (GWI) and Global Intensity Index (GII), as developed by Leiva-León et al. (2020).[4] The GWI measures the share of the world economy facing a recession at a given month, while the GII indicates how deep (buoyant) an unfolding global recession (expansion) can get, in a timely fashion. However, GWI and GII are only available till March 2021.

After calculating the daily log returns of each REIT index as the logarithm of the ratio of two consecutive daily prices, we plot in Figure 1 the time behavioural pattern of the returns of each of the six REITs and the levels of the GECON. The reader is referred to Figures A1 and A2 in the Appendix for the time series plots of GWI and GII along with the REITs.

[3] The data is available for download from: https://sites.google.com/site/cjsbaumeister/research.
[4] The relevant data can be obtained from: https://sites.google.com/site/daniloleivaleon/global_weakness.

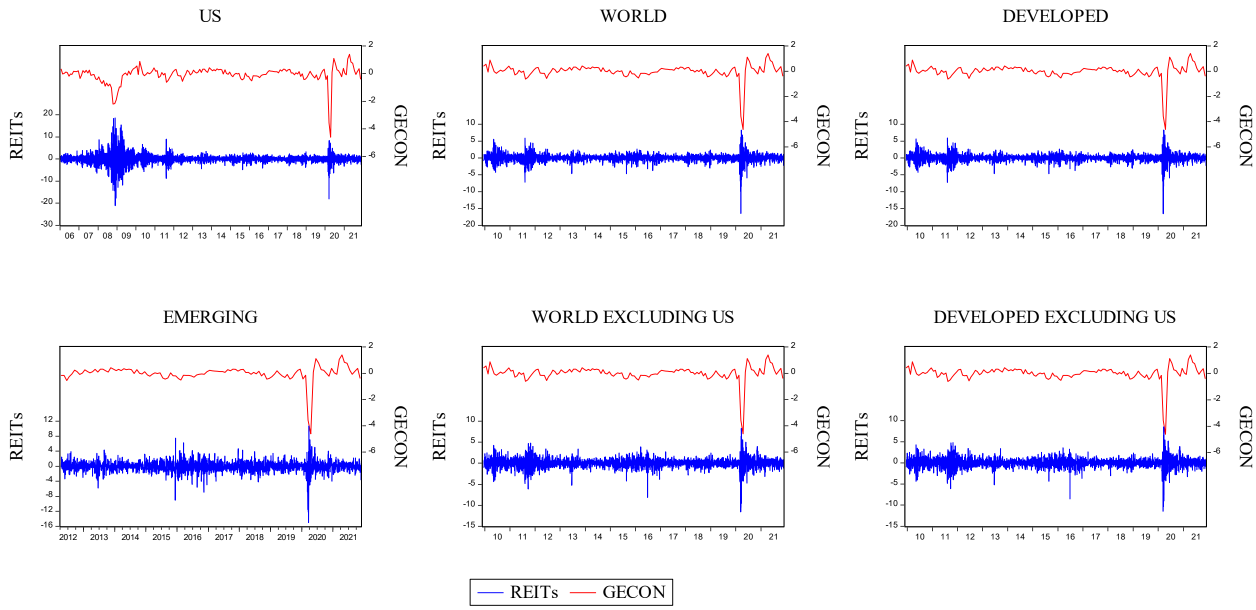

Figure 1: Time plot of the behavioural Pattern in the returns of REITs and the levels of GECON

We present some descriptive summaries (Table 1) and preliminary analysis (Table 2) of the data used in this study to better understand its behaviour, which would inform the choice of method to be adopted. The average daily returns on all the REITs (except that of emerging countries) are found to be positive, negatively skewed and leptokurtic (exhibiting excess kurtosis). The standard deviation of daily returns shows that US REITs seems to be more volatile than other REITs. However, the coefficient of variation reveals that the variability is highest for the world REITs (excluding the US REITs). The monthly series are negatively skewed for GECON and GWI, but positively skewed for GII, although they are all leptokurtic; they have 191 (GECON) and 183 (GWI and GII) data points compared to the high frequency (daily) of REITs that have data points ranging between 2,514 (corresponding the data for emerging countries) and 4,141 (corresponding the data for the US). Given that we are using a dataset involving a mixed of frequency, i.e. daily (high) REITs and monthly (low) GECON series, the adoption of the GARCH-MIDAS seems necessary and adequate to simultaneously accommodate mixed (daily and monthly) frequencies within one estimation framework. Furthermore, our preliminary analysis in Table 2 shows that all the variables exhibit conditional heteroscedasticity (except GWI) and autocorrelation at the specified lags; a formal confirmatory indication of the volatile nature of the series. Hence, the need to appropriately account for ARCH effect and serial correlation cannot be ignored. Again, the GARCH-MIDAS model framework fit in properly; hence, the justification for our choice.

Table 1: Summary Statistics

	Mean	Std. Dev.	Skewness	Kurtosis	CV	N	Frequency	Start Date	End Date
				REITs					
USA	1.42E-04	2.04E-02	-0.26	21.59	14358.45	4141	Daily	17-Jan-06	30-Nov-21
WORLD	2.33E-04	1.09E-02	-1.49	28.95	4684.12	3130	Daily	17-Dec-09	30-Nov-21
DEVELOPED	2.45E-04	1.09E-02	-1.47	28.87	4465.71	3130	Daily	17-Dec-09	30-Nov-21
EMERGING	-4.53E-04	1.40E-02	-1.11	17.46	-3091.83	2514	Daily	16-Apr-12	30-Nov-21
WORLD EX. US	1.19E-05	1.12E-02	-0.99	16.17	93722.69	3130	Daily	17-Dec-09	30-Nov-21
DEVELOPED EX. US	4.62E-05	1.11E-02	-0.93	15.73	24082.25	3130	Daily	17-Dec-09	30-Nov-21
				Global Economic Conditions					
GECON	-7.82E-02	6.09E-01	-3.63	24.52	-778.97	191	Monthly	Jan-06	Nov-21
GWI	-3.79E-02	5.70E-01	-3.08	20.88	-1500.89	183	Monthly	Jan-06	Mar-21
GII	2.73E-01	1.80E-01	1.37	6.48	65.82	183	Monthly	Jan-06	Mar-21

Note: This table shows the summary statistics of daily returns of REITs, and the level of three global economic conditions (GECON, GWI, GII). Std. Dev. is the standard deviation of the variables; CV is the coefficient of variation, obtained as the percentage ratio of the standard deviation to the mean; N is the sample size in each case.

Table 2: Preliminary Results

	$ARCH(5)$	$ARCH(10)$	$ARCH(20)$	$Q(5)$	$Q(10)$	$Q(20)$	$Q^2(5)$	$Q^2(10)$	$Q^2(20)$
				REITs					
USA	333.25***	210.97***	117.69***	15.27***	31.62***	89.91***	2473.20***	4830.40***	8616.30***
WORLD	260.15***	148.95***	82.30***	65.51***	118.58***	173.35***	1569.70***	2263.50***	2800.30***
DEVELOPED	254.30***	145.54***	80.70***	64.54***	117.75***	172.74***	1548.80***	2236.20***	2773.60***
EMERGING	234.22***	147.89***	81.92***	11.90**	27.66***	51.32***	1633.20***	2337.50***	2639.90***
WORLD EX. US	237.45***	125.73***	66.32***	14.19***	33.15***	68.52***	1917.30***	2803.70***	3290.20***
DEV EX. US	218.23***	116.58***	61.60***	13.78**	31.60***	67.73***	1748.60***	2585.40***	3043.60***
				Global Economic Conditions					
GECON	23.29***	11.73***	5.66***	13.49**	22.89***	37.71***	78.52***	78.85***	79.67***
GWI	0.29	0.54	0.26	16.98***	27.07***	43.83***	1.68	6.42	7.59
GII	9.78***	4.96***	2.44***	15.80***	18.51**	20.81	35.71***	35.77***	36.04**

Note: ***, ** and * indicate significance of tests at 1%, 5% and 10% levels, respectively. The preliminary results for the REITs returns' series for the country/region are presented in the first panel titled, 'REITs', while three global economic conditions, namely GECON, GWI, GII are presented in the second panel titled, 'GECON'. The applied tests consist of the Autoregressive Conditional Heteroscedasticity (ARCH) effect test, which is a formal test for volatility; and the Q-statistic and Q^2–statistic testing for the presence of autocorrelation and higher order autocorrelation, respectively; at lags 5, 10, and 20.

3. Methodology

The aim of this study is to predict the volatility in a daily response variable (REITs) with a predictor variable (GECON) that is naturally occurring in a lower, monthly, frequency. The GARCH-MIDAS model framework is well suited for such data frequency mix, given its merit of circumventing the problems of information loss due to data aggregation and biases through data disaggregation (using some splicing techniques). The feats of this model framework ensures that the information inherent in the original data are adequately harnessed, since the variables are simultaneously incorporated in their natural frequencies. The MIDAS-based model framework has been shown to outperform alternative models that impose uniformity in the frequency of the variables that are incorporated in the predictive model.[5]

The REITs return series is defined as $r_{i,t} = ln\left(P_{i,t}\right) - ln\left(P_{i-1,t}\right)$, where $P_{i,t}$ is the price on the i^{th} day of the t^{th} month, $t = 1, 2, \ldots, T$ and $i = 1, \ldots, N_t$ respectively denote the monthly and daily frequencies, while N_t indicates the number of days in a given month *t*. The GARCH-MIDAS model essentially focuses on the conditional variance equation comprising two components: the short-run and long-run components, which are both captured in equation (1):[6]

$$r_{i,t} = \mu + \sqrt{\tau_t \times h_{i,t}} \times \varepsilon_{i,t}, \qquad \forall\ i = 1, \ldots, N_t \tag{1}$$

$$\varepsilon_{i,t} \left| \Phi_{i-1,t} \sim N\left(0,1\right)\right. \tag{2}$$

where μ, is the unconditional mean of the return series, $h_{i,t}$ is the short-run component of the conditional variance and it is of a high (daily) frequency that typically follows: GARCH(1,1) process, and τ_t is the long-run component with a low (monthly) frequency. The disturbance term in equation (2), $\varepsilon_{i,t}$, follows a Gaussian distribution, and $\Phi_{i-1,t}$ denotes information set at day $i-1$ of month t.

[5] See Salisu et al. (2020, 2022a, b) and Salisu and Gupta (2021) for recent applications of the GARCH-MIDAS variant albeit without considering REITs return volatility. Engle et al. (2013) provide technical details of the multiplicative decomposition of conditional variance into high- and low-frequency components of the MIDAS model.

[6] Although, a typical GARCH model has two equations, the mean and the variance equations both of which can accommodate predictor series, however, in the GARCH-MIDAS case, the predictor series are limited to the variance (long run) equation. In other words, the GARCH-MIDAS is more suitable for the predictability of volatility rather than returns. In any case, investors pay more attention to the risks and uncertainties associated with their securities whose behavior can be evaluated with the long run component of the GARCH-MIDAS model.

The short-run component of the conditional variance $\left(h_{i,t}\right)$ is defined in (3):

$$h_{i,t} = (1-\alpha-\beta) + \alpha \frac{\left(r_{i-1,t}-\mu\right)^2}{\tau_i} + \beta h_{i-1,t} \tag{3}$$

where α and β represent the ARCH and GARCH terms, respectively; conditioned to be positive and/or at least zero ($\alpha > 0$ and $\beta \geq 0$) and sum up to less than one $(\alpha + \beta < 1)$. The low (monthly) frequency long-run component (τ_t) is transformed into daily frequency (τ_i), without loss of generality (see for technical details, Engle et al., (2013)). In essence, the days in month t are rolled back without keeping track of it, and in turn yields the daily long-run component defined in (4):

$$\tau_i^{(rw)} = m^{(rw)} + \theta^{(rw)} \sum_{k=1}^{K} \phi_k\left(w_1, w_2\right) X_{i-k}^{(rw)} \tag{4}$$

where the "(rw)" appearing as superscript indicates that a rolling window framework (which allows the secular long-run component to vary daily) is implemented; m is the long-run component intercept; θ is the MIDAS slope coefficient that indicates the predictive value of the incorporated exogenous predictor X_{i-k} where $\phi_k\left(w_1, w_2\right) \geq 0,\ \ k = 1,...,K$ is the weighting scheme that must sum to unity for the identification of the model parameters. Hinging on the documented flexibility and popularity of the beta weighting scheme (Colacito et al., 2011), the two-parameter-beta polynomial is transformed into one-parameter- beta polynomial weighting scheme, by setting w_1 to one, and $w_2 = w$, so that a monotonically decreasing optimal weighting function is obtained (Engle et al. 2013). The weighting function is thus defined as:

$$\phi_k\left(w_1, w_2\right) = \frac{\left[k/(K+1)\right]^{w_1-1} \times \left[1-k/(K+1)\right]^{w_2-1}}{\sum_{j=1}^{K}\left[j/(K+1)\right]^{w_1-1} \times \left[1-j/(K+1)\right]^{w_2-1}} \Leftrightarrow \phi_k(w) \frac{\left[1-k/(K+1)\right]^{w-1}}{\sum_{j=1}^{K}\left[1-j/(K+1)\right]^{w-1}} \tag{5}$$

where, the weights are positive such that higher weights are assigned to more recent observations. Given the above description, we are able to evaluate the in-sample predictability of the exogenous factor which is the global economic condition in the return volatility of REITs wherein we test whether the MIDAS slope coefficient (θ), a measure of the predictive value of GECON, is statistically different zero or not. While a statistically significant slope coefficient would indicate that GECON does influence REITs return volatility, the associated sign determines the direction of the relationship.

We further conduct out-of-sample forecast evaluation of our GECON-based GARCH-MIDAS model as significant in-sample predictability of GECON may not necessarily translate into improved out-of-sample forecasts of the return volatility of REITs. We compare the forecasts of our proposed GARCH-MIDAS model (GARCH-MIDAS-GECON) that incorporates GECON as a predictor with the conventional GARCH-MIDAS that is based on realized volatility (GARCH-MIDAS-RV) which typically serves as the benchmark model in the absence of an exogenous factor. The out-of-sample forecasts are evaluated under three forecast horizons (h = 30, 60 and 120) using an appropriate forecast evaluation tool. Here, we employ the modified Diebold and Mariano (1995; DM) test statistic proposed by Harvey et al. (1997), which is defined as:

$$DM^{*}=\left(\sqrt{\frac{T+1-2h+T^{-1}h\left(h-1\right)}{T}}\right)DM \qquad (6)$$

where DM^{*} is the modified DM statistic and h is the forecast horizon. The original DM test is defined in (6) as:

$$DM=\frac{\bar{d}}{\sqrt{V\left(d\right)/T}}\sim N\left(0,1\right) \qquad (6)$$

where $\bar{d}=\frac{1}{T}\sum_{t=1}^{T}d_{t}$ is the mean of the loss differential $d_t \equiv g\left(\varepsilon_{it}\right)-g\left(\varepsilon_{jt}\right)$; $g\left(\varepsilon_{it}\right)$ and $g\left(\varepsilon_{jt}\right)$ are loss functions of the forecast errors (ε_{it} and ε_{jt}, respectively) from the competing models; and $V\left(d_t\right)$ is the unconditional variance of the loss differential d_t. We test the null hypothesis that asserts that the forecast precision of the contending model pairs are equal, that is, $H_0: d=0$ against an alternative hypothesis, $H_0: d\neq 0$. A rejection of the null would imply that both model forecasts are statistically different and the associated sign would indicate the direction of preference; with negative DM statistics indicating preference in favour of our predictive GARCH-MIDAS-GECON over GARCH-MIDAS-RV model, while the reverse holds for positive DM statistics. We use 75% of the full sample for the out-of-sample forecast evaluation; and consider three out-of-sample forecast horizons: 30-day-, 60-day-, and 120-day ahead.

4. Empirical results

Our results are presented in two main stages. The first stage is focused on the in-sample predictability of monthly GECON for daily return volatilities of the considered REITs, wherein our interest is in the statistical significance of the GARCH-MIDAS slope coefficient, among other significant parameters of the model (see Table 3). The second stage is to ascertain that the observed in-sample performance is not dependent on the estimation sample period. In essence, we examine the out-of-sample performance of our GARCH-MIDAS model construct that incorporates information on global economic conditions in comparison with the conventional GARCH-MIDAS variant that is based on realized volatility. The interest is to ascertain whether the incorporation of the exogenous variable (here, GECON) provides additional information to improve the forecast of the modelled volatility. Therefore, we consider both statistical and economic-based (economic significance) validation of the incorporated exogenous variable and the results are respectively presented in Tables 4 and 5. On the former, we consider different out-of-sample forecast horizons, h = 30, 60 and 120; where one-day ahead forecasts are iteratively generated over the specified forecast horizons, using a rolling window approach.

4.1. Results on the forecasting power of GECON for the return volatility of REITs

Table 3 presents the in-sample predictability results for the REITs return volatility over the available sample periods. The table contains the estimates of the parameters of the GARCH-MIDAS model that incorporates GECON as a predictor variable. The parameters include the unconditional mean for the returns (μ); the ARCH term (α); the GARCH term (β); the MIDAS slope coefficient (θ) for the exogenous factor; the adjusted beta polynomial weight (w); and the long-run constant term (m). We consider the statistical significance of all the GARCH-MIDAS model parameters, but more importantly the MIDAS slope coefficient (θ) that indicates the stance of predictability of REITs return volatility due to GECON. All the model parameters are statistically significant except the unconditional mean of the REITs returns of emerging, world excluding US, and developed markets excluding US. The one-parameter beta polynomial weight (w) is observed to be greater than one and statistically significant across the six considered REITs, an indication of the fact that far distant lags of the observations are assigned less weights than the more recent observations. We find evidence of high volatility persistence with mean-reverting characteristics given that the statistically significant ARCH (α) and GARCH (β) terms of the short-run component across the six REITs sum up to values less than one. By implication, shocks impact on REITs return volatilities would not be permanent but may take a longer time to completely fizzle out.

Table 3: GARCH-MIDAS Estimation Results

REITs Coverage	μ	α	β	θ	w	m
USA	5.11E-04*** [1.58E-04]	1.36E-01*** [1.03E-02]	8.25E-01*** [1.27E-02]	-8.23E-02*** [2.50E-02]	3.80E+01* [2.12E+01]	1.14E-04*** [1.29E-05]
WORLD	3.59E-04** [1.78E-04]	1.53E-01*** [1.44E-02]	7.82E-01*** [2.00E-02]	-9.76E-02*** [3.09E-02]	1.00E+01*** [3.29E+00]	7.87E-05*** [8.55E-06]
DEVELOPED	3.80E-04** [1.80E-04]	1.51E-01*** [1.44E-02]	7.82E-01*** [2.01E-02]	-9.63E-02*** [2.95E-02]	1.03E+01*** [3.36E+00]	7.89E-05*** [8.22E-06]
EMERGING	-2.56E-04 [3.04E-04]	1.11E-01*** [1.82E-02]	8.13E-01*** [3.31E-02]	-1.12E-01*** [2.25E-02]	3.91E+01*** [1.33E+01]	1.53E-04*** [1.30E-05]
WORLD EX. US	1.47E-04 [1.81E-04]	1.38E-01*** [1.61E-02]	8.10E-01*** [2.42E-02]	-1.64E-01*** [5.29E-02]	7.06E+00*** [2.20E+00]	9.21E-05*** [9.09E-06]
DEVELOPED EX. US	2.31E-04 [1.79E-04]	1.41E-01*** [1.61E-02]	8.07E-01*** [2.45E-02]	-1.93E-01*** [5.86E-02]	6.49E+00*** [1.78E+00]	9.23E-05*** [9.15E-06]

Note: The figures in each cell are the estimates of the GARCH-MIDAS-GECON model parameters in Equation 4 and their corresponding standard errors in square brackets. ***, ** and * indicate statistical significance at 1%, 5% and 10% level, respectively.

The statistical significance of the MIDAS slope coefficient (θ) indicates whether the incorporated exogenous variable has potential predictive power for the modelled volatility. From the results in Table 3, the estimates of θ are negative and statistically significant across all the REITs returns. The observed negative slope coefficients, in line with theory, suggest that improvements in global economic conditions may lower the risk associated with REITs regardless of the unit involved, i.e., whether developed or emerging markets with or without the US is considered. This outcome supports the in-sample predictive value of GECON for the return volatility of REITs. However, this evidence may not necessarily translate into improved out-of-sample forecasts. Thus, we further ascertain this feat of GECON predictability for the out-of-sample scenario using the modified DM test of Harvey et al. (1997) as a statistical tool, and thereafter we assess the economic gains of incorporating GECON in the GARCH-MIDAS model framework for REITs return volatility. The idea of considering the economic significance of the out-of-sample forecasts is to see whether an investor can exploit the information contents of GECON in the predictive model to obtain significant increases in REITs returns.

4.2. Out-of-Sample forecast evaluation

The main interest here is to compare the out-of-sample forecast performance of the GARCH-MIDAS-GECON with the conventional GARCH-MIDAS-RV. We consider three out-of-sample forecast horizons (h) where h = *30, 60* and *120* days ahead, under a rolling window approach that iteratively generates one-day ahead forecast. We employ the modified DM test, and expect a negative and statistically significant DM statistic for our GARCH-MIDAS model (GARCH-MIDAS-GECON) construct that incorporates GECON as a predictor variable to outperform the conventional GARCH-MIDAS-RV model based on realized volatility. The results from Table 4 show statistically significant negative test statistics across all the REITs under study, except for developed markets excluding the US. The outcome of the latter category reinforces the historical dominance of the US in the context of financial markets of developed countries (see Salisu et al., (2022c)), to the extent that excluding it from this category tends to undermine the out-of-sample predictability of GECON. Notwithstanding, our GARCH-MIDAS model construct has more cases where it is preferred and the feat is consistent across the out-of-sample forecast horizons. The implication of the result is that GECON can be considered a good predictor when assessing the risk associated with REITs of the US and emerging markets in particular, and by extension, profit maximizing investors may find the outcome useful when taking investment decisions particularly those that relate to the portfolio in question. In the next section, we further evaluate the possibility of gaining higher returns on REITs by exploiting the predictive value of GECON.

Table 4: Modified DM test results

REITs Coverage	$h = 30$	$h = 60$	$h = 120$
USA	-4.1219***	-6.5834***	-10.3345***
WORLD	-4.7509***	-7.1469***	-10.8169***
DEVELOPED	-4.6591***	-7.1102***	-10.7602***
EMERGING	-7.2774***	-7.9787***	-11.8340***
WORLD EX. US	-6.5346***	-8.6940***	-11.0278***
DEVELOPED EX. US	6.5981***	9.0774***	2.3987**

Note: This table reports the modified DM test statistics that compare the predictive power of the GARCH-MIDAS-GECON model against the GARCH-MIDAS-RV specification. A significantly negative value indicates preference of former over the latter, while significant positive values suggest otherwise. *** denotes statistical significance at 1% level.

4.3. Economic significance

Having ascertained the statistical significance of the out-of-sample forecast performance of our GARCH-MIDAS model in comparison with the conventional variant that is based on realized volatility (GARCH-MIDAS-RV), it is also important to provide some practical results that will appeal to potential and existing investors in REITs. This analysis involves examining the economic significance of our out-of-sample forecasts (see, Liu et al. (2019); Salisu et al. (2022a, b)), by determining whether the incorporation of GECON in the forecast model provides additional gains to REITs investors. Put differently, can the forecasting gains translate into economic? To answer this, we follow Liu et al. (2019) approach to examine the economic significance of the forecast performance of our GARCH-MIDAS-GECON model relative to the GARCH-MIDAS-RV model. Assuming a typical mean-variance utility investor who holds investment positions in a risky asset and a risk-free asset; the optimal weight, ψ_t, allocated to the risky asset in the optimization procedure is defined as:

$$\psi_t = \frac{1}{\gamma}\frac{\lambda \hat{r}_{t+1} + \left(\lambda - 1\right)\hat{r}_{t+1}^{f}}{\lambda^2 \hat{\sigma}_{t+1}^2} \tag{7}$$

where γ denotes a risk aversion coefficient; λ denotes a leverage ratio that is set to 6 and 8, on the premise that a margin account at 10% level is often maintained by investors (Zhang et al., 2018); $\hat{r}_{t+1}$ denotes a commodity return forecast at time $t+1$; $\hat{r}_{t+1}^{f}$ denotes a risk-free rate (here, 3-month US Treasury bill rate, derived from the FRED database of the Federal Reserve Bank of St. Louis); and $\hat{\sigma}_{t+1}^2$ denotes a 30-day moving window estimate of daily return volatility. The certainty equivalent return (CER) is defined based on the investor's optimal weight (ψ_t) and given in equation (8) as

$$CER = \bar{R}_p - 0.5(1/\gamma)\sigma_p^2 \tag{8}$$

where, $\bar{R}_p$ and σ_p^2 are respectively the mean and variance of the out-of-sample period portfolio return (R_p) in which $R_p = \psi\lambda(r - r^f) + (1-\psi)r^f$ and its variance is defined as $Var(R_p) = \psi^2\lambda^2\sigma^2$; where σ^2 denotes excess return volatility. The economic significance is thus assessed by maximizing the objective utility function defined in equation (9)

$$\begin{aligned} U(R_p) &= E(R_p) - 0.5(1/\gamma)Var(R_p) \\ &= \psi\lambda(r - r^f) + (1-\psi)r^f - 0.5(1/\gamma)\psi^2\lambda^2\sigma^2 \end{aligned} \tag{9}$$

In Table 5 and in line with Liu et al. (2019) and Salisu et al. (2022a, b), we present the results of the economic gains arising from the inclusion of GECON in the GARCH-MIDAS model framework relative to the GARCH-MIDAS-RV. The table contains six panels, each representing one REIT index. We adjust our contending GARCH-MIDAS models' predicted returns using a risk-free rate, and subsequently obtain the relevant statistics earlier described, which will form the basis for determining the preferred GARCH-MIDAS model variant, in economic sense. The reported statistics include the mean portfolio returns, volatility, certainty equivalent returns, Sharpe ratios (the risk-adjusted returns) which is defined as $SP = (R_p - r^f)\big/\sqrt{Var(R_p)}$. We then assess the economic gains on the basis of the contending model that yields the maximum returns, CER and risk-adjusted returns (SP); and minimum volatility (see, Liu et al. (2019)). With the level of risk aversion and leverage ratio specified as 3 and 6, respectively; we find GARCH-MIDAS-GECON model to yield higher economic gains than the GARCH-MIDAS-RV across the REITs except in the case of World and Emerging, given that the GARCH-MIDAS-GECON based risk-adjusted returns are higher than those of the GARCH-MIDAS-RV. Similar feats are observed when the leverage parameter is specified as 8 and the risk aversion specified as 3, an indication of insensitivity of the results to the model parameters (see Table 5).

From the foregoing, we find that accounting for global economic conditions in the predictive model for REITs return volatility not only yields more precise volatility forecasts in the in-sample as well as in the out-of-sample, but also yields some significant economic gains. Our conclusion of economic gains is determined by the model with the large Sharpe Ratio. Although, there are two cases (emerging and world excluding the US) where our statistically preferred model does not yield higher economic gains than the GARCH-MIDAS-RV, we focus on the cases where the gains are higher in the former (GARCH-MIDAS-GECON) than in the latter (GARCH-MIDAS-RV), but with a caveat that the stance may be REITs-specific. In the case of higher economic gains, which are in higher proportion, it is imperative that GECON does have predictive potentials that are both statistically and economically significant; and hence, GECON can be considered an important predictor variable when modelling REITs return volatility. This happens particularly to be the case for the US, world, and developed REITs, but to some extent this result is driven by the US. Interestingly, while GECON can produce statistical gains for emerging REITs but not economic gains, the reverse holds true for developed markets after excluding the US.

Table 5: Economic significance of incorporating GECON in the forecasting model

Predictor	Returns	Volatility	CER	SP	Returns	Volatility	CER	SP
	$\gamma = 3$ and $\lambda = 6$				$\gamma = 3$ and $\lambda = 8$			
				US REITs				
RV	9.4277	0.1698	9.4277	18.8352	11.6570	0.3025	11.6570	18.1646
GECON	9.4610	0.1694	9.4610	**18.9375**	11.7008	0.3018	11.7008	**18.2635**
				WORLD REITs				
RV	6.9856	0.1043	6.9856	16.4714	8.5148	0.1857	8.5148	15.8897
GECON	7.1230	0.1045	7.1230	**16.8762**	8.6922	0.1862	8.6922	**16.2806**
				DEVELOPED REITs				
RV	7.1490	0.1085	7.1490	16.6404	8.7240	0.1933	8.7240	16.0510
GECON	7.2461	0.1086	7.2461	**16.9270**	8.8495	0.1935	8.8495	**16.3279**
				EMERGING REITs				
RV	13.4021	0.4198	13.4021	18.1118	16.7547	0.7463	16.7547	17.4651
GECON	13.1829	0.4119	13.1829	17.9436	16.4673	0.7318	16.4673	17.3009
				WORLD EXCLUDING US REITs				
RV	2.7311	0.0796	2.7311	3.7717	3.0511	0.1414	3.0511	3.6805
GECON	2.4850	0.0798	2.4850	2.8949	2.7349	0.1418	2.7348	2.8352
				DEVELOPED EXCLUDING US REITs				
RV	5.2561	0.0855	5.2561	12.2721	6.2864	0.1521	6.2863	11.8434
GECON	5.9605	0.0923	5.9605	**14.1350**	7.1923	0.1641	7.1923	**13.6401**

Note: This table presents the economic gains from incorporating the GECON as a predictor in the GARCH-MIDAS model over the alternative specification that excludes GECON as a predictor.

4.4. Additional analyses

As a form of robustness, as stated earlier, we consider additional analyses involving other recent measures of global economic conditions developed by Leiva-León et al. (2020) namely, the Global Weakness Index (GWI) and Global Intensity Index (GII). We consider these indices (GWI and GII) singly and thereafter, each in combination with extant global economic conditions (GECON) to generate a factor from the principal component analysis framework. In all, there are four different variants to be considered in this section and these include GWI, GII, GECON+GWI and GECON+GII. Again, the resulting forecast from the models are subjected to out-of-sample evaluation using the statistical-based tool (modified Diebold and Mariano) as well as the economic-based tool.

On the statistical-based evaluation (Table 6), the incorporation of GWI and GII on its own into the GARCH-MIDAS framework does not seem to yield additional information that is not already captured by the realized volatility, since both GARCH-MIDAS-GWI and GARCH-MIDAS-GII fail to outperform the conventional GARCH-MIDAS-RV across the country/region REITs considered, except for the case of Emerging REITs. However, in combination with GECON which was earlier used in the main estimation, the out-of-sample forecast performance seems to improve, and consistently so across the three specified forecast horizons and REITs composition (except in the case of Developed excluding USA). This stance obtained from incorporating the principal components analysis (PCA) factor variable aligns with that of GECON in the main estimation result, with some improvement of the former after combining with other indices of global economic conditions. This goes to show the need for investors to not only monitor the global economic dynamics with GECON but also juxtapose this with the behavior of other indices such as GWI and GII in order to take well informed and optimal investment decisions. On the economic significance of incorporating global economic condition measures, we find GWI to yield economic gains in the case of US, world and developed markets excluding the US REITs; while for GII, economic gains are observed under REITs of the world excluding the US and developed excluding the US (Table 7). However, when combined with GECON, the economic gains are higher and observed in more REITs composition than in the cases where GWI and GII are singly incorporated. It appears, though unsurprisingly, that US REITs is a major driving force in REITs, since we observe a reduction in and/or no economic gains when the US is excluded from the REITs composition. Again, global economic condition is not just statistically significant but also economically relevant in the prediction of REITs, irrespective of the defined composition.

But in general, we also highlight that the GECON index being a broader index beyond economic activity variables (such as) in the GII and GWI index, carries relatively stronger predictive value, which should not come as a surprise, given the widespread evidence that REITs are connected with not only the real economy, but other financial markets, and are also affected by behavioral variables and climate-related risks (Ajmi et al., 2014; Sadhwani et al., 2019; Tiwari et al., 2020; Giglio et al., 2021, among others).

Table 6: Modified DM test result

h	US	WORLD	DEVELOPED	EMERGING	WORLD EX. US	DEVELOPED EX. US
			GWI			
30	4.9758***	5.6365***	5.4940***	-7.5630***	6.6232***	5.8540***
60	7.7918***	8.2601***	8.2096***	-8.2745***	9.0279***	8.5359***
120	11.8197***	11.5412***	11.5384***	-12.7333***	11.6253***	11.1070***
			GII			
30	5.0749***	5.7133***	5.5796***	-7.4918***	6.9945***	6.4755***
60	8.0256***	8.5526***	8.5024***	-8.1213***	9.4070***	9.0969***
120	12.6255***	12.6963***	12.6819***	-12.2911***	11.5221***	11.1793***
			GECON+GWI			
30	-4.1309***	-4.7540***	-4.6618***	-7.2774***	-6.5345***	6.5981***
60	-6.5953***	-7.1523***	-7.1157***	-7.9786***	-8.6938***	9.0774***
120	-10.3528***	-10.8262***	-10.7692***	-11.8339***	-11.0275***	2.3986**
			GECON+GII			
30	-4.1219***	-4.7509***	-4.6618***	-7.2774***	-6.5345***	6.5979***
60	-6.5834***	-7.1469***	-7.1156***	-7.9787***	-8.6938***	9.0772***
120	-10.3346***	-10.8169***	-10.7692***	-11.8341***	-11.0275***	2.3977**

Table 7: Economic Significance

		Returns	Volatility	CER	SP	Returns	Volatility	CER	SP
		$\gamma = 3 \quad and \quad \lambda = 6$				$\gamma = 3 \quad and \quad \lambda = 8$			
		Global Weakness Index							
US	RV	9.4277	0.1698	9.4277	18.8352	11.6570	0.3025	11.6570	18.1646
	GWI	9.4200	0.1694	9.4199	**18.8388**	11.6469	0.3017	11.6468	**18.1680**
World	RV	6.9856	0.1043	6.9856	16.4714	8.5148	0.1857	8.5148	15.8897
	GWI	6.9556	0.1031	6.9556	**16.4718**	8.4763	0.1836	8.4762	**15.8903**
Developed	RV	7.1490	0.1085	7.1490	16.6404	8.7240	0.1933	8.7240	16.0510
	GWI	7.1178	0.1073	7.1178	16.6367	8.6839	0.1912	8.6839	16.0475
Emerging	RV	13.4021	0.4198	13.4021	18.1118	16.7547	0.7463	16.7547	17.4651
	GWI	13.2849	0.4145	13.2849	18.0450	16.6034	0.7369	16.6033	17.3998
World EX. US	RV	2.7311	0.0796	2.7311	3.7717	3.0511	0.1414	3.0511	3.6805
	GWI	2.9653	0.0792	2.9653	4.6128	3.3402	0.1408	3.3402	4.4581
Developed EX. US	RV	5.2561	0.0855	5.2561	12.2721	6.2864	0.1521	6.2863	11.8434
	GWI	5.3296	0.0828	5.3296	**12.7281**	6.3807	0.1473	6.3807	**12.2830**
		Global Intensity Index							
US	RV	9.4277	0.1698	9.4277	18.8352	11.6570	0.3025	11.6570	18.1646
	GII	9.4018	0.1692	9.4018	18.8048	11.6240	0.3014	11.6239	18.1358
World	RV	6.9856	0.1043	6.9856	16.4714	8.5148	0.1857	8.5148	15.8897
	GII	6.9647	0.1036	6.9647	16.4616	8.4883	0.1845	8.4883	15.8811
Developed	RV	7.1490	0.1085	7.1490	16.6404	8.7240	0.1933	8.7240	16.0510
	GII	7.1268	0.1078	7.1268	16.6262	8.6959	0.1921	8.6959	16.0380
Emerging	RV	13.4021	0.4198	13.4021	18.1118	16.7547	0.7463	16.7547	17.4651
	GII	13.1997	0.4097	13.1997	18.0179	16.4935	0.7283	16.4935	17.3735
World EX. US	RV	2.7311	0.0796	2.7311	3.7717	3.0511	0.1414	3.0511	3.6805
	GII	2.9645	0.0798	2.9645	**4.5942**	3.3504	0.1417	3.3504	**4.4715**
Developed EX. US	RV	5.2561	0.0855	5.2561	12.2721	6.2864	0.1521	6.2863	11.8434
	GII	5.1983	0.0812	5.1983	**12.3943**	6.2118	0.1444	6.2118	**11.9610**
		PCA1: Global Economic Condition + Global Weakness Index							
US	RV	9.4277	0.1698	9.4277	18.8352	11.6570	0.3025	11.6570	18.1646
	PCA1	9.4671	0.1695	9.4671	**18.9450**	11.7086	0.3021	11.7086	**18.2708**
World	RV	6.9856	0.1043	6.9856	16.4714	8.5148	0.1857	8.5148	15.8897
	PCA1	7.1230	0.1046	7.1230	**16.8713**	8.6922	0.1863	8.6922	**16.2759**
Developed	RV	7.1490	0.1085	7.1490	16.6404	8.7240	0.1933	8.7240	16.0510
	PCA1	7.2474	0.1087	7.2474	**16.9268**	8.8513	0.1936	8.8513	**16.3277**
Emerging	RV	13.4021	0.4198	13.4021	18.1118	16.7547	0.7463	16.7547	17.4651
	PCA1	13.1829	0.4119	13.1829	17.9435	16.4673	0.7318	16.4673	17.3009
World EX. US	RV	2.7311	0.0796	2.7311	3.7717	3.0511	0.1414	3.0511	3.6805
	PCA1	2.4849	0.0798	2.4849	2.8946	2.7347	0.1418	2.7347	2.8348
Developed EX. US	RV	5.2561	0.0855	5.2561	12.2721	6.2864	0.1521	6.2863	11.8434
	PCA1	5.9603	0.0923	5.9603	**14.1346**	7.1921	0.1641	7.1921	**13.6398**
		PCA2: Global Economic Condition + Global Intensity Index							
US	RV	9.4277	0.1698	9.4277	18.8352	11.6570	0.3025	11.6570	18.1646
	PCA2	9.4610	0.1694	9.4610	**18.9375**	11.7008	0.3018	11.7008	**18.2636**
World	RV	6.9856	0.1043	6.9856	16.4714	8.5148	0.1857	8.5148	15.8897
	PCA2	7.1230	0.1045	7.1230	**16.8762**	8.6922	0.1862	8.6922	**16.2806**
Developed	RV	7.1490	0.1085	7.1490	16.6404	8.7240	0.1933	8.7240	16.0510
	PCA2	7.2475	0.1087	7.2475	**16.9269**	8.8513	0.1936	8.8513	**16.3277**
Emerging	RV	13.4021	0.4198	13.4021	18.1118	16.7547	0.7463	16.7547	17.4651
	PCA2	13.1829	0.4119	13.1829	17.9435	16.4673	0.7318	16.4673	17.3009
World EX. US	RV	2.7311	0.0796	2.7311	3.7717	3.0511	0.1414	3.0511	3.6805
	PCA2	2.4849	0.0798	2.4849	2.8945	2.7347	0.1418	2.7347	2.8348
Developed EX. US	RV	5.2561	0.0855	5.2561	12.2721	6.2864	0.1521	6.2863	11.8434
	PCA2	5.9604	0.0923	5.9604	**14.1348**	7.1922	0.1641	7.1922	**13.6400**

5. Conclusion

In this study, we examine the predictive value of global economic conditions (GECON) in forecasting the volatility of international REITs. To this end, we employ the GARCH-MIDAS framework since the naturally occurring frequencies for the variables of interest are mixed and given its merit of circumventing the problems of information loss due to data aggregation and biases through data disaggregation. Our empirical analysis is conducted for both the in-sample and out-of-sample forecasts (with multiple forecast horizons) while the modified Diebold and Mariano test is used for the forecast evaluation of the contending models (that is, GARCH-MIDAS-GECON and the conventional GARCH-MIDAS which is the variant with Realized Volatility). The first results indicate that GECON has a statistically significant negative impact on the return volatility of international REITs implying that improvements in global economic conditions have the potential of lowering the risk associated with the international REITs. We further show evidence of forecast gains in the predictive model that accommodates GECON across multiple forecast horizons. We also demonstrate how an investor can derive higher returns on REITs by constructing an optimal portfolio that accounts for the information content of GECON. A robustness analysis indicates that other measures of global economic conditions such as Global Weakness Index (GWI) and Global Intensity Index (GII) contain lower predictive value than GECON but with significant improvements when combined with the latter using the principal components analysis.

Our results have important implications for both investors and policymakers. By using the information content of an index summarizing global economic conditions around the world (i.e., GECON), investors and portfolio managers could accurately forecast the volatility of REITs market returns, particularly of the US and emerging economies, which could help them to design optimal portfolios, especially under the current extreme situation of deteriorating economic conditions due to the outbreak of COVID-19. Moreover, with REITs volatility providing a high-frequency measure of uncertainty in the housing sector, its accurate forecasting would provide information about the future path of the domestic economy contingent on the evolution of uncertainty. This can then be incorporated into mixed-frequency models to produce forecasts of wide ranges of low-frequency variables measuring domestic economic activity, thus allowing the design of appropriate policy responses to prevent the possibility of economic downturns.

In future research, it would be interesting to use the GECON to forecast the volatility of REITs of individual developed (besides the US) and emerging markets, and possibly forecast variability at the sectoral level of REITs.

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Appendix

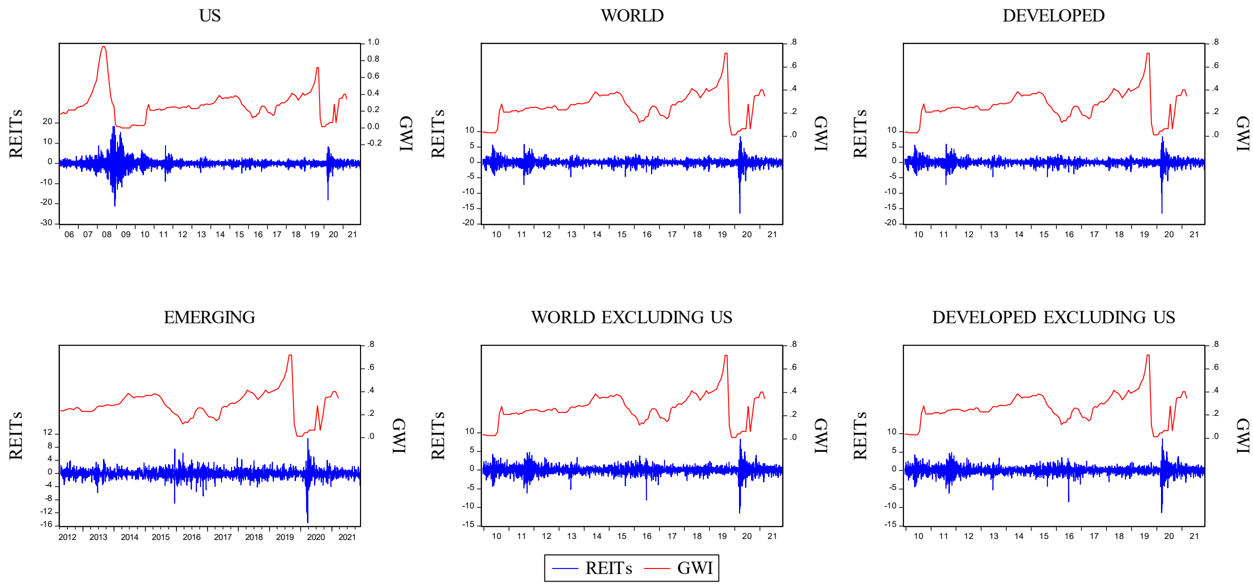

Figure A1: Time plot of the behavioural Pattern in REITs and GWI

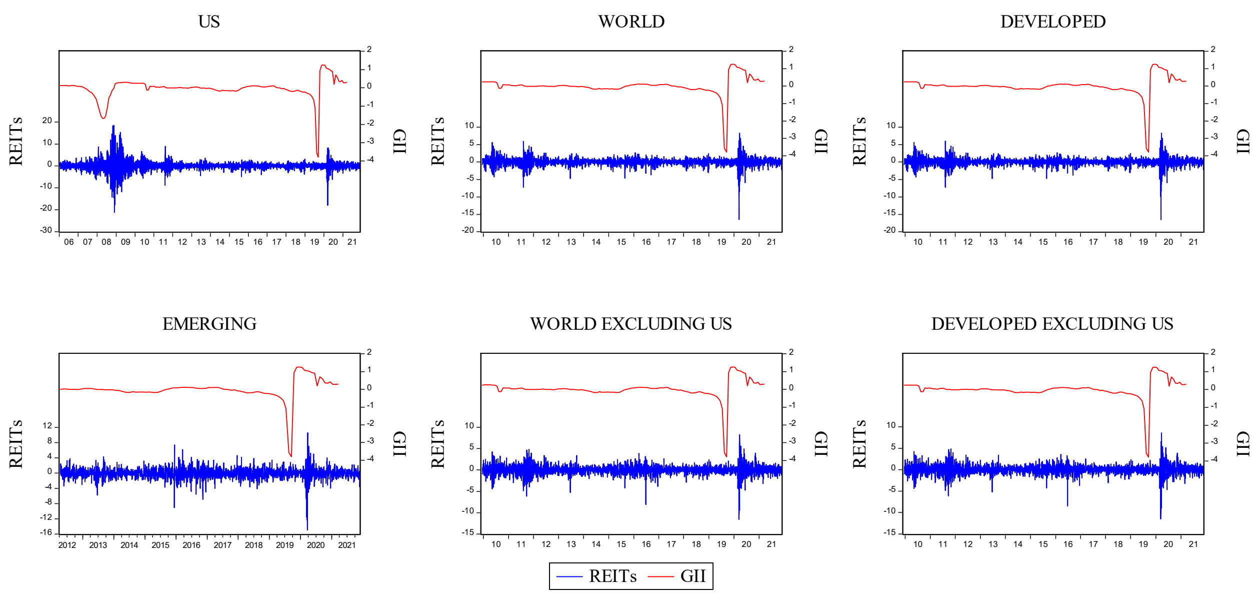

Figure A2: Time plot of the behavioural Pattern in REITs and GII