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Book

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Energy Market Uncertainties and US State-Level Stock Market Volatility: A GARCH-MIDAS Approach

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Abstract

In this paper, we employ the generalized autoregressive conditional heteroscedasticity-mixed data sampling (GARCH-MIDAS) framework to forecast the daily volatility of state-level stock returns in the United States (US) based on monthly metrics of oil price uncertainty (OPU), and relatively broader energy market-related uncertainty index (EUI). We find that over the daily period of (February) 1994 to (September) 2022 and various forecast horizons, in 37 out of the 50 states, the GARCH-MIDAS model with EUI can outperform the benchmark, i.e., the GARCH-MIDAS-realized volatility (RV), which, in turn, holds for at most 18 cases under OPU. The statistical evidence is further strengthened when we are able to detect higher utility gains delivered for 42 states by the GARCH-MIDAS-EUI in comparison to the GARCH-MIDAS-RV. Our findings have important implications for investors and policymakers.

JEL Codes: C32, C53, G10, Q02

Keywords: Monthly Oil Price and Energy Market Uncertainties, Daily State-Level Stock Returns Volatility, GARCH-MIDAS, Forecasting

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1. Introduction

There exists a large literature relating oil price uncertainty to both in- and out-of-sample predictability of stock returns (see Rahman (2021), Balcilar et al. (2022), and Salisu et al. (2022a) for detailed reviews).[1] Surprisingly, the number of studies successfully predicting the second-moment movement of aggregate and sectoral-level stock market due to oil price uncertainty is currently restricted to a few published works (see, for example, Feng et al. (2017), Dutta et al. (2020), Qin and Bai (2022), Salisu et al. (forthcoming a)).[2] We aim to build on this limited line of research by, first, studying the forecasting ability of the recently developed measure of oil price uncertainty (OPU) by Abiad and Qureshi (2023) for the volatility of the stock returns of the 50 states of the United States (US). Second, realizing that oil prices are not necessarily a good proxy for energy prices (Kilian, 2008; Melichar, 2016; Cross and Nguyen, 2018), we analyze whether the forecasting performance of regional stock returns volatility can be improved by the energy-related uncertainty indexes (EUIs) of Dang et al. (2023), which improves upon the OPU of Abiad and Qureshi (2023), by combining information on the uncertainties associated with the overall energy market and the macroeconomy. These OPU and EUI indexes, as will be discussed in the next section in detail, rely on counts of terms related to the oil or energy markets and uncertainty in the economy from newspapers and country-reports, and, hence, are likely to be exogenous to the volatility in stock markets, by not being model-generated volatilities (Ludvigson et al., 2021). This is important to ensure that our predictive models do not suffer from the issue of endogeneity bias, given that there are indeed studies that have delved into the conditional volatility spillovers between the oil and equity markets (see, for example, Bouri et al. (2015), Maghyereh et al. (2016), Antonakakis et al. (2017)).

Our inclination towards a regional analysis is rooted in the understanding that primary business activities of companies tend to be concentrated around their headquarters (Pirinsky and Wang, 2006; Chaney et al., 2012). Consequently, stock prices likely reflect a notable regional influence, leading investors to favour local firms in their investment portfolios (Coval and Moskowitz, 1999, 2001; Korniotis and Kumar, 2013). Obviously, the forecasting exercise we undertake in this research should be of immense value to investors, given that accurate forecasts of stock-market

[1] Detailed discussions of the stock-oil nexus can be found in Degiannakis et al. (2018) and Smyth and Narayan (2018).
[2] The reader is also referred to the working paper of Vlastakis et al. (2020) in this context.

volatility carry widespread implications for portfolio selection, derivative pricing, and risk management (Poon and Granger, 2003; Rapach et al., 2008).

As far as the econometric framework is concerned, we use the generalized autoregressive conditional heteroskedasticity (GARCH) variant of the mixed data sampling (MIDAS), i.e., the GARCH-MIDAS model, as originally developed by Engle et al. (2013).[3] The reason behind this is that, while the stock market data is at a daily frequency, the OPU and EUI used as predictors are available only at the monthly frequency, and hence, the modelling of volatility requires a MIDAS-based approach, with this aspect ensuring that there is no loss of information by averaging the daily data to a lower frequency (Clements and Galvão, 2008). Technically speaking, the GARCH-MIDAS approach is motivated by the argument 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 aspect, with the latter likely to be affected by slow-moving predictors, i.e., the OPU and EUI in our case. At this stage, we must emphasize that the decision to forecast state-level stock returns 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), but also because high-frequency forecasts are important for investors in terms of making timely portfolio decisions, given that daily volatility forecast features prominently in the context of Value-at-Risk (VaR) estimates (Ghysels and Valkanov, 2012). Naturally, a real-time forecasting analysis, being a well-established, stronger test of predictability (Campbell, 2008), should be of immense value to investors than in-sample predictions.

Before we move on to the econometrics analyses, it would make sense to outline the main theoretical background through which OPU and EUI are likely to impact the stock returns volatility. In this regard, we rely on the present value model of asset prices, as outlined in Shiller (1981a; 1981b). This framework can be used to show that asset (stock) market volatility depends on the variability of cash flows and the discount factor. Therefore, time-variation in asset (stock) market volatility can be linked to the evolving degree of uncertainty regarding future discount factors and expected cash flows (Bernanke, 1983). 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

[3] There exists a large literature involving the utilization of variants of the GARCH-MIDAS models to predict daily US stock returns volatility, and the reader is referred to Salisu et al. (2022b, 2023, forthcoming b, c) and Segnon et al. (2024) in this regard.

uncertainties associated with the oil market or the overall energy sector, as well as future macroeconomic conditions, would cause a proportional change in the asset (stock) returns volatility (Schwert, 1989). Furthermore, as outlined above, oil market uncertainty can impact stock returns and, hence, indirectly, stock market volatility through the so-called "leverage effect" of Black (1976).

To the best of our knowledge, this is the first paper to compare the role of narrow and broad measures of uncertainties associated with the forecastability of the stock returns of the 50 US states. The rest of the paper is structured as follows: Section 2 provides an overview of the data, while Section 3 outlines the basics of the methodology. Section 4 presents the results, and Section 5 concludes the paper.

2. Data and Preliminary Analyses

As pointed out earlier, the GARCH-MIDAS model is used to assess the out-of-sample predictability of daily state-level stock returns volatility due to monthly measures of oil- and energy market-related uncertainties, i.e., OPU and EUI. The state-level stock market indices, from which we compute the log returns, are derived from the Bloomberg terminal, which, in turn, creates these indexes by taking the capitalization-weighted index of equities domiciled in a given state.

Abiad and Qureshi (2023) constructed their OPU index based on frequency counts of newspaper articles, following the methods outlined in Baker et al. (2016). In constructing their index, Abiad and Qureshi (2023) consider the set of English-language articles with at least 100 words published in 50 newspapers around the world lodged in the Factiva database. For this set of articles, and for each newspaper and month, these authors count the ones that contain the words: "oil", "petrol", "petroleum", "gas" or "gasoline" within two words of "pric*", and in which "pric*" appears within two words of "uncert*", "volatil*", "fluct*", "erratic", "unstable", "unsteady", "chang*", "unpredict*", "vary*", "swing*" or "move*". They scale these raw OPU counts by the number of articles in the same newspaper and month. Next, they standardize each newspaper's scaled frequency counts to have a unit standard deviation during the period of its data coverage. Finally, they average over the resulting newspaper-level series by month and normalize the average OPU index value to a mean of 100 over the associated sample size.[4]

[4] The data is available for download from: https://policyuncertainty.com/oil_uncertainty.html.

Dang et al. (2023) construct monthly EUI indexes in three steps. First, they construct an economic uncertainty index for each country, as in Ahir et al. (2022), by counting the frequency of terms like "uncertain," "uncertainty," and "uncertainties" in each monthly country report of the Economist Intelligence Unit. They then divide that count by the number of words in the same report and normalize each resulting country-level index to a mean of 100 over time. In the second step, the authors take the same approach to construct an energy-related index for each country from the same source. For this purpose, they use the energy-related keywords listed in Table 1 of their paper, most of which are in line with Afkhami et al. (2017). Finally, in the third step, they compute the monthly (28) country-level EUI values as the simple mean of the economic uncertainty index and the energy-related index. Since we are working with US stock market data, we use the corresponding EUI in our analyses.[5]

Based on data availability, the OPU-based exercise covers (1st) February 1994 to (31st) December 2019, while the sample period associated with the EUI is (1st) February 1996 to (30th) September 2022.

Table 1 displays the summary statistics and some preliminary results, showing the data characteristics of the stock returns from the 50 US states, and OPU and EUI. On average, all US state stock returns were positive, with Washington showing the least variability and Wyoming the highest. Approximately 48% of cases displayed positive skewness, while 52% showed negative skewness alongside leptokurtic distributions. Evidence of conditional heteroscedasticity was present in most cases, except for Maine and New Mexico, while serial correlation was detected in all states except New Mexico. The EUI and OPU displayed positive averages, positive skewness and leptokurtic distributions, with evidence of conditional heteroscedasticity and serial correlation. The observed features cum the mixed frequency of our data are most appropriately accommodated in a GARCH-MIDAS framework, which we discuss next.

[INSERT TABLE 1 HERE]

[5] The data can be accessed at: https://policyuncertainty.com/energy_uncertainty.html.

3. Methodology

We describe the GARCH-MIDAS model, as outlined by Engle et al. (2013), which comprises an unconditional mean and a conditional variance that is multiplicatively decomposed into high and low-frequency components. The GARCH-MIDAS model specification is defined in Equations (1) to (5) as:

$$r_{i,t} = \mu + \sqrt{h_{i,t} \times \tau_t} \times \varepsilon_{i,t}, \qquad \forall\ i = 1,2,...,N_t \tag{1}$$

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

$$\tau_i^{(rw)} = m_i^{(rw)} + \theta_i^{(rw)} \sum_{k=1}^{K} \phi_k\left(\omega\right) X_{i-k}^{(rw)} \tag{3}$$

$$\phi_k\left(w\right) = \frac{\left[1-k/\left(K+1\right)\right]^{w-1}}{\sum_{j=1}^{K}\left[1-j/\left(K+1\right)\right]^{w-1}} \tag{4}$$

$$\varepsilon_{i,t} \mid \Phi_{i-1,t} \sim N(0,1) \tag{5}$$

where $r_{i,t} = ln\left(P_{i,t}\right) - ln\left(P_{i-1,t}\right)$ is the i^{th} day of the month t state-level stock price $\left(P_{i,t}\right)$ returns for fifty states of the US, with N_t indicating the number of days in month t; μ is the unconditional mean of the stock returns; $h_{i,t}$ and τ_t are respectively the short-run (assumed to follow a GARCH(1,1) process) and long-run components of the conditional variance $\left(\sqrt{h_{i,t} \times \tau_t}\right)$ part of Equation (1); α and β in Equation (2) represent the ARCH and GARCH terms, respectively, that are constrained by the following restrictions, $\alpha > 0$, $\beta \geq 0$ and $\alpha + \beta < 1$; in Equation (3) m is the long-run constant, θ is the slope coefficient that indicates the impact of the realized volatility (RV) or the incorporated exogenous variable (OPU and EUI) for the state-level stock returns volatility; $\phi_k\left(w\right)$ is a flexible (Colacito et al., 2011) one parameter beta polynomial weighting scheme6, such that $\phi_k\left(w\right) \geq 0$, $k = 1,2,\ldots,K$ and $\sum_{k=1}^{K} \phi_k\left(w\right) = 1$, for the model identification

6 This is obtained from the two-parameter beta weighting scheme $\phi_k\left(w_1, w_2\right) = \left[k/\left(K+1\right)\right]^{w_1-1} \times \left[1-k/\left(K+1\right)\right]^{w_2-1} \Big/ \sum_{j=1}^{K}\left[j/\left(K+1\right)\right]^{w_1-1} \times \left[1-j/\left(K+1\right)\right]^{w_2-1}$ by constraining w_1 to 1 and setting $w = w_2$.

condition to be satisfied; the imposed constraint $(w > 1)$ ensures that more recent lag observations are larger weights than distant lag observations, X_{i-k} represents the exogenous predictor (OPU or EUI); and the superscript "*rw*" denotes that a rolling window framework is employed for the estimation exercise; while $\varepsilon_{i,t} \mid \Phi_{i-1,t}$ is the information set that is available at the $(i-1)^{th}$ day of the month t is normally distributed.

The out-of-sample forecast precisions of our predictive GARCH-MIDAS-uncertainty variants are compared with the GARCH-MIDAS-RV (benchmark) model. We employ the modified Diebold-Mariano test of Harvey et al. (1997; DM*) defined in Equation (6), which is an extension of the conventional Diebold and Mariano (1995; DM) test defined in Equation (7), that is suited for paired non-nested model comparisons. The statistics are defined as follows in Equations (6) and (7):

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

$$DM = \frac{\bar{d}}{\sqrt{V(d)/T}} \sim N(0,1) \tag{7}$$

where DM^* denotes the modified DM statistic; T represents the number of the out-of-sample periods of the forecast errors and h represents the forecast horizon; $\bar{d} = 1/T\left[\sum_{t=1}^{T} d_t\right]$ indicates the average of the loss differential, $d_t \equiv g(\varepsilon_{it}) - g(\varepsilon_{jt})$; $g(\varepsilon_{it})$ and $g(\varepsilon_{jt})$ are loss functions of the forecast errors (ε_{it} and ε_{jt}, respectively) from the paired competing models; while $V(d_t)$ is the unconditional variance of the loss differential d_t. The DM* test null hypothesis asserts equality in the forecast precision of the paired non-nested contending models $(H_0 : d = 0)$ against a mutually exclusive alternative, $(H_1 : d \neq 0)$. Non-rejection of the null would imply that the forecast precisions of the paired models are equal, while the rejection would suggest inequality. The associated sign of the DM* statistic determines the direction of preference, such that a negative DM* statistic indicates outperformance of GARCH-MIDAS-uncertainty over the GARCH-MIDAS-RV model, and the converse if the DM* statistic is positive. The in-sample estimation is carried out on 75% of the full sample, while out-of-sample forecast evaluation is examine using the remaining 25%; under 20-, 60- and 120-day ahead forecast horizons.

4. Empirical Results

4.1. Statistical Significance

Here, we present the out-of-sample predictability results for the state-level stock returns volatility based on the RV and our incorporated uncertainty indexes (OPU or EUI). For the forecast evaluation, we employ the investigation of the DM^* test statistic. In this regard, we compare both the GARCH-MIDAS-uncertainty model variants with the conventional benchmark i.e., the GARCH-MIDAS-RV model, with the results reported in Table 2. The GARCH-MIDAS-OPU model is found to produce significantly accurate forecasts compared to the benchmark (GARCH-MIDAS-RV) in only 12, 18 and 17 states under h = 20, 60 and 180, respectively, with the benchmark being the standout performer in 28, 21 and 23 states for the corresponding forecast horizons.[7] However, when we look at the GARCH-MIDAS-EUI model, it outperforms the benchmark in a statistically significant manner in 37 states, while it is outperformed only in 4 regional units, consistently across the 3 forecasting horizons considered. The stark, stable, superior performance of the EUI is understandable, given its broader nature in capturing the uncertainty of the energy market relative to the OPU, thus vindicating our decision to utilize the former in our forecasting exercise.[8]

The results from the GARCH-MIDAS-EUI model are revealing in several ways. Firstly, the statistically significant negative values indicate that the EUI-based model provides a better fit and more accurate predictions of future volatility compared to the RV-based model. This underlines

[7] As a robustness check, we also utilized the stochastic volatility of the unpredictable component of oil price-reliant Oil Market Uncertainty Index – OMUI (Nguyen et al., 2022; Cross et al., 2022), with the data available for download from: https://sites.google.com/site/nguyenhoaibao/datasets/oil-market-uncertainty?authuser=0. But as can be seen from Table A1 in the Appendix, over the period of (1st) February, 1994 to (29th) May, 2020, the GARCH-MIDAS-OMUI model, just like its OPU variant, tends to produce weak results by outperforming the benchmark in a statistically significant manner for only 20 states.

[8] In a recent study, Sheng et al. (2022) depicted that the persistence of uncertainty tends to increase due to climate shocks, given this, we analysed if the newspapers-based metric of climate policy uncertainty (CPU), as developed by Gavriilidis (2021), when interacted with EUI can produce more accurate results for state-level stock returns volatility compared to those reported only for EUI. The CPU data can be downloaded from: https://policyuncertainty.com/climate_uncertainty.html. As can be seen from Table A2 in the Appendix, over the period of (1st) February, 1996 till (30th) September, 2022, the model with interaction outperforms the GARCH-MIDAS-RV only in 28 cases and is outperformed in 12 cases across the three forecast horizons. Clearly, the forecasting gains are lower in number when compared to that of the standalone EUI model, which is again indicative of the broad nature of the EUI possibly incorporating some of the information in the climate-related uncertainty as well.

the importance of incorporating broader market uncertainties, especially from the energy sector, into volatility forecasting models. Secondly, the significant predictive ability of the EUI-based model across multiple horizons suggests that energy market uncertainties have a persistent and prolonged impact on the volatility of stock returns, which is crucial for investors and policymakers in managing risks and formulating strategies. Thirdly, the strong performance of the EUI-based model across diverse states highlights the heterogeneous impact of energy uncertainties on different regional markets. This reinforces the idea that while some states may be more susceptible to energy market fluctuations due to their economic structure, the EUI serves as a comprehensive measure that captures these varied impacts effectively. The superiority of the EUI-based model could be attributed to its comprehensive nature, capturing a broader spectrum of uncertainties within the energy market which are highly relevant to the stock markets due to the critical role of energy in the economy. Finally, the enhanced predictability suggests that market participants consider a wide range of uncertainties beyond just oil prices when evaluating the future state of the economy and the stock market.

[INSERT TABLE 2 HERE]

4.2. Economic Significance

Having established the statistical superiority of the EUI over the EPU, we next examine the economic gains of incorporating the former as predictor for stock return volatility in the 50 states of the US, compared to that of the GARCH-MIDAS-RV model. This is essential to provide economic-based support to the statistical findings obtained through the DM* test-statistic.

In this regard, we consider a typical investor who guided by mean-variance utility consistently optimizes portfolios in comparison to a risk-free asset. The optimization involves the allocation of shares among investment options using optimal weight, w_t, defined as

$$w_t = \frac{1}{\gamma} \frac{\delta \hat{r}_{t+1} + \left(\delta - 1\right) \hat{r}^f_{t+1}}{\delta^2 \hat{\sigma}^2_{t+1}} \tag{8}$$

where γ denotes the coefficient of risk aversion; δ is a leverage ratio that we set to 6 and 8, given that investors often maintain a 10% margin; $\hat{r}_{t+1}$ is the stocks returns forecast at time $t+1$; $\hat{r}^f_{t+1}$ is a risk-free asset (3-month Treasury bill rate, as obtained from the FRED database of the Federal

Reserve Bank of St. Louis[9]); and $\hat{\sigma}^2_{t+1}$ is an estimate of return volatility, obtained as a 30-day moving window of daily returns. The certainty equivalent return (CER) for the investor's optimal portfolio allocation is defined in Equation (9)

$$CER = \bar{R}_p - 0.5\left(1/\gamma\right)\sigma_p^2 \tag{9}$$

where $\bar{R}_p$ is the out-of-sample mean; and σ_p^2 is the out-of-sample variance of the portfolio return, defined as $R_p = w\delta\left(r - r^f\right) + \left(1 - w\right)r^f$. The economic significance is determined by maximizing an objective function of a utility as in equation (10)

$$U\left(R_p\right) = E\left(R_p\right) - 0.5\left(1/\gamma\right)Var\left(R_p\right) = w\delta\left(r - r^f\right) + \left(1 - w\right)r^f - 0.5\left(1/\gamma\right)w^2\delta^2\sigma^2 \tag{10}$$

where $Var\left(R_p\right) = w^2\delta^2\sigma^2$ is the variance of the portfolio return, and σ^2 represents excess return volatility. A model is considered to have a more advantageous economic gain if it produces the highest returns, CER, and Sharpe ratio, defined by: $SR = \left(R_p - r^f\right)/\sqrt{Var\left(R_p\right)}$; and minimum volatility (see, Liu et al. (2019)).

Table 3 presents the outcomes of integrating EUI as a predictor for the volatility of stock returns across the 50 states in the US. The table showcases the average portfolio returns, volatility levels, and Sharpe ratios derived from GARCH-MIDAS-EUI and the benchmark GARCH-MIDAS-RV models. In comparison with the benchmark GARCH-MIDAS-RV model, our predictive model variant with EUI yield higher returns and Sharpe ratio metrics across 42 states. When the leverage ratio is set at either 6 or 8, the inclusion of EUI in our GARCH-MIDAS models produces enhanced economic benefits compared to the benchmark model. While similar economic advantages are observed regardless of the leverage parameters, returns and economic gains are relatively diminished when the leverage ratio is set at 8. Overall, the economic evaluation of portfolios constructed based on returns volatility forecasts indicates that integrating EUI not only leads to more accurate out-of-sample predictions but also results in greater utility gains, thus confirming the superior performance highlighted by the statistical approach involving the DM* test.

[9] The data can be downloaded from: https://fred.stlouisfed.org/series/DTB3.

An intuitive extension of the observed results reveals a direct link between incorporating broader economic indicators, such as the EUI, and the ability to predict stock returns volatility more accurately. The EUI encompasses a wider range of uncertainties, including those stemming from the energy sector, which is integral to the functioning of various state economies. This comprehensive approach provides a more robust framework for capturing market sentiments and potential risks, thus allowing for more informed investment strategies. By integrating the EUI into the volatility models, investors can gain nuanced insights that account for broader economic fluctuations, which are essential for optimizing risk-adjusted returns. The consistent outperformance of the EUI model across a significant number of states emphasizes the relevance of broad-based economic indicators in capturing market dynamics and underscores the necessity for investors to consider such measures in their risk assessment processes.

Moreover, the leverage ratio analysis, as indicated in the results, showcases the impact of different investment strategies under varying market conditions. By examining the performance of the EUI model under different leverage scenarios, investors can better understand the implications of leveraging in the context of uncertain market environments. The nuanced decrease in economic gains with higher leverage settings underlines the importance of leverage management in portfolio optimization, especially when dealing with predictive models that incorporate wide-ranging economic uncertainties. These findings underscore the practical implications of adopting advanced econometric models that integrate comprehensive economic indicators like the EUI. For policymakers and investors alike, the enhanced predictive capabilities and economic benefits offered by the EUI model provide compelling evidence for its application in forecasting stock return volatility. This not only aids in better portfolio management but also contributes to more resilient financial planning and policy formulation aimed at mitigating economic uncertainties. In summary, EUI serves as an effective predictor capable of enhancing the out-of-sample forecast accuracy of predictive models and delivering improved economic outcomes for investors.

[INSERT TABLE 3 HERE]

5. Conclusions

In this paper, we forecast daily US state-level stock returns volatility based on monthly measures of oil price uncertainty (OPU), and relatively broader energy market-related uncertainty index (EUI) using the GARCH-MIDAS framework over the period of February 1994 to September 2022. We find that in 37 out of the 50 states, the GARCH-MIDAS model with EUI can outperform the benchmark GARCH-MIDAS-RV, which, in turn, holds for at most 18 cases under OPU, emphasizing the need to look at a general measure of uncertainty associated with the overall energy market and the macroeconomy. This statistical evidence is further strengthened when we detect higher economic gains delivered for 42 states by the EUI-based GARCH-MIDAS in comparison to the benchmark.

On the basis of our findings, we can conclude that investors should rely more on elaborate indexes of energy market uncertainty, rather than the same for just the oil market while making their stock portfolio decisions. At the same time, being a measure of financial market uncertainty, the variability of stock returns is also a concern from a policy perspective, as it has been shown to impact economic activity negatively (Bloom, 2009; Jurado et al., 2015). Hence, high-frequency forecasts of stock market uncertainty, based on the information contained in EUI, would help policymakers to predict in real-time, i.e., nowcast, the future path of low-frequency state-level real activity variables, using MIDAS models (Bańbura, 2011), and in the process, allow them to develop appropriate and early policy responses to prevent possible regional recessions. Furthermore, the incorporation of broader energy market uncertainties into investment strategies and risk management practices could significantly benefit investors, particularly those with heavy exposures to state-level markets or energy sector assets. Investment funds, portfolio managers, and individual investors could refine their asset allocation, hedging strategies, and risk assessment models based on the enhanced forecasting performance of the EUI-based models, leading to potentially improved risk-adjusted returns.

For future research, several avenues appear promising. First, looking at a similar analysis at a wide-range of major industries locally and globally, could also be very informative from the perspective of investment implications (Wang et al., 2023). Second, investigating the interplay between energy market uncertainties and other macroeconomic factors, such as technological advancements, geopolitical events, or environmental policies, could yield deeper insights into the multifaceted drivers of stock market volatility.

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Table 1: Summary Statistics and Preliminary Analysis

States	Mean	Coefficient of Variation	Skewness	Kurtosis	$ARCH(5)$	$ARCH(10)$	$Q(5)$	$Q(10)$	$Q^2(5)$	$Q^2(10)$
Daily Data										
Alabama	3.78E-04	44.81	0.47	31.19	100.74***	82.65***	5.2427	24.5***	696.43***	1489.7***
Alaska	4.25E-04	43.97	1.50	78.34	124.39***	62.37***	25.139***	45.649***	585.83***	594.17***
Arizona	4.58E-04	37.63	0.36	21.69	102.74***	66.85***	5.0092	31.227***	708.01***	1257.3***
Arkansas	4.94E-04	31.25	0.34	8.62	139.23***	88.05***	33.647***	56.456***	1078.7***	1902***
California	6.26E-04	26.31	0.34	11.29	158.32***	98.81***	6.8852	37.119***	1209.5***	2169***
Colorado	2.11E-04	71.05	0.17	15.17	175.85***	109.17***	7.3465	23.038**	1262.8***	2305.7***
Connecticut	4.63E-04	33.63	0.00	13.08	249.49***	157.61***	9.9974*	19.514**	1907.3***	3529.7***
Delaware	3.19E-04	54.77	0.20	12.11	138.38***	90.89***	2.1264	14.947	1043.2***	1986.9***
Florida	3.39E-04	38.36	-0.35	14.46	387.11***	220.57***	4.4844	40.433***	2994.5***	5109.1***
Georgia	3.99E-04	30.56	-0.32	13.77	383.03***	213.80***	6.7649	31.344***	2790.5***	4548.2***
Hawaii	2.66E-04	52.27	0.13	14.91	246.97***	139.44***	10.704*	35.293***	2049.5***	3280***
Idaho	8.71E-04	35.92	1.31	20.46	12.46***	11.79***	5.4609	23.745***	73.314***	162.87***
Illinois	3.49E-04	31.74	-0.56	14.51	502.36***	283.11***	7.2638	37.159***	3639.4***	6075.1***
Indiana	5.37E-04	27.92	-0.79	27.26	34.61***	34.62***	4.8922	20.564**	221.08***	521.14***
Iowa	4.48E-04	35.54	0.26	21.98	178.39***	125.14***	0.4893	21.744**	1361.4***	2598.7***
Kansas	7.92E-05	237.92	0.71	23.57	56.46***	36.75***	2.1664	14.003	389.9***	631.71***
Kentucky	4.44E-04	30.37	-0.40	10.05	386.75***	214.28***	1.1032	14.977	2957.5***	5033.4***
Louisiana	2.30E-04	56.75	-0.39	16.89	383.22***	217.02***	6.6293	41.247***	3091.7***	4936.2***
Maine	9.43E-04	27.89	-3.49	253.54	0.29	0.33	10.504*	30.167***	1.4592	3.3868
Maryland	3.69E-04	39.34	-0.05	14.16	203.74***	137.17***	4.7212	14.203	1645.3***	3280.7***
Massachusetts	5.14E-04	31.64	0.23	12.26	169.28***	104.47***	26.298***	43.373***	1303.3***	2306***
Michigan	2.48E-04	53.83	-0.46	14.02	197.08***	115.38***	3.0238	28.018***	1500.5***	2542.1***
Minnesota	4.67E-04	25.77	-0.06	13.94	351.51***	214.96***	8.027	52.105***	2827.3***	5298.6***
Mississippi	3.77E-04	40.06	0.35	18.00	178.41***	109.45***	8.585	30.857***	1417.1***	2516.8***
Missouri	4.53E-04	28.29	-0.03	18.08	347.63***	205.05***	7.3435	27.574***	2674.9***	4846.1***
Montana	6.52E-04	38.25	0.84	18.63	33.98***	22.30***	12.904**	21.148**	215.73***	339.57***
Nebraska	3.82E-04	33.62	-0.05	18.99	113.50***	64.63***	16.5***	52.908***	855.16***	1270.1***
Nevada	4.51E-04	47.52	0.65	26.05	46.69***	31.79***	1.7179	14.468	305.9***	520.13***
New Hampshire	3.15E-04	54.78	0.19	20.57	125.29***	80.47***	9.8635*	41.644***	921.85***	1631.4***
New Jersey	4.01E-04	28.47	-0.12	11.58	309.71***	173.02***	6.3935	26.308***	2509.9***	4198***
New Mexico	7.43E-04	39.47	6.65	170.76	0.96	0.74	2.81	7.4441	5.0154	8.1265
New York	2.05E-04	65.56	-0.22	14.88	276.59***	169.38***	8.9843	24.73***	2163***	3958.2***
North Carolina	3.74E-04	42.74	0.30	21.71	155.42***	114.29***	10.045*	27.099***	1171.9***	2459.7***
North Dakota	3.53E-04	44.53	0.26	22.28	200.90***	109.79***	15.532***	31.088***	1473.9***	2188.7***
Ohio	3.45E-04	31.65	-0.39	13.12	519.31***	278.39***	11.282**	30.678***	4259.6***	7085***
Oklahoma	4.72E-04	41.21	0.04	35.92	95.29***	60.89***	3.5901	30.971***	678.61***	1083.4***
Oregon	5.54E-04	30.35	-0.31	17.38	54.72***	38.85***	12.367**	24.725***	354.65***	664.42***
Pennsylvania	2.81E-04	44.25	-0.17	17.35	309.88***	176.42***	5.9192	28.247***	2467.4***	4297.6***
Rhode Island	4.57E-04	34.00	-0.41	15.92	92.83***	54.91***	3.6887	15.426	632.62***	925.54***
South Carolina	2.34E-04	60.18	-0.11	9.06	237.42***	135.80***	7.346	29.457***	1919.9***	3201.5***
South Dakota	3.66E-04	41.19	-0.49	13.70	461.60***	240.65***	17.224***	42.109***	3354.1***	4631.9***
Tennessee	3.60E-04	38.03	-0.35	13.98	347.60***	190.61***	2.9798	15.499	2686.7***	4320.3***
Texas	3.13E-04	43.88	-0.17	19.84	269.50***	145.65***	5.289	24.499***	2044***	3196.7***
Utah	2.76E-04	56.03	-0.53	15.38	151.08***	107.47***	6.6343	35.996***	1099.1***	2255.4***
Vermont	9.00E-04	27.20	-0.88	76.36	5.59***	3.25***	10.433*	15.2	29.928***	36.819***
Virginia	3.53E-04	34.64	-0.43	13.40	388.69***	218.98***	1.9597	16.775*	2940.4***	4917.5***
Washington	8.12E-04	21.63	0.15	9.91	116.78***	73.69***	7.0991	16.472*	842.24***	1511.3***
West Virginia	2.81E-04	58.58	0.27	11.13	192.37***	112.33***	14.66**	24.485***	1574.2***	2648.7***
Wisconsin	4.13E-04	33.23	-0.05	12.32	374.56***	216.37***	5.4602	18.313*	2934.9***	5338.8***
Wyoming	4.51E-05	850.44	0.99	13.55	16.73***	8.66***	3.6048	5.949	98.954***	106.23***
Monthly Data										
EUI	2.32E+01	0.59	1.08	4.56	2.610**	1.51	10.651*	12.902	13.529**	17.247*
OPU	1.03E+02	0.75	1.40	5.09	1.12	0.61	17.646***	20.162**	6.3387	7.1344

Note: The daily stock returns summary statistics cover the overall sample period of 1st February 1994 to 30th September 2022, while EUI runs from February 1996 to September 2022, and OPU involves the data over February 1994 to December 2019. ***, **, and * indicate statistical significance at 1%, 5%, and 10%, respectively.

Table 2: Out-of-Sample forecast Evaluation

State	$h = 20$	$h = 60$	$h = 120$	$h = 20$	$h = 60$	$h = 120$
	OPU vs RV			EUI vs RV		
Alabama	0.876	-0.515	-0.829	-5.19***	-5.235***	-5.24***
Alaska	-1.285	-1.224	-1.180	-1.486	-1.47	-1.459
Arizona	6.939***	6.095***	6.748***	-4.743***	-4.766***	-4.65***
Arkansas	0.150	-0.819	-0.904	2.809***	2.49**	2.075**
California	-0.868	-2.597**	-2.263**	-4.098***	-4.293***	-4.257***
Colorado	3.123***	1.435	1.517	-5.944***	-6.017***	-5.917***
Connecticut	7.312***	6.036***	6.658***	-3.896***	-3.953***	-3.871***
Delaware	1.183	0.374	0.594	-3.387***	-3.533***	-3.452***
Florida	12.185***	11.611***	10.638***	-4.34***	-4.422***	-4.309***
Georgia	2.754***	1.579	1.385	-4.847***	-4.867***	-4.839***
Hawaii	4.596***	3.7***	2.74***	-6.762***	-6.831***	-6.882***
Idaho	-9.178***	-9.721***	-8.045***	-4.277***	-4.369***	-4.014***
Illinois	2.276**	1.34	2.183**	-0.292	-0.331	-0.498
Indiana	-2.645***	-4.379***	-3.612***	-4.721***	-4.78***	-4.751***
Iowa	13.254***	12.714***	11.895***	-4.368***	-4.464***	-4.592***
Kansas	5.239***	4.845***	4.238***	0.081	0.047	0.167
Kentucky	7.01***	5.638***	6.658***	-4.73***	-4.85***	-4.795***
Louisiana	5.309***	4.466***	5.03***	5.507***	5.398***	5.128***
Maine	-8.422***	-7.793***	-6.363***	-7.656***	-7.558***	-7.4***
Maryland	15.222***	14.329***	13.496***	-5.699***	-5.78***	-5.684***
Massachusetts	-13.24***	-15.411***	-14.337***	-4.763***	-4.916***	-4.813***
Michigan	-10.775***	-12.946***	-12.138***	-3.633***	-3.754***	-3.67***
Minnesota	-9.832***	-11.335***	-10.245***	-4.005***	-4.093***	-3.995***
Mississippi	3.601***	2.656***	2.186**	-4.469***	-4.473***	-4.443***
Missouri	-16.597***	-18.695***	-17.873***	-4.055***	-4.12***	-4.051***
Montana	-1.836*	-2.213**	-2.086**	-1.24	-1.261	-1.295
Nebraska	3.249***	2.871***	2.858***	-4.625***	-4.647***	-4.626***
Nevada	-1.967**	-2.647***	-2.684***	-3.792***	-3.759***	-3.718***
New Hampshire	14.231***	14.13***	13.557***	-2.493**	-2.546**	-2.596**
New Jersey	9.495***	8.302***	7.771***	-0.266	-0.8	-0.905
New Mexico	9.055***	8.435***	7.731***	8.918***	8.938***	8.895***
New York	9.571***	9.139***	9.592***	-2.475**	-2.453**	-2.601***
North Carolina	-1.416	-2.82***	-2.183**	-3.459***	-3.515***	-3.466***
North Dakota	1.187	0.28	0.314	-2.29**	-2.336**	-2.3**
Ohio	6.033***	4.856***	4.499***	0.733	0.725	0.521
Oklahoma	-1.938*	-2.498**	-1.099	-2.437**	-2.49**	-2.437**
Oregon	2.643***	3.011***	3.163***	0.392	0.191	0.088
Pennsylvania	-1.526	0.968	5.683***	-3.583***	-4.035***	-3.963***
Rhode Island	10.02***	8.973***	8.026***	-2.7***	-2.716***	-2.739***
South Carolina	4.863***	4.138***	4.292***	-2.37**	-2.383**	-2.306**
South Dakota	15.792***	15.502***	15.652***	-3.287***	-3.314***	-3.315***
Tennessee	-11.82***	-13.821***	-13.13***	5.009***	4.872***	4.532***
Texas	-9.437***	-11.366***	-11.467***	-3.422***	-3.53***	-3.506***
Utah	17.812***	17.152***	17.01***	-4.514***	-4.738***	-4.698***
Vermont	-5.480***	-5.209***	-7.039***	-4.758***	-4.595***	-4.646***
Virginia	-0.786	-2.719***	-3.56***	-5.118***	-5.099***	-5.066***
Washington	-1.076	-1.561	-1.213	-2.701***	-2.877***	-2.849***
West Virginia	1.669*	1.355	0.991	-0.091	-0.062	-0.004
Wisconsin	-12.749***	-14.751***	-14.002***	-4.62***	-4.718***	-4.656***
Wyoming	-1.755*	-2.258**	-1.739*	-0.618	-0.769	-0.653
Sig. Neg. DM*	**12 (30.00)**	**18 (46.15)**	**17 (42.50)**	**37 (90.24)**	**37 (90.24)**	**37 (90.24)**
Sig. Pos. DM*	**28 (70.00)**	**21 (53.85)**	**23 (57.50)**	**4 (9.76)**	**4 (9.76)**	**4 (9.76)**

Note: The figures in each cell are the modified Diebold and Mariano statistics with ***, **, and * indicating statistical significance at 1%, 5%, and 10%, respectively. The significant negative estimates imply the outperformance of the external uncertainty-based GARCH-MIDAS model over the realized volatility (RV)-based variant, while significant positive estimates denote the outperformance of the latter over the former.

Table 3: Economic Significance

State	Model	Returns	Volatility	Sharpe Ratio	Returns	Volatility	Sharpe Ratio
		$\gamma = 3$ and $\theta = 6$			$\gamma = 3$ and $\theta = 8$		
Alabama	RV	9.107	2.418	5.231	11.426	4.299	5.042
	EUI	9.308	1.460	**6.899**	11.685	2.596	**6.649**
Alaska	RV	6.661	10.514	1.754	8.277	18.679	1.690
	EUI	7.666	5.547	**2.842**	9.572	9.859	**2.739**
Arizona	RV	8.174	1.797	5.372	10.227	3.195	5.178
	EUI	8.440	0.843	**8.134**	10.569	1.499	**7.839**
Arkansas	RV	8.849	0.997	7.887	11.095	1.773	7.602
	EUI	9.884	1.578	7.095	12.426	2.805	6.839
California	RV	9.150	1.231	7.370	11.482	2.189	7.103
	EUI	9.450	0.889	**8.990**	11.867	1.581	**8.665**
Colorado	RV	9.696	1.085	8.376	12.184	1.929	8.073
	EUI	9.097	0.567	**10.787**	11.415	1.009	**10.398**
Connecticut	RV	8.855	1.791	5.891	11.103	3.183	5.678
	EUI	9.851	0.794	**9.968**	12.384	1.411	**9.608**
Delaware	RV	7.313	1.144	5.928	9.115	2.034	5.710
	EUI	8.923	0.527	**10.948**	11.190	0.938	**10.551**
Florida	RV	8.180	1.828	5.332	10.236	3.249	5.139
	EUI	7.994	1.038	**6.893**	9.997	1.845	**6.644**
Georgia	RV	9.057	1.637	6.320	11.363	2.909	6.092
	EUI	9.705	1.001	**8.730**	12.196	1.779	**8.416**
Hawaii	RV	9.338	1.683	6.449	11.723	2.991	6.216
	EUI	9.695	1.528	**7.058**	12.183	2.716	**6.803**
Idaho	RV	7.791	0.605	8.764	9.731	1.076	8.443
	EUI	9.106	0.349	**13.763**	11.421	0.621	**13.260**
Illinois	RV	9.457	1.596	6.716	11.877	2.837	6.474
	EUI	9.083	1.838	5.983	11.397	3.268	5.767
Indiana	RV	9.174	1.396	6.943	11.513	2.481	6.692
	EUI	9.676	0.822	**9.601**	12.159	1.461	**9.255**
Iowa	RV	7.988	2.190	4.742	9.988	3.893	4.570
	EUI	8.784	1.725	**5.948**	11.011	3.066	**5.733**
Kansas	RV	8.738	4.781	3.552	10.950	8.500	3.422
	EUI	9.347	0.829	**9.200**	11.733	1.473	**8.865**
Kentucky	RV	9.332	1.310	7.303	11.717	2.330	7.039
	EUI	9.316	0.845	**9.077**	11.696	1.502	**8.749**
Louisiana	RV	9.653	1.691	6.675	12.129	3.007	6.434
	EUI	9.873	2.426	5.714	12.412	4.314	5.508
Maine	RV	8.187	0.571	9.553	10.243	1.014	9.206
	EUI	9.698	0.291	**16.177**	12.183	0.517	**15.590**
Maryland	RV	9.804	1.449	7.336	12.322	2.577	7.071
	EUI	8.905	0.849	**8.608**	11.168	1.510	**8.298**
Massachusetts	RV	8.138	1.221	6.486	10.180	2.170	6.251
	EUI	8.706	0.788	**8.711**	10.911	1.402	**8.395**
Michigan	RV	8.537	1.360	6.486	10.694	2.418	6.251
	EUI	9.415	0.728	**9.895**	11.823	1.294	**9.538**
Minnesota	RV	9.344	1.453	6.946	11.732	2.582	6.696
	EUI	9.438	0.865	**9.102**	11.853	1.538	**8.774**
Mississippi	RV	8.106	1.751	5.392	10.139	3.112	5.196
	EUI	7.855	0.984	**6.940**	9.816	1.748	**6.689**
Missouri	RV	9.086	1.374	6.922	11.401	2.443	6.672
	EUI	9.333	0.762	**9.578**	11.718	1.355	**9.233**
Montana	RV	8.581	1.321	6.620	10.748	2.349	6.379
	EUI	8.310	0.521	**10.167**	10.400	0.926	**9.797**
Nebraska	RV	7.896	1.567	5.531	9.870	2.786	5.330

	EUI	7.979	1.052	**6.833**	9.977	1.870	**6.586**
Nevada	RV	9.475	1.894	6.178	11.897	3.367	5.954
	EUI	10.236	0.747	**10.718**	12.875	1.328	**10.329**
New Hampshire	RV	8.165	2.176	4.876	10.216	3.869	4.699
	EUI	9.377	1.483	**6.903**	11.773	2.636	**6.653**
New Jersey	RV	9.080	0.972	8.222	11.393	1.729	7.926
	EUI	8.801	0.640	**9.786**	11.035	1.138	**9.434**
New Mexico	RV	8.190	11.815	2.100	10.242	21.005	2.023
	EUI	7.986	17.006	1.701	9.981	30.234	1.638
New York	RV	9.783	1.928	6.345	12.296	3.428	6.116
	EUI	9.692	1.954	6.238	12.179	3.473	6.013
North Carolina	RV	9.851	1.937	6.380	12.383	3.443	6.149
	EUI	8.953	0.780	**9.040**	11.228	1.386	**8.713**
North Dakota	RV	7.940	1.836	5.143	9.926	3.264	4.956
	EUI	8.231	1.084	**6.973**	10.300	1.927	**6.720**
Ohio	RV	9.835	1.271	7.861	12.363	2.260	7.578
	EUI	9.264	1.579	6.598	11.630	2.808	6.360
Oklahoma	RV	6.993	4.660	2.789	8.707	8.285	2.687
	EUI	9.185	2.006	**5.799**	11.525	3.566	**5.588**
Oregon	RV	8.709	1.913	5.594	10.914	3.402	5.391
	EUI	10.197	1.212	**8.381**	12.826	2.154	**8.078**
Pennsylvania	RV	7.830	1.461	5.674	9.786	2.597	5.470
	EUI	7.938	0.881	**7.421**	9.925	1.566	**7.154**
Rhode Island	RV	9.626	1.201	7.897	12.093	2.135	7.612
	EUI	8.767	0.342	**13.321**	10.990	0.609	**12.839**
South Carolina	RV	8.295	1.037	7.190	10.382	1.844	6.929
	EUI	9.142	0.572	**10.806**	11.471	1.016	**10.415**
South Dakota	RV	7.479	1.983	4.622	9.334	3.525	4.454
	EUI	8.570	1.432	**6.349**	10.736	2.546	**6.119**
Tennessee	RV	8.920	1.505	6.479	11.187	2.675	6.245
	EUI	9.109	1.881	5.933	11.429	3.344	5.718
Texas	RV	7.634	1.843	4.907	9.533	3.277	4.729
	EUI	8.303	1.001	**7.327**	10.394	1.780	**7.062**
Utah	RV	7.784	1.477	5.606	9.727	2.625	5.403
	EUI	8.056	1.253	**6.329**	10.075	2.227	**6.100**
Vermont	RV	8.717	2.393	5.007	10.923	4.254	4.825
	EUI	8.449	0.450	**11.150**	10.579	0.799	**10.744**
Virginia	RV	7.952	1.622	5.481	9.943	2.883	5.283
	EUI	9.031	0.851	**8.737**	11.330	1.513	**8.422**
Washington	RV	8.582	1.038	7.471	10.751	1.845	7.200
	EUI	8.154	0.711	**8.520**	10.201	1.263	**8.211**
West Virginia	RV	7.676	1.352	5.765	9.586	2.404	5.556
	EUI	8.585	0.768	**8.690**	10.754	1.364	**8.374**
Wisconsin	RV	9.266	1.422	6.954	11.631	2.529	6.703
	EUI	8.722	0.768	**8.845**	10.932	1.365	**8.526**
Wyoming	RV	7.454	7.610	2.350	9.288	13.529	2.261
	EUI	9.439	1.798	**6.314**	11.843	3.197	**6.080**

Note: Bold fonts indicates stances where the EUI-based GARCH-MIDAS model yields higher economic gains than the realized volatility (RV)-based variant.

APPENDIX:

Table A1: Out-of-Sample Forecast Evaluation with OMUI

State	$h = 20$	$h = 60$	$h = 120$
Alabama	-1.6115	-1.5805	-1.5427
Alaska	-2.3051**	-2.3299**	-2.2946**
Arizona	-3.9143***	-3.8794***	-3.7955***
Arkansas	2.3031**	2.341**	2.445**
California	1.3176	1.4059	1.5858
Colorado	9.947***	10.0021***	10.1316***
Connecticut	4.2679***	4.2745***	4.3273***
Delaware	2.9525***	2.9635***	3.005***
Florida	-3.3084***	-3.2778***	-3.2112***
Georgia	-4.5084***	-4.4866***	-4.4192***
Hawaii	7.2331***	7.193***	7.0687***
Idaho	7.9239***	7.9947***	8.1254***
Illinois	-2.9279***	-2.8755***	-2.7611***
Indiana	-0.9395	-0.8986	-0.8124
Iowa	-0.6656	-0.6344	-0.5823
Kansas	1.9851**	2.0331**	2.1255**
Kentucky	6.0885***	6.0963***	6.1146***
Louisiana	-3.3683***	-3.3801***	-3.4172***
Maine	-6.2248***	-6.2221***	-6.2867***
Maryland	5.4981***	5.5038***	5.5158***
Massachusetts	-0.3509	-0.2984	-0.1685
Michigan	-7.2846***	-7.2125***	-7.1245***
Minnesota	-1.1485	-1.1069	-0.9962
Mississippi	-3.1941***	-3.1764***	-3.1131***
Missouri	-1.0116	-0.9767	-0.8738
Montana	7.7191***	7.7831***	8.0192***
Nebraska	-1.8712*	-2.1692**	-2.7286***
Nevada	2.4118**	2.4733**	2.5557**
New Hampshire	4.4951***	4.5448***	4.634***
New Jersey	-1.511	-1.4526	-1.2133
New Mexico	-1.8086*	-1.9891**	-2.3086**
New York	-1.8738*	-1.8601*	-1.8123*
North Carolina	6.8044***	6.8159***	6.8365***
North Dakota	3.578***	3.6466***	3.682***
Ohio	-5.8242***	-5.822***	-5.753***
Oklahoma	-0.505	-0.4927	-0.4745
Oregon	-4.548***	-5.0289***	-5.8994***
Pennsylvania	-4.7182***	-4.6961***	-4.6379***
Rhode Island	-4.4719***	-4.4738***	-4.3735***
South Carolina	6.6089***	6.672***	6.8617***
South Dakota	9.371***	9.4609***	9.6083***
Tennessee	4.964***	4.9672***	4.9727***
Texas	0.045	0.0725	0.1465
Utah	-2.8509***	-2.8114***	-2.7429***
Vermont	-4.9717***	-4.8197***	-4.5368***
Virginia	-3.0766***	-3.0643***	-3.0291***
Washington	8.4338***	8.4843***	8.5624***
West Virginia	3.87***	3.9834***	4.1076***
Wisconsin	-2.5238**	-2.5093**	-2.4516**
Wyoming	7.3461***	7.449***	7.6097***

Note: The figures in each cell are the modified Diebold and Mariano statistics with ***, **, and * indicating statistical significance at 1%, 5%, and 10%, respectively. The significant negative estimates imply the outperformance of the OMUI-based GARCH-MIDAS model over the realized volatility (RV)-based variant, while significant positive estimates denote the outperformance of the latter over the former.

Table A2: Out-of-Sample Forecast Evaluation with Interaction between EUI and CPU

State	$h = 20$	$h = 60$	$h = 120$
Alabama	-3.692***	-3.765***	-3.777***
Alaska	-3.41***	-3.392***	-3.355***
Arizona	2.426**	2.326**	2.301**
Arkansas	2.765***	2.435**	2.208**
California	4.922***	4.658***	4.631***
Colorado	-6.027***	-6.173***	-6.138***
Connecticut	-4.397***	-4.464***	-4.359***
Delaware	1.645	1.401	1.354
Florida	-2.475**	-2.582**	-2.469**
Georgia	-2.133**	-2.217**	-2.244**
Hawaii	28.992***	29.086***	29.239***
Idaho	15.732***	15.754***	16.04***
Illinois	-3.246***	-3.399***	-3.401***
Indiana	-4.141***	-4.224***	-4.208***
Iowa	-3.628***	-3.71***	-3.687***
Kansas	24.381***	24.444***	24.423***
Kentucky	0.296	0.080	0.059
Louisiana	-0.96	-1.023	-0.904
Maine	-2.314**	-2.299**	-2.345**
Maryland	-5.667***	-5.761***	-5.668***
Massachusetts	-6.431***	-6.604***	-6.445***
Michigan	-0.968	-1.096	-1.025
Minnesota	-3.26***	-3.366***	-3.263***
Mississippi	-0.613	-0.69	-0.759
Missouri	-2.908***	-2.978***	-2.901***
Montana	0.611	0.573	0.501
Nebraska	15.799***	15.824***	15.864***
Nevada	-3.629***	-3.665***	-3.62***
New Hampshire	-0.664	-0.748	-0.847
New Jersey	-10.391***	-11.457***	-11.856***
New Mexico	3.955***	3.894***	3.761***
New York	-4.121***	-4.164***	-4.101***
North Carolina	10.733***	10.658***	10.694***
North Dakota	-2.514**	-2.581**	-2.55**
Ohio	0.897	0.822	0.762
Oklahoma	-3.553***	-3.616***	-3.528***
Oregon	19.467***	19.491***	19.512***
Pennsylvania	-1.667*	-2.411**	-2.414**
Rhode Island	-5.749***	-5.8***	-5.76***
South Carolina	-0.755	-0.809	-0.777
South Dakota	4.197***	4.129***	4.051***
Tennessee	-4.073***	-4.18***	-4.094***
Texas	-3.615***	-3.738***	-3.709***
Utah	-5.12***	-5.257***	-5.059***
Vermont	-3.459***	-3.237***	-3.313***
Virginia	-0.157	-0.191	-0.217
Washington	12.309***	12.04***	11.881***
West Virginia	14.555***	14.53***	14.455***
Wisconsin	-3.998***	-4.095***	-4.023***
Wyoming	-5.392***	-5.681***	-5.531***

Note: The figures in each cell are the modified Diebold and Mariano statistics with ***, **, and * indicating statistical significance at 1%, 5%, and 10%, respectively. The significant negative estimates imply the outperformance of the EUI×CPU-based GARCH-MIDAS model over the realized volatility (RV)-based variant, while significant positive estimates denote the outperformance of the latter over the former.