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Economic Conditions and Predictability of US Stock Returns Volatility: Local Factor versus National Factor in a GARCH-MIDAS Model

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Abstract
The aim of this paper is to utilize the generalized autoregressive conditional heteroscedasticity-mixed data sampling (GARCH-MIDAS) framework to predict the daily volatility of state-level stock returns in the United States (US), based on the weekly metrics from the corresponding broad Economic Conditions Indexes (ECIs). In light of the importance of a common factor in explaining a large proportion of the total variability in the state-level economic conditions, we first apply a Dynamic Factor Model with Stochastic Volatility (DFM-SV) to filter out the national factor from the local components of weekly state-level ECIs. We find that both the local and national factors of the ECI generally tend to affect state-level volatility negatively. Furthermore, the GARCH-MIDAS model, supplemented by these predictors, surpasses the benchmark GARCH-MIDAS model with realized volatility (GARCH-MIDAS-RV) in a majority of states. Interestingly, the local factor often assumes a more influential role overall, compared to the national factor. Moreover, when the stochastic volatilities associated with the local and national factors are integrated into the GARCH-MIDAS model, they outperform the GARCH-MIDAS-RV in over 80 percent of the states. Our findings have important implications for investors and policymakers.

JEL Codes: C32, C53, E32, E66, G10
Keywords: Weekly Economic Conditions Index, DFM-SV, Local and National Factors, Daily State-Level Stock Returns Volatility, GARCH-MIDAS, Predictions

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1. Introduction

The present value model of asset prices (Shiller, 1981a, b) can be used to show that asset market volatility depends on the variability of cash flows and the discount factor. Given that worsening of macroeconomic conditions affects the volatility of variables that reflect future cash flows by generating economic uncertainty (Bernanke, 1983) and the discount factor (Schwert, 1989), one can, in general, hypothesize a (negative) predictive relationship between economic conditions and equity market volatility.

Against this backdrop, given that macroeconomic predictors, and at times financial and behavioural indicators, are generally available in low frequencies, i.e., primarily at monthly and quarterly, and at times weekly, basis, a large literature has developed involving the utilization of generalized autoregressive conditional heteroskedasticity (GARCH) variants of mixed data sampling (MIDAS), i.e., the GARCH-MIDAS models to predict daily aggregate and industry-level stock returns volatility of the United States (US; and internationally as well). In this regard, the reader is referred to the works of Asgharian et al. (2013), Engle et al. (2013), Conrad et al. (2014), Conrad and Loch (2015), Yu et al. (2018), Conrad and Kleen (2020), Conrad and Schienle (2020), Fang et al. (2020), Amendola, et al. (2021), Ma et al. (2022), Salisu et al. (2022, forthcoming), Segnon et al. (2023), among others.[1] While the usage of the GARCH framework is a widely-used method of modelling and predicting financial market volatility, ever since the seminal contribution of Bollerslev (1986) (as an extension of the ARCH model of Engle (1982)),[2] the MIDAS aspect ensures that there is no loss of information by averaging the daily data to a lower frequency (Clements and Galvão, 2008). Econometrically 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 associated with macroeconomic conditions.

Our empirical research aims to extend this line of literature of forecasting US stock market volatility based on GARCH-MIDAS models at the state-level rather than an aggregate one by

[1] Earlier works based on spline-GARCH can be found in Engle and Rangel (2008), and Rangel and Engle (2011).
[2] See Bollerslev (2023) for a very nice discussion on the history of GARCH models.

utilizing a novel dataset of weekly economic conditions indexes for the 50 states, as developed by Baumeister et al. (2022), that cover multiple dimensions namely, mobility measures, labor market indicators, real economic activity, expectations measures, financial indicators, and household indicators. The underlying reason for taking such a regional perspective is derived from the premise that core business activities of firms often occur close to their headquarters (Pirinsky and Wang, 2006; Chaney et al., 2012) and, hence, equity prices should contain a non-negligible regional component, so much so that investors overweight local firms in their portfolios (Coval and Moskowitz, 1999, 2001; Korniotis and Kumar, 2013). Obviously then, the forecasting exercise that we undertake in this research should be of immense value to investors, given that accurate forecasts of stock-market volatility carry widespread implications for portfolio selection, derivative pricing, risk management, and also for policy-making (Poon and Granger 2003; Rapach et al., 2008).

To more accurately measure the role of regional information, we first apply a Dynamic Factor Model with Stochastic Volatility (DFM-SV), following the methodology of Del Negro and Otrok (2008), to the state-level weekly economic-conditions indexes. The DFM-SV allows us to extract the influence of the national factor, after which we assess the predictive power of both the local (or state) factor and the national factor on the volatility of a specific state using the GARCH-MIDAS model. The differentiation of these factors is crucial given the existing evidence of the significant role that a common (national) factor plays in explaining a large part of the total variability in these state-level economic conditions, as recently demonstrated by Gupta et al. (2018) and Cepni et al. (forthcoming). This finding is also corroborated by our subsequent analysis. In other words, we aim to alleviate any concerns regarding potential overestimation of the predictive impact of state-level economic conditions on the volatility of the respective state, thereby providing a more accurate depiction of the role of these indicators. This enhanced understanding will assist investors and policymakers in making more informed decisions.

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),[3] 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). 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 would help policymakers to predict in real time, i.e., nowcast, the future path of low-frequency domestic real activity variables, using MIDAS models (Banbura, 2011), and in the process allow them to develop appropriate and early policy responses to prevent possible regional recessions.

To the best of our knowledge, our study is the first to predict, both within and beyond the sample, daily state-level stock market volatility in the US over three decades of data (1994-2023). We utilize a GARCH-MIDAS framework based on the state-level economic conditions index, which we have divided into local and national factors using a DFM-SV model. The only other related study is that of Bonato et al. (2023), where the authors predicted daily realized stock returns volatility of the states (derived from intraday data) using various climate-related risk metrics over the 2011-2021 period. Although not the primary focus of our model, the DFM-SV also enables us to obtain the state and national factors of the SV. We assess whether these measures of economic uncertainty can help forecast state-level equity price volatility, again employing the GARCH-MIDAS model. In doing so, we also contribute to the literature on the role of economic uncertainty in predicting the aggregate stock market volatility of the US (refer to Gupta et al., (2023a, b) for detailed discussions of this literature), but this time from a local perspective.

The rest of the paper is structured as follows: Section 2 provides an overview of the data, while Section 3 introduces the methodologies. Section 4 is devoted to the presentation of the results, and Section 5 concludes the paper.

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

2. Data

We employ daily stock log-returns returns and weekly local and national factors obtained from the DFM-SV model applied to the levels of ECIs (which are stationary by design) for the 50 states of the US to forecast volatility using the GARCH-MIDAS model. The state-level stock market indices 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. The weekly ECIs of the 50 US states, on which we apply the DFM-SV (which we describe below), are based on the work of Baumeister et al. (2022).[4] These authors derive the indexes from mixed-frequency DFMs with weekly, monthly, and quarterly variables that cover multiple dimensions of the aggregate and the state economies. Specifically, Baumeister et al. (2022) group variables into six broad categories: mobility measures, labor market indicators, real economic activity, expectations measures, financial indicators, and household indicators. Table 1 in their paper summarize the state-level data that they use in the construction of the weekly ECIs, and also include information on the frequency, source, transformation, seasonal adjustment, and the start date of each underlying data series utilized in the construction of the indexes. The indexes are scaled to 4-quarter growth rates of US real GDP and normalized such that a value of zero indicates national long-run growth. While, the ECIs start from the 1st week of April, 1987, based on the starting date of the stock prices, our sample period spans between 1st February 1994 and 6th April 2023, with the end-point corresponding to the latest available data at the time of writing this paper.

3. Methodologies

3.1. Dynamic factor model with stochastic volatility (DFM-SV) and preliminary data analysis

Our dynamic factor model with stochastic volatility builds upon the framework developed by Del Negro and Otrok (2008) and Bhatt et al. (2017). It dissects the ECIs into two components: a shared national factor and an individual idiosyncratic factor. The decomposition is as follows:

$$y_{i,t} = \lambda_i f_t + u_{i,t} \tag{1}$$

[4] The data is publicly available for download from: https://sites.google.com/view/weeklystateindexes/dashboard.

where $y_{i,t}$ is the ECI for the i-th state at time period t; f_t is the national common factor which captures the comovement of the ECIs of the different states; λ_i is the corresponding factor loading, and $u_{i,t}$ is the idiosyncratic state factor.

We assume each factor follows an AR(2) process with stochastic volatility:

$$f_t = b_1 f_{t-1} + b_2 f_{t-2} + \sqrt{exph_t^f}\varepsilon_t, \varepsilon_t \sim i.i.d.N\left(0, Q_f\right) \quad (2)$$

$$u_{i,t} = a_1^i u_{i,t-1} + a_2^i u_{i,t-2} + \sqrt{exph_t^i}\eta_t^i, \eta_t^i \sim i.i.d.N(0, Q_i) \quad (3)$$

$$h_t^f = h_{t-1}^f + \sigma_h^f v_t^f, v_t^f \sim i.i.d.N(0,1) \quad (4)$$

$$h_t^i = h_{t-1}^i + \sigma_h^i v_t^i, v_t^i \sim i.i.d.N(0,1) \quad (5)$$

Having outlined the DFM-SV, in Table 1, we present the average percentage contribution of the national factor for the economic conditions of the different states, which in turn ranges between 7.76% (Alaska) and 88.74% (Kentucky). As far as the cross-sectional average is concerned, this value is at 61.28%, highlighting the importance of the national factor, and the need to filter it out from the economic conditions of the states, before forecasting state-level volatility based on the information content of the local factor, and comparing it with the national one.

[INSERT TABLE 1]

The summary statistics of the variables of concern are presented in two vertical panels of Table 2; the left one is dedicated for the state-level ECI factors, and the right one is for the stock returns. Preliminary analysis in Table 3, reveal that the local and national factors of the ECIs and the stock returns series exhibit evidence of conditional heteroscedasticity and serial correlation, which suggests that a GARCH framework would be appropriate to model the stocks returns volatility-ECI nexus. But with ECI being available weekly and the stock returns daily, we need to implement the GARCH-MIDAS model, which prevents any loss of information in the volatility process due to aggregation into a lower (weekly) frequency. We describe the GARCH-MIDAS model in the next sub-section.

[INSERT TABLES 2 AND 3 HERE]

3.2. The generalized autoregressive conditional heteroskedasticity (GARCH)-mixed data sampling (MIDAS): GARCH-MIDAS model

We define $r_{i,t}$ as the daily log-returns of the stock price index, where $I = 1,\ldots.N_t$ and $t = 1,\ldots,T$ respectively denote daily and weekly frequencies, such that N_t is the number of days in a given week t. The GARCH-MIDAS model specification is given as:

$$r_{i,t} = \tau + \sqrt{\mu_t \times g_{i,t}} \times e_{i,t}, \qquad \forall \ i = 1,\ldots,N_t \tag{6}$$

where τ is the unconditional mean of the stock returns; $\sqrt{\mu_t \times g_{i,t}}$ is the conditional variance that comprises two components: (i) a long-run component (μ_t) that captures the long-run volatility, and; (ii) a $\text{GARCH}(1,1)$ based short-run component $(g_{i,t})$ that is characterized by a higher frequency with $e_{i,t}\left|\Sigma_{i-1,t} \sim N(0,1)\right.$ representing the error distribution, where $\Sigma_{i-1,t}$ denotes the information that is available as at day $i-1$ of week t.[5] The conditional variance part of the short-run component is defined in Equation (7) as:

$$g_{i,t} = (1-\alpha-\beta) + \alpha\frac{(r_{i-1,t}-\tau)^2}{\mu_i} + \beta g_{i-1,t} \tag{7}$$

where α and β denote the ARCH and GARCH terms, respectively; satisfying the following conditions $\alpha > 0$, $\beta \geq 0$ and $\alpha + \beta < 1$. In this setting, the weekly frequency ECI factors are transformed to daily frequency, without loss of originality of the model, following Engle et al. (2013). Consequently, our weekly varying long-term component (μ_t) is transformed to daily, rolling back the days across the weeks without keeping track of it. The daily long-term component (μ_i) for the realized volatility and the exogenous factor are respectively expressed in equations (8) and (9):

$$\mu_i = m + \delta\sum_{k=1}^{K}\phi_k(\omega_1,\omega_2)RV_{i-k} \tag{8}$$

$$\mu_i = m + \delta\sum_{k=1}^{K}\phi_k(\omega_1,\omega_2)X_{i-k} \tag{9}$$

where m is the long-run component intercept; δ is the coefficient of the incorporated predictor (realized volatility or ECI factors). We considered five GARCH-MIDAS variants long-run

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[5] See Engle et al. (2013) for further technical details on the construction of the GARCH-MIDAS model.

component that are distinguished by the comprising predictor(s), with the main focus being the first three, aiming to highlight the predictive impact of the ECI-based factors. These models are as follows: (i) the GARCH-MIDAS variant that is based on realized volatility (RV), which will serve as our benchmark model; (ii) RV and local factor of the ECI; (iii) RV and national factor of the ECI. In addition, we also consider as part of the forecasting analyses, the cases where we look into RV and state factor of the SV of the ECI, and RV and national factor of the SV associated with the ECI. For the last four variants interacted with RV, the principal components analysis (PCA) is employed to combine the information of the comprising variables into a single factor.

The $\phi_k\left(w_1, w_2\right) \geq 0,\ \ k=1,\ldots,K$ in Equations (8) and (9) is a beta polynomial weight function, with a summation constrained to unity for the purpose of achieving model parameters identification. The secular component of the MIDAS weights is filtered using $(K=20)$ MIDAS weeks, which is the optimal lag for our specification. We adopt the one-parameter beta polynomial, based on Colacito et al. (2011) highlights on the flexibility of the beta weighting scheme. The weighting scheme allows for the transformation of a two-parameter beta weighting function: $\phi_k\left(w_1, w_2\right)=\left[k/(K+1)\right]^{w_1-1}\times\left[1-k/(K+1)\right]^{w_2-1} \Big/ \sum_{j=1}^{K}\left[j/(K+1)\right]^{w_1-1}\times\left[1-j/(K+1)\right]^{w_2-1}$ to a one-parameter beta weighting function $\left[\phi_k(w)=\left[1-k/(K+1)\right]^{w-1} \Big/ \sum_{j=1}^{K}\left[1-j/(K+1)\right]^{w-1}\right]$, by constraining w_1 to unity and setting $w = w_2$. This imposes a monotonically decreasing function (Engle et al. 2013) where the weights (ϕ_k) are positive and sum to unity $\left(\sum_{k=1}^{K}\phi_k=1\right)$. Also, the constraint imposed on the parameter (w), such that it is greater than unity $(w>1)$ ensures that more recent observation lags are assigned larger weights than the more distant observation lags.

We ascertain the in-sample predictability of the local and national factors of the ECI for stocks returns volatility by testing the hypothesis of the statistical significance of the slope parameter (δ). A statistically significant estimate would imply predictability of the incorporated predictor(s) for stocks returns volatility. A priori, ECI-based factors: local or national, are expected to impact stock market volatility negatively, as outlined in the introduction. Our major focus however in this study is on the out-of-sample forecast performance of the contending model variants that incorporate the information from the factors of the ECIs as predictors in comparison with the GARCH-MIDAS model variant used as the benchmark model. In this regard, we also investigate the forecasting ability of the SVs associated with the state and national factors.

For the out-of-sample forecast evaluation, we employ a 75:25 data split between the in- and out-sample periods and conduct the relative root mean square (RRMSE) and the modified Diebold-Mariano (DM) test (Harvey et al., 1997) to assess the relative performance of the competing models. The RRMSE statistics is obtained as the ratio of our predictive model and the benchmark, with a value of less than unity suggesting that the loss associated with our ECI-based models are smaller than that of the benchmark model, and hence preferred.

4. Empirical Results

Following from the methods described above, we present the empirical results of the three contending GARCH-MIDAS models, with focus on the comparative predictive performances of the model variants. Essentially, we are interested in ascertaining whether the incorporation of the local or national factors associated with the state-level ECIs as predictors in the GARCH-MIDAS model framework improves the predictability of the stock returns volatility of the corresponding state. Consequently, to start off, we present the in-sample predictability in Table 4. The main observation which is consistent with our a priori expectation is that the nexus between stock returns volatility and local and national factors of economic conditions is negative, in general, in a statistically significant manner (except the case of Washington under the local factor). This implies that improvements of economic conditions are likely to reduce the uncertainty in the stock market of the considered US states. Having said that, there are 10 and 13 states (with 2 and 1 insignificant) positive effects due to local and nations ECI factors. Intuitively, it is possible that better economic conditions are associated with lower degrees of risk aversion (Bekaert et al., 2022), which in turn, could lead to higher trading volumes in stock market and translate into increased volatility (Clark, 1973; Copeland, 1976). Note that, similar reasoning could be drawn from the observation of Ludvigson et al. (2021), whereby the levels of financial uncertainty in the wake of a positive shock to output was seen to rise for the aggregate US economy. In other words, economic conditions can lead to either a reduction or increase in stock returns volatility, and hence, is primarily an empirical issue.

[INSERT TABLE 4 HERE]

We next turn our attention to the main focus of the paper, i.e., out-of-sample forecasting. Given this, in addition to the comparative examination of the forecast performances of the model pairs comprising our local and national ECI-based factors with the conventional GARCH-MIDAS-RV, we are also interested in the performance the GARCH-MIDAS involving the local factor with that of the national factor. We perform a similar set of analyses involving the SVs associated with local and national ECI factors, as part of our additional results. We examine the performances of any given pair of contending models using the RRMSE, and the modified DM test. For the RRMSE, we are looking for a value less than unity for our model with ECI-based predictors to be preferred over the benchmark model. For the modified DM test, we expect a significantly negative statistic. The results are presented in Tables 5 to 7 and discussed accordingly.

From the RRMSE results in Table 5, we find that there are several cases where our predictive GARCH-MIDAS model that incorporates the information content of an ECI-based predictor outperformed the conventional GARCH-MIDAS-RV. Specifically speaking, in 72% of the cases (i.e., 36 states out of 50 states), and 74% of the cases (i.e., 37 states out of 50 states) the local and nation ECI factors respectively, outperformed the benchmark. The corresponding values for the SVs involving the ECI factors were 80% and 78%. Based on the modified DM test statistics in Table 6, the outperformance of the ECI-based GARCH-MIDAS models, in a statistically significant manner, are formally confirmed, in approximately 79% and 75% of the cases due to the local and national ECI factors compared to the GARCH-MIDAS-RV, where the RRMSE is less than unity. Approximately, similar number of statistically significant outperformance of 83% of cases where RRMSE is less than 1, are observed for the local and national SVs of the factors. This implies that the incorporation of the variants of ECIs in level or variance-form as a predictor in the GARCH-MIDAS model framework tends improve the precision of forecasts over the GARCH-MIDAS model variant that is based on just the realized volatility. The outperformance stance is observed to be consistent across the specified out-of-sample forecast horizons. This is an indication that the outperformance results involving the ECIs is not sensitive to the chosen out-of-sample forecast horizons.

[INSERT TABLES 5 AND 6]

Next, we turn our attention to comparing the importance of the local and national factors and their associated SVs, with the results on the corresponding RRMSE and modified DM test results reported in Table 7. In the contending model pairs, we consider the models with the national ECI-based factor and SV as the benchmark. We observe relatively more out-performances, in approximately 62% of the states, based on the local ECI-factor compared to the national factor. But when considering the SVs, in approximately 55% of the states, national ECI factor-based SVs produce better performance than the SV involving the state-level factor. This observation transcends the out-of-sample forecast horizons used in the study. Imperatively, while our results are robust to the choice of forecast horizons, the stances of out-performance of GARCH-MIDAS with either local or national ECI factors and their volatilities are sensitive to the state being considered and imply that investors need to be aware of the importance of this predictor contingent on where the specific firm is located that they are investing into.

[INSERT TABLE 7]

5. Conclusion

In this paper, we predict daily US state-level stock returns volatility based on weekly metrics of corresponding broad metrics of economic conditions using the GARCH-MIDAS framework. But to achieve our objective, we first utilize a DFM-SV model to filter out the national factor from the local components of weekly state-level ECIs, given the importance of a common factor in explaining a large proportion of the total variability in the state-level economic conditions. In terms of in-sample predictability, in line with intuition, we find that, in the majority of the states, both the local and national factor of the ECI tends to impact volatility negatively. When we delve into the out-of-sample forecasting exercise, the GARCH-MIDAS model with these predictors outperforms the benchmark GARCH-MIDAS-RV in dominant number of the states, with the local factor tending to play a relatively more important role overall, than the national factor. As an additional analysis, the recovered SVs, used to mimic local and national uncertainties, when incorporated in the GARCH-MIDAS model, also outperforms the GARCH-MIDAS-RV consistently over 80 percent of the states. But now, national uncertainty is found to be more important than the local one.

While these are overall results consistently detected across short- and long-forecast horizons, the existence of underlying heterogeneity in terms of the importance of national and local component of the ECI is indeed state-specific. The same also holds true for the associated uncertainties. Naturally then, investors, depending upon the firms that they invest in, and their location, need to monitor both local and national components of the ECIs with varying degrees of importance while making their portfolio decisions. With state-level stock market volatility also capturing regional financial uncertainties, policymakers too need to be aware of the relative roles of local versus national factors and their variability in coming up with policy measures to prevent possible recessionary impact. Academically speaking, our research highlights the importance of separating out the national component from the local one when analyzing the predictive role of state-level economic conditions for stock market volatility across the US.

As part of future research, in light of the well-established oil-stock nexus (Degiannakis et al., 2018; Smyth and Narayan, 2018), it would be interesting to delve into the role of oil price movements, for example, the shocks driving the oil market and its associated uncertainty in forecasting the state-level volatility, and to check if the results are contingent on the degree of oil-dependence of the states.

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Table 1: Variance decomposition of the state-level ECIs due to the national factor

Alabama	77.06
Alaska	7.76
Arizona	61.98
Arkansas	73.27
California	56.42
Colorado	71.78
Connecticut	61.75
Delaware	64.81
Florida	73.81
Georgia	85.88
Hawaii	27.09
Idaho	52.81
Illinois	87.32
Indiana	74.73
Iowa	82.71
Kansas	69.13
Kentucky	88.74
Louisiana	39.85
Maine	53.85
Maryland	63.47
Massachusetts	52.26
Michigan	71.66
Minnesota	70.54
Mississippi	57.39
Missouri	85.82
Montana	53.97
Nebraska	48.17
Nevada	58.58
New Hampshire	55.01
New Jersey	65.18
New Mexico	46.54
New York	39.61
North Carolina	79.50
North Dakota	13.38
Ohio	81.40
Oklahoma	55.77
Oregon	68.96
Pennsylvania	76.32
Rhode Island	47.09
South Carolina	77.84
South Dakota	58.52
Tennessee	76.51
Texas	62.03
Utah	44.24
Vermont	65.03
Virginia	71.17
Washington	55.52
West Virginia	42.29
Wisconsin	85.26
Wyoming	23.96

Note: Entries are in percentages.

Table 2: Summary Statistics

States	ECI Factors (1521 Observations)				Stock Returns (7349 Observations)			
	Mean	Standard Deviation	Skewness	Kurtosis	Mean	Standard Deviation	Skewness	Kurtosis
Alabama	-0.116	0.538	0.152	3.137	3.66E-04	0.017	0.457	30.741
Alaska	0.022	0.540	0.121	3.250	4.28E-04	0.019	1.493	78.150
Arizona	0.059	0.811	0.158	6.234	4.68E-04	0.017	0.364	21.373
Arkansas	-0.106	0.571	0.557	4.160	4.99E-04	0.015	0.337	8.626
California	0.040	0.575	-1.154	5.861	6.37E-04	0.016	0.346	11.132
Colorado	0.008	0.522	-0.330	3.234	2.15E-04	0.015	0.167	14.960
Connecticut	0.125	0.592	-0.921	9.194	4.67E-04	0.016	0.000	13.013
Delaware	-0.056	0.840	-0.355	7.805	3.24E-04	0.017	0.204	11.917
Florida	0.002	0.614	0.392	4.640	3.34E-04	0.013	-0.334	14.265
Georgia	-0.003	0.602	-3.478	27.410	4.03E-04	0.012	-0.305	13.591
Hawaii	-0.137	0.805	-1.654	7.957	2.47E-04	0.014	0.104	14.638
Idaho	-0.096	0.759	0.627	4.130	8.75E-04	0.031	1.309	20.566
Illinois	-0.034	0.496	-1.183	10.090	3.61E-04	0.011	-0.544	14.338
Indiana	-0.162	0.701	0.495	4.562	5.38E-04	0.015	-0.785	27.218
Iowa	-0.139	0.485	-0.445	4.185	4.46E-04	0.016	0.256	21.697
Kansas	-0.019	0.812	-1.178	10.164	8.44E-05	0.019	0.701	23.231
Kentucky	-0.102	0.450	-1.705	16.065	4.49E-04	0.013	-0.391	10.039
Louisiana	0.041	0.866	-1.682	10.803	2.18E-04	0.013	-0.372	16.496
Maine	0.063	0.654	-0.470	5.577	9.60E-04	0.026	-3.443	250.457
Maryland	0.001	0.702	-0.336	4.219	3.78E-04	0.014	-0.047	14.099
Massachusetts	0.197	0.558	-0.066	3.682	5.20E-04	0.016	0.236	12.217
Michigan	-0.015	0.888	0.814	5.384	2.61E-04	0.013	-0.438	13.734
Minnesota	-0.092	0.811	-0.116	5.547	4.63E-04	0.012	-0.058	13.779
Mississippi	-0.106	0.730	0.129	7.399	3.61E-04	0.015	0.336	17.712
Missouri	-0.001	0.450	0.043	4.820	4.52E-04	0.013	-0.027	17.908
Montana	0.027	0.755	0.131	2.596	6.03E-04	0.025	0.838	18.574
Nebraska	-0.139	0.905	-0.358	3.382	3.93E-04	0.013	-0.040	18.693
Nevada	-0.099	0.789	-0.201	3.173	4.52E-04	0.021	0.643	25.872
New Hampshire	0.161	0.481	0.480	3.368	3.52E-04	0.017	0.190	20.428
New Jersey	0.099	0.537	0.294	3.447	4.05E-04	0.011	-0.117	11.511
New Mexico	-0.045	0.853	-1.352	6.463	7.34E-04	0.029	6.627	170.869
New York	0.153	0.854	-0.092	3.480	2.11E-04	0.013	-0.210	14.752
North Carolina	-0.050	0.624	0.630	5.466	3.68E-04	0.016	0.300	21.462
North Dakota	0.082	0.826	-0.313	5.641	3.49E-04	0.016	0.263	22.069
Ohio	-0.045	0.561	0.259	3.832	3.58E-04	0.011	-0.376	12.911
Oklahoma	0.127	0.849	-3.890	32.277	4.46E-04	0.019	0.004	35.512
Oregon	-0.112	0.581	0.117	2.468	5.72E-04	0.017	-0.301	17.110
Pennsylvania	0.024	0.555	-0.575	4.591	2.93E-04	0.012	-0.156	17.051
Rhode Island	0.112	0.713	-0.402	3.969	4.26E-04	0.016	-0.422	15.832
South Caroli	-0.037	0.522	-0.111	2.249	2.38E-04	0.014	-0.096	8.914
South Dakota	-0.029	0.702	-0.611	10.062	3.72E-04	0.015	-0.485	13.561
Tennessee	-0.074	0.623	0.943	4.403	3.67E-04	0.014	-0.346	13.896
Texas	0.094	0.623	-0.380	2.429	3.11E-04	0.014	-0.168	19.417
Utah	-0.012	0.698	0.039	3.131	2.63E-04	0.016	-0.539	15.164
Vermont	0.026	0.630	0.028	3.382	8.88E-04	0.024	-0.874	76.311
Virginia	-0.008	0.610	0.076	3.239	3.59E-04	0.012	-0.420	13.253
Washington	-0.015	0.704	-2.520	22.692	8.10E-04	0.018	0.161	9.765
West Virginia	0.081	0.941	-6.658	94.823	2.66E-04	0.016	0.265	11.020
Wisconsin	-0.092	0.522	-2.264	18.779	4.22E-04	0.014	-0.041	12.112
Wyoming	0.038	0.757	-0.728	4.351	-4.08E-05	0.038	0.991	13.623
National	-0.025	1.564	-2.005	11.970				

Table 3: Preliminary Analyses

	ECI Factors (1521 Observations)						Stock Returns (7349 Observations)					
	$ARCH(5)$	$ARCH(10)$	$Q(5)$	$Q(10)$	$Q^2(5)$	$Q^2(10)$	$ARCH(5)$	$ARCH(10)$	$Q(5)$	$Q(10)$	$Q^2(5)$	$Q^2(10)$
Alabama	76.78***	48.12***	379.03***	426.39***	380.95***	399.40***	102.44***	83.96***	5.6	24.6***	708.3***	1513.3***
Alaska	4.55***	2.33***	124.12***	136.47***	24.74***	25.02***	127.01***	63.65***	23.2***	42.9***	597.3***	605.9***
Arizona	64.53***	32.60***	416.19***	426.39***	335.92***	344.25***	104.09***	67.76***	5.2	33.1***	717.1***	1273.5***
Arkansas	203.43***	102.20***	16.964***	28.463***	750.47***	754.66***	141.73***	89.50***	33.3***	56.8***	1098.1***	1932.7***
California	167.94***	84.77***	307.85***	337.02***	519.12***	564.33***	158.96***	99.35***	7.7	36.9***	1213.4***	2176.7***
Colorado	84.28***	64.46***	92.518***	112.8***	343.23***	347.31***	177.61***	110.27***	8.2	24.4***	1276.2***	2328.7***
Connecticut	100.34***	50.02***	57.689***	61.262***	298.86***	298.86***	253.30***	160.13***	9.8*	19.0**	1936.7***	3585.9***
Delaware	23.38***	12.36***	78.184***	87.238***	122.81***	127.94***	139.81***	91.66***	2.4	15.2	1053.2***	2001.1***
Florida	104.71***	63.80***	315.93***	465.60***	492.91***	693.96***	390.70***	222.77***	4.5	40.8***	3022.5***	5158.1***
Georgia	18.81***	9.51***	171.64***	183.92***	101.00***	102.93***	384.03***	214.60***	7.4	34.1***	2802.1***	4567.8***
Hawaii	77.76***	45.61***	636.16***	753.84***	482.14***	512.42***	246.72***	139.04***	10.2*	36.2***	2042.2***	3252.2***
Idaho	36.58***	19.60***	61.397***	63.34***	217.33***	255.32***	12.86***	12.86***	5.7	24.7***	75.688***	168.1***
Illinois	55.51***	32.40***	212.81***	229.51***	369.18***	516.18***	509.21***	286.95***	6.6	37.1***	3692.1***	6163.8***
Indiana	31.48***	19.17***	361.39***	397.24***	204.66***	250.19***	35.29***	35.29***	4.9	20.8**	225.5***	531.3***
Iowa	17.96***	9.34***	54.388***	73.311***	103.26***	107.48***	181.21***	127.14***	0.4	23.3**	1383.3***	2639.7***
Kansas	54.99***	29.59***	198.96***	211.75***	345.03***	466.50***	57.26***	37.28***	2.1	14.3	395.2***	640.3***
Kentucky	235.33***	130.28***	189.34***	218.24***	1157.40***	1198.80***	393.83***	217.97***	1.1	15.2	3007.7***	5120.5***
Louisiana	45.41***	23.09***	530.75***	557.09***	321.74***	332.59***	387.08***	219.20***	7.3	45.6***	3125.1***	4987.0***
Maine	417.93***	214.18***	87.415***	150.75***	1171.50***	1204.40***	0.29	0.33	11.3**	31.0***	1.5	3.5
Maryland	76.13***	47.81***	180.55***	217.45***	542.78***	654.81***	206.97***	139.39***	4.9	14.6	1671.3***	3332.8***
Massachusetts	19.06***	9.64***	45.106***	48.502***	100.56***	101.52***	171.91***	106.15***	27.3***	44.8***	1323.6***	2343.1***
Michigan	72.44***	47.61***	163.85***	188.37***	408.17***	503.81***	199.19***	116.59***	2.6	28.8***	1518.6***	2569.2***
Minnesota	8.58***	4.42***	246.88***	285.27***	42.71***	42.74***	356.65***	218.19***	8.3	52.9***	2869.3***	5377.8***
Mississippi	65.38***	33.05***	513.79***	603.47***	479.06***	516.91***	181.04***	111.02***	8.1	30.3***	1436.9***	2550.3***
Missouri	59.50***	31.02***	91.536***	110.67***	258.37***	266.49***	353.12***	208.36***	7.4	26.9***	2718.8***	4926.0***
Montana	28.85***	15.20***	101.09***	106.46***	195.20***	198.96***	34.66***	22.73***	13.0**	20.7**	220.06***	346.5***
Nebraska	34.40***	18.14***	60.505***	75.172***	202.20***	220.53***	115.05***	65.53***	16.9***	53.0***	866.4***	1287.5***
Nevada	173.63***	87.82***	310.42***	330.15***	482.32***	483.92***	47.50***	32.34***	1.7	14.5	311.3***	529.2***
New Hampshire	70.13***	36.33***	101.39***	107.88***	300.26***	303.38***	127.41***	81.84***	9.8*	42.2***	937.3***	1658.7***
New Jersey	11.41***	6.57***	131.23***	133.76***	67.64***	82.96***	314.61***	175.79***	6.7	26.7***	2549.6***	4265.9***
New Mexico	17.90***	12.58***	71.40***	94.95***	129.32***	196.30***	0.98	0.76	2.8	7.1	5.1	8.3
New York	20.78***	11.32***	87.386***	91.68***	143.25***	169.07***	280.47***	171.81***	9.1	26.1***	2193.7***	4014.1***
North Carolina	30.70***	18.01***	122.22***	149.19***	190.06***	203.35***	157.83***	116.07***	9.8*	27.5***	1189.9***	2497.1***
North Dakota	65.35***	34.04***	203.48***	214.50***	479.48***	479.95***	204.02***	111.52***	14.5**	29.2***	1497.0***	2223.0***
Ohio	47.51***	35.83***	225.70***	304.02***	324.27***	585.73***	524.41***	281.42***	11.5**	32.7***	4306.4***	7167.0***
Oklahoma	77.43***	72.49***	261.32***	298.98***	514.67***	1031.20***	95.19***	60.99***	3.4	30.9***	676.2***	1082.1***
Oregon	18.70***	11.25***	57.559***	88.22***	127.96***	179.08***	54.35***	38.34***	13.3**	25.8***	351.4***	651.9***
Pennsylvania	5.23***	2.61***	22.392***	30.69***	27.42***	27.48***	313.79***	178.77***	6.2	28.5***	2500.4***	4356.0***
Rhode Island	58.24***	32.14***	152.18***	181.75***	282.65***	347.83***	93.60***	55.33***	3.6	15.6	638.1***	931.4***
South Caroli	7.75***	5.15***	143.78***	156.49***	40.37***	57.33***	237.85***	136.06***	7.4	29.6***	1921.2***	3201.8***
South Dakota	336.17***	205.24***	299.26***	384.58***	1782.70***	2104.70***	466.19***	243.07***	16.2***	41.0***	3391.9***	4682.7***
Tennessee	57.63***	30.54***	306.41***	311.85***	378.27***	440.09***	352.14***	193.28***	3.3	15.7	2721.4***	4379.3***
Texas	64.12***	33.18***	166.91***	185.43***	529.58***	592.66***	272.58***	147.40***	4.7	25.0***	2068.8***	3236.3***
Utah	75.41***	40.09***	216.94***	224.49***	477.55***	555.10***	150.17***	107.52***	6.8	37.5***	1091.6***	2247.4***
Vermont	18.08***	9.55***	208.78***	228.18***	103.05***	119.64***	5.71***	3.32***	10.4*	15.4	30.6***	37.6***
Virginia	30.81***	15.68***	24.75***	50.33***	186.23***	203.74***	393.85***	222.06***	1.7	16.8*	2981.9***	4988.8***
Washington	277.00***	167.86***	468.11***	540.37***	1632.90***	1936.80***	117.13***	74.04***	8.1	17.5*	842.9***	1512.4***
West Virginia	31.92***	15.91***	149.45***	158.64***	205.98***	206.07***	194.99***	113.89***	13.5**	23.6***	1594.5***	2683.2***
Wisconsin	52.78***	26.48***	77.16***	87.33***	272.65***	273.23***	378.22***	218.84***	5.4	19.3**	2964.1***	5394.9***
Wyoming	28.33***	14.68***	52.96***	74.65***	198.47***	204.54***	17.31***	8.98***	3.7	6.1	102.6***	110.5***
National	105.03***	60.18***	1579.30***	1645.20***	678.11***	693.78***						

Note: $ARCH(\#)$, $Q(\#)$ and $Q^2(\#)$ are formal tests for the presence of ARCH effects, first and higher order serial correlation respectively, at the specified lags. ***, ** and * respectively denote the statistical significance of the formal tests at 1%, 5% and 10% levels of significance. The statistical significance of these tests indicates evidence of the presence of conditional heteroscedasticity and serial correlation.

Table 4: In-Sample Predictability

	Local Factor ECI	National Factor ECI
Alabama	-6.769*** [0.711]	-6.768*** [0.711]
Alaska	-5.506*** [0.669]	-5.017*** [0.639]
Arizona	-2.913** [1.303]	-4.804*** [1.398]
Arkansas	-5.298*** [1.157]	5.067*** [0.300]
California	-7.939*** [1.237]	-4.396*** [1.106]
Colorado	-6.686*** [1.338]	-6.689*** [1.338]
Connecticut	-13.595*** [1.386]	-13.053*** [1.385]
Delaware	-9.818*** [2.086]	-8.021*** [1.575]
Florida	1.288 [1.486]	3.316*** [1.230]
Georgia	-6.221*** [1.088]	-8.509*** [1.430]
Hawaii	-5.626*** [0.609]	-5.626*** [0.609]
Idaho	-3.757* [2.030]	0.865 [0.918]
Illinois	0.639 [0.453]	-7.300*** [1.402]
Indiana	-8.030*** [1.102]	-10.770*** [1.224]
Iowa	-12.690*** [1.013]	-12.681*** [1.010]
Kansas	-17.617*** [1.854]	-23.906*** [2.081]
Kentucky	-6.968*** [1.248]	-13.016*** [1.921]
Louisiana	4.898*** [0.187]	4.898*** [0.187]
Maine	-5.552*** [1.177]	-7.464*** [0.957]
Maryland	-9.733*** [1.345]	-4.249*** [0.831]
Massachusetts	-6.935*** [1.131]	-7.531*** [1.236]
Michigan	-7.145*** [1.765]	2.543*** [0.655]
Minnesota	-7.209*** [0.849]	-7.209*** [0.849]
Mississippi	-8.253*** [0.795]	3.043*** [0.254]
Missouri	-6.456*** [0.692]	-6.453*** [0.692]
Montana	9.456*** [0.502]	10.629*** [0.453]
Nebraska	-8.151*** [0.747]	-8.154*** [0.747]
Nevada	1.890*** [0.320]	-9.251*** [0.921]
New Hampshire	-8.215*** [1.967]	-3.444*** [0.777]
New Jersey	2.695*** [0.075]	2.696*** [0.075]
New Mexico	-2.598*** [0.877]	-2.720*** [0.872]
New York	-15.988*** [0.994]	-10.467*** [0.906]
North Carolina	-2.965*** [0.767]	-2.320*** [0.751]
North Dakota	3.115*** [0.856]	-6.196*** [0.817]
Ohio	-7.051*** [0.712]	-7.051*** [0.712]
Oklahoma	2.894*** [0.320]	2.891*** [0.321]
Oregon	-3.245*** [1.202]	-5.710*** [1.219]
Pennsylvania	-10.367*** [1.274]	-10.417*** [1.019]
Rhode Island	-12.594*** [2.721]	-22.096*** [3.054]
South Caroli	-6.472*** [1.304]	2.384*** [0.314]
South Dakota	-6.627*** [1.474]	-6.626*** [1.474]
Tennessee	-4.240*** [1.164]	10.145*** [0.427]
Texas	-9.777*** [1.539]	-9.494*** [1.301]
Utah	-22.302*** [0.901]	-21.208*** [0.856]
Vermont	-3.719*** [0.677]	-7.526*** [1.350]
Virginia	3.509*** [0.338]	2.995*** [0.346]
Washington	-1.035 [0.688]	-6.245*** [0.926]
West Virginia	7.504*** [0.826]	8.123*** [0.679]
Wisconsin	-8.196*** [0.625]	-8.198*** [0.625]
Wyoming	-6.230*** [0.909]	-6.230*** [0.909]

Note: Entries correspond to the estimate and significance of the parameter δ in equation (9).

Table 5: Relative RMSE (Benchmark Model: GARCH-MIDAS-RV)

STATE	$h = 20$	$h = 60$	$h = 120$	$h = 20$	$h = 60$	$h = 120$	$h = 20$	$h = 60$	$h = 120$	$h = 20$	$h = 60$	$h = 120$
	Factor						SV					
	Local ECI			National ECI			Local ECI Factor			National ECI Factor		
Alabama	0.9632	0.9627	0.9624	0.9632	0.9627	0.9624	0.9632	0.9627	0.9624	0.9631	0.9626	0.9623
Alaska	0.7808	0.7800	0.7786	0.7961	0.7954	0.7940	0.7969	0.7962	0.7948	0.7947	0.7939	0.7925
Arizona	0.9865	0.9861	0.9865	0.9799	0.9792	0.9799	0.9866	0.9861	0.9865	0.9866	0.9861	0.9865
Arkansas	0.9548	0.9546	0.9538	0.9502	0.9523	0.9541	0.9505	0.9527	0.9545	0.9432	0.9425	0.9422
California	0.9466	0.9455	0.9440	0.9528	0.9519	0.9501	0.9484	0.9484	0.9466	0.9577	0.9565	0.9552
Colorado	0.9117	0.9102	0.9079	0.9116	0.9101	0.9078	0.9116	0.9101	0.9078	0.9116	0.9101	0.9078
Connecticut	0.9663	0.9663	0.9675	0.9733	0.9733	0.9744	0.9668	0.9668	0.9680	0.9888	0.9898	0.9899
Delaware	0.9897	0.9902	0.9907	0.9633	0.9645	0.9640	0.9646	0.9659	0.9654	0.9583	0.9595	0.9590
Florida	1.0242	1.0223	1.0227	1.0410	1.0392	1.0399	1.0243	1.0223	1.0228	0.9182	0.9175	0.9162
Georgia	0.7846	0.7828	0.7797	0.8496	0.8478	0.8455	0.8285	0.8265	0.8239	0.7846	0.7828	0.7797
Hawaii	0.9643	0.9637	0.9663	0.9643	0.9637	0.9663	0.9643	0.9638	0.9663	0.9643	0.9637	0.9663
Idaho	0.9092	0.9078	0.9056	0.9286	0.9272	0.9254	0.9093	0.9080	0.9058	0.9093	0.9080	0.9058
Illinois	0.9244	0.9235	0.9211	0.8857	0.8842	0.8822	0.8856	0.8841	0.8822	0.9244	0.9235	0.9211
Indiana	0.9467	0.9460	0.9445	0.9496	0.9490	0.9476	0.9473	0.9467	0.9452	0.9470	0.9464	0.9449
Iowa	0.9330	0.9317	0.9311	0.9331	0.9318	0.9312	0.9330	0.9317	0.9311	0.9330	0.9317	0.9311
Kansas	1.0296	1.0301	1.0311	1.0598	1.0610	1.0636	1.0333	1.0339	1.0346	1.0206	1.0209	1.0206
Kentucky	1.0239	1.0248	1.0258	1.0729	1.0717	1.0745	1.1193	1.1206	1.1242	1.1057	1.1066	1.1097
Louisiana	1.0437	1.0451	1.0458	1.0437	1.0451	1.0458	0.9549	0.9550	0.9541	1.0437	1.0451	1.0458
Maine	0.9241	0.9231	0.9211	0.9595	0.9581	0.9569	0.9750	0.9740	0.9730	0.9750	0.9740	0.9730
Maryland	0.9398	0.9386	0.9377	0.9816	0.9810	0.9803	0.9392	0.9380	0.9372	0.9456	0.9445	0.9433
Massachusetts	1.0036	1.0030	1.0026	0.9893	0.9885	0.9879	0.9257	0.9265	0.9256	0.9980	0.9973	0.9968
Michigan	0.9163	0.9150	0.9132	0.9704	0.9701	0.9692	0.9706	0.9703	0.9694	0.9163	0.9150	0.9132
Minnesota	0.9498	0.9491	0.9478	0.9498	0.9491	0.9478	0.9498	0.9491	0.9478	0.9498	0.9491	0.9478
Mississippi	1.0440	1.0440	1.0449	0.9393	0.9404	0.9395	1.0440	1.0440	1.0449	1.0331	1.0327	1.0335
Missouri	1.0023	1.0014	1.0013	1.0023	1.0014	1.0013	0.9424	0.9423	0.9421	0.9424	0.9423	0.9421
Montana	1.1593	1.1595	1.1628	1.1914	1.1919	1.1953	1.0262	1.0277	1.0299	1.1817	1.1820	1.1851
Nebraska	1.0113	1.0114	1.0120	1.0113	1.0115	1.0120	1.0113	1.0114	1.0120	1.0113	1.0114	1.0120
Nevada	0.9718	0.9719	0.9710	0.9687	0.9678	0.9666	0.9733	0.9734	0.9726	0.9682	0.9674	0.9662
New Hampshire	0.9396	0.9389	0.9366	1.0349	1.0336	1.0332	0.9397	0.9391	0.9368	0.9395	0.9389	0.9366
New Jersey	1.0057	1.0058	1.0059	1.0057	1.0058	1.0059	1.0057	1.0058	1.0059	1.0057	1.0058	1.0059
New Mexico	0.9895	0.9876	0.9879	0.9898	0.9879	0.9883	0.8976	0.8983	0.8955	0.9904	0.9885	0.9889
New York	0.9058	0.9040	0.9033	0.9038	0.9029	0.9015	0.9037	0.9029	0.9015	0.9064	0.9046	0.9039
North Carolina	0.9713	0.9713	0.9688	0.9728	0.9726	0.9701	0.9731	0.9730	0.9704	0.9729	0.9727	0.9702
North Dakota	0.9720	0.9717	0.9710	1.2583	1.2605	1.2652	1.1845	1.1859	1.1894	1.3091	1.3123	1.3179
Ohio	0.9225	0.9216	0.9197	0.9225	0.9216	0.9197	0.9299	0.9293	0.9270	0.9225	0.9216	0.9197
Oklahoma	0.9676	0.9677	0.9673	0.9677	0.9677	0.9674	0.9556	0.9545	0.9539	0.9558	0.9546	0.9541
Oregon	0.9101	0.9202	0.9165	0.8947	0.9040	0.9013	0.9111	0.9214	0.9174	0.8963	0.9057	0.9028
Pennsylvania	0.9673	0.9664	0.9646	0.9314	0.9319	0.9308	0.9316	0.9322	0.9310	0.9312	0.9318	0.9306
Rhode Island	0.9621	0.9614	0.9609	0.9640	0.9634	0.9628	0.9802	0.9795	0.9796	0.9690	0.9685	0.9678
South Caroli	0.9607	0.9598	0.9586	0.9829	0.9833	0.9829	0.9826	0.9830	0.9825	0.9840	0.9844	0.9840
South Dakota	0.9760	0.9750	0.9737	0.9760	0.9750	0.9737	0.9760	0.9750	0.9737	0.9760	0.9750	0.9737
Tennessee	0.9275	0.9275	0.9247	1.1388	1.1378	1.1395	0.9233	0.9233	0.9205	0.9252	0.9251	0.9224
Texas	0.9598	0.9583	0.9573	0.9483	0.9471	0.9459	0.9594	0.9579	0.9569	0.9475	0.9464	0.9450
Utah	1.5321	1.5418	1.5713	1.4726	1.4816	1.5089	1.5310	1.5407	1.5701	1.5321	1.5418	1.5713
Vermont	1.1153	1.1154	1.1173	0.9334	0.9311	0.9299	0.9881	0.9865	0.9861	1.1244	1.1246	1.1268
Virginia	0.9745	0.9749	0.9761	0.9750	0.9755	0.9764	0.9911	0.9911	0.9920	0.9916	0.9916	0.9924
Washington	1.0064	1.0070	1.0073	0.9819	0.9815	0.9811	0.9813	0.9809	0.9806	1.0064	1.0070	1.0073
West Virginia	1.0907	1.0897	1.0910	1.0896	1.0884	1.0898	1.0907	1.0897	1.0910	0.9089	0.9088	0.9065
Wisconsin	0.9943	0.9960	0.9977	0.9943	0.9961	0.9977	0.9943	0.9961	0.9977	0.9943	0.9960	0.9977
Wyoming	0.9416	0.9401	0.9392	0.9416	0.9401	0.9392	0.9416	0.9401	0.9392	0.9416	0.9401	0.9392

Note: The table contains both RRMSE values of the GARCH-MIDAS model with an ECI-based predictor relative to the GARCH-MIDAS-RV.

Table 6: Modified Diebold-Mariano Test Results (Benchmark Model: GARCH-MIDAS-RV)

STATE	$h = 20$	$h = 60$	$h = 120$	$h = 20$	$h = 60$	$h = 120$	$h = 20$	$h = 60$	$h = 120$	$h = 20$	$h = 60$	$h = 120$
	Factor						**SV**					
	Local ECI			**National ECI**			**Local ECI Factor**			**National ECI Factor**		
Alabama	-2.030**	-2.036**	-2.002**	-2.031**	-2.036**	-2.002**	-2.030**	-2.036**	-2.002**	-2.036**	-2.041**	-2.008**
Alaska	-4.498***	-4.496***	-4.496***	-4.280***	-4.278***	-4.279***	-4.267***	-4.265***	-4.265***	-4.302***	-4.300***	-4.301***
Arizona	-3.256***	-3.293***	-3.100***	-4.568***	-4.634***	-4.328***	-3.244***	-3.280***	-3.089***	-3.248***	-3.284***	-3.092***
Arkansas	-3.766***	-3.733***	-3.712***	-3.733***	-3.524***	-3.345***	-3.661***	-3.454***	-3.277***	-4.436***	-4.426***	-4.350***
California	-3.523***	-3.547***	-3.541***	-3.709***	-3.729***	-3.758***	-7.232***	-7.105***	-7.151***	-2.692***	-2.743***	-2.740***
Colorado	-4.214***	-4.218***	-4.225***	-4.217***	-4.221***	-4.228***	-4.216***	-4.220***	-4.228***	-4.217***	-4.221***	-4.228***
Connecticut	-5.592***	-5.472***	-5.118***	-4.602***	-4.508***	-4.166***	-5.612***	-5.491***	-5.137***	-3.804***	-3.420***	-3.346***
Delaware	-1.841*	-1.757*	-1.654*	-5.794***	-5.512***	-5.455***	-5.319***	-5.052***	-5.007***	-5.686***	-5.433***	-5.362***
Florida	3.751***	3.456***	3.483***	4.990***	4.732***	4.747***	3.760***	3.465***	3.492***	-3.415***	-3.392***	-3.375***
Georgia	-4.669***	-4.666***	-4.662***	-3.376***	-3.388***	-3.391***	-3.887***	-3.900***	-3.899***	-4.669***	-4.666***	-4.662***
Hawaii	-9.575***	-9.512***	-8.517***	-9.575***	-9.512***	-8.517***	-9.575***	-9.512***	-8.517***	-9.575***	-9.512***	-8.517***
Idaho	-3.648***	-3.624***	-3.617***	-4.961***	-4.946***	-4.945***	-3.645***	-3.621***	-3.614***	-3.645***	-3.621***	-3.614***
Illinois	-6.332***	-6.309***	-6.323***	-5.191***	-5.173***	-5.110***	-5.198***	-5.180***	-5.117***	-6.334***	-6.310***	-6.324***
Indiana	-2.763***	-2.758***	-2.778***	-2.501**	-2.496**	-2.509**	-2.659***	-2.654***	-2.671***	-2.692***	-2.687***	-2.705***
Iowa	-5.919***	-5.948***	-5.880***	-5.912***	-5.941***	-5.873***	-5.921***	-5.950***	-5.882***	-5.921***	-5.950***	-5.881***
Kansas	1.194	1.193	1.193	2.172**	2.175**	2.205**	1.368	1.366	1.350	0.889	0.885	0.833
Kentucky	2.671***	2.727***	2.782***	6.403***	6.197***	6.324***	6.145***	6.095***	6.151***	6.542***	6.476***	6.523***
Louisiana	5.672***	5.878***	5.739***	5.672***	5.878***	5.739***	-9.724***	-9.495***	-9.518***	5.672***	5.878***	5.739***
Maine	-3.732***	-3.720***	-3.720***	-2.204**	-2.246**	-2.247**	-1.609	-1.650*	-1.661*	-1.608	-1.650*	-1.661*
Maryland	-3.530***	-3.527***	-3.468***	-1.474	-1.498	-1.517	-3.524***	-3.520***	-3.459***	-3.518***	-3.518***	-3.486***
Massachusetts	-0.442	-0.492	-0.499	-1.142	-1.191	-1.192	-5.433***	-5.278***	-5.233***	-0.713	-0.760	-0.767
Michigan	-3.646***	-3.632***	-3.625***	-1.332	-1.318	-1.331	-1.267	-1.252	-1.264	-3.646***	-3.632***	-3.625***
Minnesota	-2.634***	-2.635***	-2.640***	-2.633***	-2.634***	-2.639***	-2.633***	-2.634***	-2.639***	-2.633***	-2.634***	-2.639***
Mississippi	1.313	1.273	1.270	-3.655***	-3.492***	-3.458***	1.313	1.273	1.270	1.005	0.951	0.958
Missouri	0.394	0.183	0.184	0.388	0.176	0.178	-8.430***	-8.330***	-8.169***	-8.430***	-8.330***	-8.169***
Montana	6.419***	6.299***	6.263***	7.105***	6.986***	6.931***	3.176***	3.297***	3.479***	6.965***	6.839***	6.782***
Nebraska	2.983***	2.972***	3.076***	2.993***	2.982***	3.086***	2.983***	2.972***	3.077***	2.983***	2.972***	3.076***
Nevada	-4.921***	-4.892***	-4.966***	-1.710*	-1.748*	-1.780*	-4.449***	-4.422***	-4.491***	-1.660*	-1.695*	-1.725*
New Hampshire	-3.571***	-3.505***	-3.493***	2.528**	2.270**	2.144**	-3.563***	-3.497***	-3.485***	-3.571***	-3.505***	-3.493***
New Jersey	1.070	1.082	1.079	1.070	1.082	1.079	1.070	1.082	1.079	1.069	1.081	1.077
New Mexico	-1.035	-1.189	-1.136	-1.013	-1.162	-1.111	-4.787***	-4.657***	-4.665***	-0.980	-1.121	-1.072
New York	-3.747***	-3.765***	-3.725***	-3.635***	-3.610***	-3.593***	-3.636***	-3.611***	-3.594***	-3.715***	-3.733***	-3.693***
North Carolina	-2.034**	-2.017**	-2.087**	-2.076**	-2.073**	-2.152**	-2.042**	-2.036**	-2.115**	-2.071**	-2.068**	-2.147**
North Dakota	-0.853	-0.835	-0.838	3.782***	3.734***	3.727***	3.468***	3.414***	3.411***	3.828***	3.791***	3.786***
Ohio	-3.045***	-3.041***	-3.028***	-3.045***	-3.041***	-3.028***	-2.911***	-2.901***	-2.917***	-3.045***	-3.041***	-3.029***
Oklahoma	-3.607***	-3.520***	-3.466***	-3.610***	-3.523***	-3.469***	-6.963***	-7.052***	-6.996***	-6.960***	-7.063***	-7.001***
Oregon	-4.645***	-3.957***	-3.980***	-5.037***	-4.382***	-4.334***	-4.620***	-3.927***	-3.962***	-5.012***	-4.354***	-4.313***
Pennsylvania	-3.208***	-3.253***	-3.334***	-5.249***	-5.124***	-5.093***	-5.320***	-5.189***	-5.162***	-5.285***	-5.157***	-5.126***
Rhode Island	-3.025***	-3.054***	-3.043***	-2.995***	-3.021***	-3.018***	-1.252	-1.293	-1.262***	-3.182***	-3.200***	-3.222***
South Caroli	-2.078**	-2.094**	-2.109**	-0.691	-0.662	-0.665	-0.702	-0.673	-0.676	-0.655	-0.626	-0.629
South Dakota	-1.252	-1.302	-1.338	-1.251	-1.301	-1.338	-1.251	-1.301	-1.337	-1.252	-1.302	-1.338
Tennessee	-3.568***	-3.516***	-3.551***	9.318***	9.086***	8.992***	-3.704***	-3.651***	-3.678***	-3.670***	-3.618***	-3.649***
Texas	-2.780***	-2.854***	-2.846***	-3.694***	-3.725***	-3.724***	-2.824***	-2.897***	-2.889***	-3.848***	-3.873***	-3.885***
Utah	7.932***	7.957***	8.060***	7.878***	7.905***	8.024***	7.928***	7.953***	8.056***	7.932***	7.957***	8.060***
Vermont	2.863***	2.802***	2.786***	-2.746***	-2.790***	-2.772***	-0.866	-0.931	-0.930	2.950***	2.891***	2.877***
Virginia	-2.560**	-2.470**	-2.317**	-2.986***	-2.875***	-2.709***	-7.300***	-7.296***	-6.585***	-7.304***	-7.300***	-6.577***
Washington	0.447	0.530	0.553	-2.412**	-2.447**	-2.454**	-2.258**	-2.290**	-2.284**	0.446	0.529	0.552
West Virginia	7.914***	7.673***	7.627***	8.223***	7.962***	7.940***	7.914***	7.673***	7.627***	-4.828***	-4.749***	-4.756***
Wisconsin	-1.444	-1.087	-0.757	-1.442	-1.086	-0.755	-1.443	-1.087	-0.756	-1.444	-1.087	-0.757
Wyoming	-3.095***	-3.134***	-3.126***	-3.094***	-3.134***	-3.125***	-3.094***	-3.134***	-3.125***	-3.095***	-3.134***	-3.125***

Note: The figures in each cell are the modified Diebold-Mariano test statistics with the corresponding indication of statistical significance at 1%, 5% and 10%, respectively denoted by ***, ** and *. The model pair comprises a GARCH-MIDAS with ECI-based predictors and GARCH-MIDAS-RV, wherein significantly negative statistics implies that the former is preferred, while significantly positive statistic implies that the benchmark model is preferred.

Table 7: RRMSE and DM Test Results: Local versus Benchmark (National) GARCH-MIDAS Models

STATE	Factor						SV					
	RRMSE			Modified DM Test			RRMSE			Modified DM Test		
	$h = 20$	$h = 60$	$h = 120$	$h = 20$	$h = 60$	$h = 120$	$h = 20$	$h = 60$	$h = 120$	$h = 20$	$h = 60$	$h = 120$
Alabama	1.0000	1.0000	1.0000	0.796	0.820	0.847	1.0001	1.0001	1.0001	3.948***	3.881***	3.819***
Alaska	0.9808	0.9807	0.9805	-5.685***	-5.683***	-5.678***	1.0028	1.0029	1.0029	5.557***	5.554***	5.551***
Arizona	1.0067	1.0070	1.0067	5.921***	6.049***	5.554***	1.0000	1.0000	1.0000	1.657*	1.791*	1.543
Arkansas	1.0049	1.0024	0.9997	0.317	0.203	0.106	1.0078	1.0108	1.0130	0.133	0.254	0.320
California	0.9935	0.9933	0.9936	-1.790*	-1.837*	-1.642	0.9902	0.9915	0.9911	-1.159	-0.994	-1.026
Colorado	1.0001	1.0001	1.0001	5.682***	5.576***	5.519***	1.0000	1.0000	1.0000	5.171***	5.152***	4.951***
Connecticut	0.9928	0.9928	0.9928	-14.896***	-14.556***	-14.190***	0.9778	0.9768	0.9779	-4.038***	-4.202***	-3.818***
Delaware	1.0274	1.0266	1.0277	4.475***	4.247***	4.311***	1.0066	1.0067	1.0067	3.670***	3.661***	3.513***
Florida	0.9839	0.9837	0.9835	-6.041***	-5.990***	-5.964***	1.1155	1.1143	1.1164	3.907***	3.806***	3.799***
Georgia	0.9418	0.9404	0.9389	-1.568	-1.590	-1.598	0.9438	0.9423	0.9406	-1.574	-1.599	-1.611
Hawaii	1.0000	1.0000	1.0000	-3.743***	-2.970***	-2.419**	1.0000	1.0000	1.0000	6.165***	5.774***	5.136***
Idaho	0.9791	0.9791	0.9787	-1.846*	-1.812*	-1.798*	1.0000	1.0000	1.0000	-3.267***	-3.224***	-3.172***
Illinois	1.0437	1.0444	1.0441	3.577***	3.567***	3.419***	0.9581	0.9574	0.9577	-3.589***	-3.580***	-3.432***
Indiana	0.9969	0.9968	0.9966	-1.008	-1.011	-1.084	1.0003	1.0003	1.0003	0.566	0.539	0.633
Iowa	0.9999	0.9999	0.9999	-4.387***	-4.322***	-4.264***	1.0000	1.0000	1.0000	-6.001***	-5.802***	-5.722***
Kansas	0.9715	0.9709	0.9694	-4.336***	-4.351***	-4.467***	1.0125	1.0127	1.0138	2.689***	2.700***	2.841***
Kentucky	0.9544	0.9562	0.9547	-3.989***	-3.777***	-3.848***	1.0123	1.0126	1.0131	3.649***	3.676***	3.762***
Louisiana	1.0000	1.0000	1.0000	-2.429**	-2.447**	-2.411**	0.9149	0.9138	0.9123	-10.585***	-10.573***	-10.452***
Maine	0.9631	0.9634	0.9626	-6.472***	-6.276***	-6.280***	1.0000	1.0000	1.0000	-3.355***	-3.345***	-3.317***
Maryland	0.9573	0.9567	0.9566	-5.508***	-5.447***	-5.263***	0.9933	0.9931	0.9935	-2.741***	-2.714***	-2.440**
Massachusetts	1.0144	1.0147	1.0149	3.739***	3.731***	3.692***	0.9276	0.9290	0.9285	-1.916*	-1.812*	-1.786*
Michigan	0.9442	0.9432	0.9423	-1.995**	-1.992**	-1.981**	1.0593	1.0604	1.0615	1.988**	1.985**	1.974**
Minnesota	1.0000	1.0000	1.0000	-3.249***	-3.212***	-3.220***	1.0000	1.0000	1.0000	6.532***	6.434***	6.209***
Mississippi	1.1114	1.1102	1.1122	2.257**	2.168**	2.154**	1.0105	1.0109	1.0110	3.007***	3.093***	3.026***
Missouri	1.0000	1.0000	1.0000	6.075***	5.870***	5.748***	1.0000	1.0000	1.0000	4.486***	4.453***	4.370***
Montana	0.9730	0.9728	0.9727	-5.240***	-5.188***	-5.095***	0.8684	0.8695	0.8690	-8.014***	-7.802***	-7.655***
Nebraska	0.9999	0.9999	0.9999	-5.169***	-5.117***	-5.058***	1.0000	1.0000	1.0000	2.907***	2.880***	2.798***
Nevada	1.0032	1.0042	1.0045	-0.186	-0.133	-0.128	1.0053	1.0063	1.0066	-0.200	-0.147	-0.144
New Hampshire	0.9079	0.9084	0.9065	-5.986***	-5.722***	-5.613***	1.0002	1.0002	1.0002	6.877***	6.723***	6.474***
New Jersey	1.0000	1.0000	1.0000	-0.673	-0.683	-0.669	1.0000	1.0000	1.0000	9.494***	9.498***	9.485***
New Mexico	0.9997	0.9996	0.9996	0.029	-0.026	-0.025	0.9063	0.9087	0.9056	-6.113***	-5.815***	-5.878***
New York	1.0022	1.0012	1.0019	0.967	0.749	0.859	0.9971	0.9981	0.9973	-1.079	-0.858	-0.969
North Carolina	0.9985	0.9987	0.9987	-0.806	-0.665	-0.624	1.0002	1.0003	1.0003	0.771	1.034	0.992
North Dakota	0.7725	0.7709	0.7675	-3.454***	-3.409***	-3.404***	0.9049	0.9037	0.9025	-3.978***	-3.967***	-3.961***
Ohio	1.0000	1.0000	1.0000	3.552***	3.536***	3.358***	1.0081	1.0084	1.0080	3.201***	3.269***	2.924***
Oklahoma	1.0000	1.0000	1.0000	-1.050	-0.881	-0.808	0.9997	0.9998	0.9998	-1.043	-0.821	-0.904
Oregon	1.0172	1.0180	1.0169	5.831***	5.852***	5.218***	1.0165	1.0173	1.0162	5.771***	5.855***	5.170***
Pennsylvania	1.0385	1.0370	1.0364	5.975***	5.606***	5.370***	1.0004	1.0004	1.0004	0.230	0.312	0.150
Rhode Island	0.9998	0.9998	0.9998	-3.397***	-3.337***	-3.337***	1.0000	1.0000	1.0000	-3.701***	-3.660***	-3.629***
South Caroli	0.9774	0.9761	0.9753	-0.534	-0.560	-0.564	0.9986	0.9986	0.9985	-1.775*	-1.773*	-1.775*
South Dakota	1.0000	1.0000	1.0000	-4.213***	-4.233***	-4.131***	1.0000	1.0000	1.0000	3.338***	3.385***	3.315***
Tennessee	0.8145	0.8151	0.8115	-6.134***	-6.000***	-5.980***	0.9980	0.9980	0.9980	-3.679***	-3.613***	-3.437***
Texas	1.0121	1.0118	1.0121	5.464***	5.266***	5.313***	1.0125	1.0121	1.0126	5.579***	5.362***	5.470***
Utah	1.0404	1.0406	1.0413	8.104***	8.108***	8.110***	0.9993	0.9993	0.9993	-9.306***	-9.313***	-9.305***
Vermont	1.1949	1.1978	1.2016	4.045***	4.020***	3.997***	0.8788	0.8773	0.8752	-3.639***	-3.618***	-3.604***
Virginia	0.9995	0.9995	0.9997	-0.447	-0.459	-0.384	0.9995	0.9995	0.9995	-5.982***	-5.993***	-5.591***
Washington	1.0250	1.0260	1.0267	4.587***	4.776***	4.823***	0.9751	0.9741	0.9734	-3.619***	-3.765***	-3.785***
West Virginia	1.0010	1.0012	1.0010	-0.201	-0.125	-0.218	1.2001	1.1991	1.2035	6.338***	6.187***	6.172***
Wisconsin	1.0000	1.0000	1.0000	0.915	0.477	-0.197	1.0000	1.0000	1.0000	0.891	0.500	-0.049
Wyoming	1.0000	1.0000	1.0000	-4.545***	-4.477***	-4.474***	1.0000	1.0000	1.0000	3.972***	3.914***	3.906***

Note: The table contains both RRMSE values and modified Diebold-Mariano test statistics, with the corresponding indication of statistical significance of the modified DM statistics at 1%, 5% and 10% respectively denoted by ***, ** and *. The model pair comprises a GARCH-MIDAS with a local predictor and the corresponding national predictor-based GARCH-MIDAS, wherein significantly negative statistics implies that the former is preferred, while significantly positive statistic implies that the benchmark model is preferred.