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Business applications and state-level stock market realized volatility: A forecasting experiment

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Abstract

We analyze the predictive value of (the surprise component of) state-level business applications, as a proxy of local investor sentiment, for the state-level realized US stock-market volatility. We use high-frequency data for the period from September 2011 to October 2021 to compute realized volatility. Using an extended version of the popular heterogeneous autoregressive realized volatility model and accounting for the possibility that users of forecasts have an asymmetric loss function, we show that business applications tend to have predictive value for realized state-level stock-market volatility, as well as for upside ("good") and downside ("bad") realized volatility, for users of forecasts who suffer a larger loss from an underprediction of realized volatility than from an overprediction of the same (absolute) seize, after controlling for realized moments (realized skewness, realized kurtosis, realized jumps, and realized tail risks). We also highlight that the COVID-19 period is a major driver of our empirical results.

KEYWORDS

business applications, forecasting, realized volatility, state-level investor sentiment, state-level stock markets

1 | INTRODUCTION

Accurate forecasting of stock-market volatility has ample implications in terms of portfolio selection, derivative pricing, risk management, and, not at least, policy decisions (Poon & Granger, 2003; Rapach et al., 2008). Naturally, the associated literature for the United States (USA), and also internationally, is vast. In this literature, researchers have used a wide array of (univariate and multivariate, linear and nonlinear) forecasting models and (macroeconomic and financial) predictors (see the discussions in Ben Nasr et al. (2016), Liu et al. (2020), Salisu, Demirer & Gupta ((2022)), Salisu, Gupta & Ogbonna ((2022)), Segnon et al. (2023)). Borrowing from the studies that investor sentiment tends to predict (aggregate and firm-level (excess)) stock returns of the USA (see Bathia et al. (2013), Gebka (2014), Da et al. (2015), and Zhou (2018) for detailed reviews of this literature), given that market agents tend to make overly optimistic or pessimistic judgments and choices (Baker & Wurgler, 2006, 2007), a recent line of research has added to the literature by emphasizing the importance of investor sentiment as a driver of the second moment of the aggregate US equity market (Balcilar et al., 2018a, 2018b, Bekiros et al., 2016, Escobari & Jafarinejad, 2019, Gupta, 2019, Gupta et al., 2023, Liu & Gupta, 2022, Li et al., 2021, Naeem et al., 2020, Olson & Nowak 2019, Zhang et al., 2016).

In terms of economic theory, as laid out by Kumari and Mahakud (2015), PH and Rishad (2020), and Gong et al. (2022), the second-moment effect could reflect the presence of so-called noise traders in the market. Various types of noise trading have been discussed in the vast extant literature. Noise traders, for example, may buy or sell in response to recent price trends so as to reinforce such trends. Hence, as is well-known, in the presence of noise traders, equity prices may drift further from fundamentals, which then results in higher liquidity in terms of trading volume and, consequently, higher risk, that is, volatility.[1]

As stressed by the above-mentioned researchers, another line of explanation emphasizes the fact that investor sentiment captures cognitive bias and, hence, encompasses the heterogeneity among investors regarding two important psychological phenomena: conservatism and the representativeness heuristic. Conservatism induces investors not to change their beliefs rapidly when new evidence emerges in the market, leading to underreaction. On the other hand, the representativeness heuristic implies that investors perceive patterns in genuinely random sequences, resulting in overreaction. The underreaction and overreaction of investors, and consequently stock prices, to the arrival of news in the market, is also a potential driver of volatility.

We contribute to the growing empirical literature on the predictability of stock-market volatility of the USA due to investor sentiment, but now from a state-level perspective, rather than the overall US. The underlying reason for taking a regional angle is based on the premise that core business activities of firms often occur within proximity to their headquarters (Chaney et al., 2012; Pirinsky & Wang, 2006), and, hence, asset prices should contain a non-negligible regional component, to the extent that investors tend to overweight local firms in their portfolios (Coval & Moskowitz, 1999, 2001, Korniotis & Kumar, 2013). Naturally, the forecasting exercise that we undertake in this research should be of immense value to investors.

Econometrically, we forecast state-level weekly realized volatility using an extended version of the heterogeneous autoregressive realized volatility (HAR-RV) model of Corsi (2009), which incorporates the role of investor sentiment of the corresponding state over the period from September, 2011 to October, 2021. Realized volatility, which in our case is captured by square root of the sum of squared intraday log-returns (of equities domiciled in a given state) over a week (following Andersen and Bollerslev (1998)), has the advantage that it is an accurate, observable, and unconditional metric of volatility (McAleer & Medeiros, 2008), unlike in the case of the popular generalized autoregressive conditional heteroscedastic (GARCH) and stochastic volatility (SV) models. At the same time, the benchmark HAR-RV model, despite having a simple structure, is flexible enough to capture long-memory and multiscaling properties often observed for stock-market volatility (Mei et al., 2017; Salisu et al., 2023). In this regard, the key feature of the HAR-RV model is that it uses volatilities from different time resolutions to model and to forecast realized volatility. The model, thereby, captures in a tractable way the key idea underlying the so-called heterogeneous-market hypothesis (Müller et al., 1997), which stipulates that different types of market participants populate the stock market who differ in their sensitivity to information flows at different time horizons.

It is important to highlight that (investor) sentiment is not directly measurable or observable.[2] Therefore, in our empirical research, we need to use a proxy. In this regard, similar to Baumeister et al. (2022), we use weekly business applications (BAs), which signal the intent of establishing new businesses and serve as forward-looking variables indicative of expected economic conditions. To the best of our knowledge, this is the first paper to forecast state-level realized volatility based on BAs. In this regard, we focus on the surprise component of BAs, capturing uncertainty related to investors, rather than the variable on its own, by removing its recurring seasonal pattern. Furthermore, we use an asymmetric one as well to evaluate the potential forecasting gains from using the surprise component of BAs as a predictor of stock-market volatility for different types of investors. An asymmetric loss function captures the possibility that the loss investors incur in case of an overprediction of stock-market volatility differs from the loss they incur in case of an underprediction of the same (absolute) magnitude, et vice versa. An asymmetric loss function, which nests as special cases the popular symmetric quadratic and absolute loss functions commonly studied in the literature dealing with the drivers of the US stock-market volatility, is a natural candidate when one seeks to emulate a utility function-based approach while evaluating forecasts, when risk-averse policymakers seek to gauge the potential impact of stock-price movements on the overall economy, and in a risk-management context when forecasters or their customers use predictions of stock-market volatility, for example, to implement option-trading strategies (Gkillas et al., 2020, 2021).

At the same time, besides being of immense value to investors, forecasting high-frequency, that is, weekly realized state-level stock-market volatility helps to trace out the future path of a metric of state-level financial uncertainty, which can then be fed into mixed-frequency models to predict low-frequency (monthly or quarterly) real-activity variables, and assist policymakers in designing appropriate localized policy responses to tackle a potential recessionary impact of uncertainty in a timely-manner. We organize the remainder of this research as follows. In Section 2, we describe our data. In Section 3, we describe the methods we use in our empirical research. In Section 4, we report our empirical results. In Section 5, we conclude this study.

2 | DATA

We study 5-min intraday data on the Bloomberg State level stock market indices covering 50 US states. Bloomberg terminal creates these stock market indices by taking the capitalization-weighted index of equities domiciled in a given state.

We use the classical estimator of realized variance, RV, that is, the sum of squared intraday returns (Andersen & Bollerslev, 1998). We have

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

where $r_{t,i}$ denotes the intraday $M \times 1$ return vector and $i = 1, ..., M$ is the number of intraday returns. We calculate the weekly RV^w by aggregating the daily RV_t over a trading week (i.e., from Monday to Friday):

$$RV_t^w = \sum_{i=Monday}^{Friday} RV_t^i. \tag{2}$$

Because the realized variance exhibits occasional large peaks typical of financial market data, we study, in our empirical analysis in Section 4, the realized volatility, computed by taking the square root of the realized variance given in Equation (2).[3]

We measure state-level investor sentiment using BA, captured as part of the Business Formation Statistics of the US Census Bureau, which are publicly available for download from the Census Bureau's website.[4] BA represent a subset of all Employer Identification Number (EIN)[5] applications. As detailed on the internet page of the Census Bureau, BA include "all applications for an EIN, except for applications for tax liens, estates, trusts, or certain financial filings, applications outside of the 50 states, and DC or with no state-county geocodes, applications with certain NAICS codes in sector 11 (agriculture, forestry, fishing and hunting) or 92 (public administration) that have low transition rates, and applications in certain industries (for example, private households, civic and social organizations).

In addition to BA, we also examine the roles of CBA (BAs from a corporation), HBA (high-propensity business applications), and WBA (business applications with planned wages) for forecasting state-level RV.[6] CBA involves HBAs from a corporation or personal service corporation, as defined based on the legal form of organization stated in the IRS Form SS-4. HBA involves BAs that have a high propensity of becoming businesses with payroll. It should be noted that such high-propensity applications are identified based on the characteristics of applications shown on the IRS Form SS-4 that are associated with a high rate of business formation. Finally, WBA involves HBAs that indicate a first wages-paid date on the IRS Form SS-4, and such an indication is associated with a high likelihood of transitioning into a business with payroll. For every state, the number of observations, the beginning and end dates of our sample period, are shown in Table A1 at the end of the paper (Appendix), as determined by the data availability, with the weekly frequency of our analysis governed by the BA, which to the best of our knowledge is the only available high-frequency variable that captures expectations of business about future economic conditions at the state-level.[7]

3 | METHODS

Our first group of predictors consists the current realized volatility, the biweekly realized volatility, RV_{bw}, and the monthly, RV_m realized volatility. The biweekly realized volatility is computed as the average realized volatility from period $t-2$ to period $t-1$, and the monthly realized volatility is computed as the average realized volatility from period $t-4$ to period $t-1$. The predictors in our first group form the constituent elements of the so-called heterogeneous autoregressive realized variance (HAR-RV) model of Corsi (2009). The HAR-RV model is one of the most popular models in the literature on modeling and forecasting realized volatility. The HAR-RV model is given by

$$RV_{t+h} = \beta_0 + \beta_1 RV_t + \beta_2 RV_{bw,t} + \beta_3 RV_{m,t} + \theta X_t + u_{t+h}, \tag{3}$$

where $\beta_j, j = 0, .., 3$ and θ are the coefficients to be estimated, u_{t+h} is the usual disturbance term, and RV_{t+h} is the average realized volatility over the forecast horizon, h. We set $h = 1, 2, 4, 8, 12, 16$ and construct the data matrix such that its dimension is the same for all forecast horizons. The term X_t denotes an additional predictor (we are mainly interested in the predictive value of BA (as well as of CBA, HBA, and WBA) or a vector of additional predictors (i.e., realized moments, in which case θ is an appropriately dimensioned vector of coefficients).

The model given in Equation (3) can be interpreted as a classic long-horizon prediction model. Such models have a deep-rooted historical background in empirical studies of asset market movements (see, e.g., the detailed discussions in Campbell and Shiller, Campbell and Shiller (1988, 1998) and more recently, Welch and Goyal (2008) and Rapach et al. (2010)). The model can be estimated using the conventional ordinary least squares technique, which yields robust results even under non-Gaussian errors.

To estimate the coefficients of the model given in Equation (3), we use a recursive-estimation window with a training period of 50 weeks (approximately one year of data) to initialize the estimations. Since BA exhibits a strong seasonal component, and what matters for RV is investors' uncertainty regarding BA (or CBA, HBA, WBA), capturing systematic risks rather than BA per se (Escobari & Jafarinejad, 2019; Liu & Gupta, 2022), we shift the recursive-estimation window across the sample period and estimate a regression model of BA (or, depending on the series we study, CBA, HBA, WBA) on a constant, a trend, a week-of-the-year dummy, and a month-of-the-year dummy. To measure uncertainty, we use the absolute residuals of this regression model as our predictor. Similarly, we use this regression model, along with updated predictors, to forecast BA (or the other BA-based predictors) for the forecasting period. We then subtract this prediction from the realization of BA (or the other BA-based predictors) and use the absolute value of this difference to measure the surprise component. We compute a forecast of BA (or CBA, HBA, WBA) using this surprise component.

We use a flexible approach to evaluate the contribution of the surprise component to the overall forecasting performance of the model given in Equation (3). Specifically, we allow a forecaster to have an asymmetric loss function. An asymmetric loss function accounts for the possibility that a forecaster attaches a different weight to an underestimation of RV relative to an overestimation of the same absolute magnitude. The specific asymmetric loss function in our case is given by $\mathcal{L}(k,\alpha)=[\alpha+(1-2\alpha)\mathbf{1}(fe<0)]|fe|^k$, where fe denotes the forecast error (where we have dropped the time index for notational convenience) and $\mathbf{1}$ denotes the indicator function (Elliott et al., 2005, 2008). According to this loss function, a forecaster's loss depends on the parameter $k=1{,}2$, which governs whether the loss function is a quasi-linear or a squared function of fe, and the parameter $\alpha\in(0,1)$, which regulates the asymmetry of the loss function. Symmetry of the loss function obtains for $\alpha=0.5$, and a standard symmetric quadratic loss function obtains if we set, in addition, $k=0$. Moreover, in the range $\alpha>0.5$ ($\alpha<0.5$), a forecaster incurs a larger loss from and underestimation (overestimation) of RV than from an overestimation (underestimation) of the same absolute size.

We compare forecasts from different forecasting models in two ways. First, we use the following out-of-sample statistic, $R^k(\alpha)=1-\sum\mathcal{L}(k,\alpha)_R/\sum\mathcal{L}(k,\alpha)_B$, where $B=$ benchmark model and $R=$ rival model. For $R^k(\alpha)>0$, we have $R\succ B$, et vice versa. For $k=2,\alpha=0.5$, we obtain the standard out-of-sample R^2 statistic, $R^2=1-\sum f\underset{R}{e}^2/\sum f\underset{B}{e}^2$. Second, we use the familiar modified Diebold and Mariano (1995) test (Harvey et al., 1997), which can be easily adapted to a setting with an asymmetric loss function, to shed light on the statistical significance of accuracy differences across different forecasts for a given asymmetric loss function.

While our main focus is on whether the surprise component of BAs improves the forecast of RV from the benchmark HAR-RV model, another group of predictors consists of the intraday data-based variables that have been widely studied in the literature on the modeling of realized volatility: realized jumps, $JUMPS$, realized upside and downside tail risks, TR_u and TR_d, and realized skewness, RSK, as well as realized kurtosis, RKU. Like Amaya et al. (2015), we use RSK to capture the asymmetry of the returns distribution, and RKU accounts for extremes. We compute RSK as

$$RSK_t=\frac{\sqrt{M}\sum_{i=1}^{M}r_{(i,t)^3}}{RV_t^{3/2}} \tag{4}$$

and RKU as

$$RKU_t=\frac{M\sum_{i=1}^{M}r_{(i,t)^4}}{RV_t^2}, \tag{5}$$

where the scaling by $(M)^{1/2}$ and M turns the statistics into the corresponding daily skewness and kurtosis values. We derive weekly realized skewness and kurtosis as the weekly averages over the Monday to Friday aggregation.

We compute the realized jumps using the formula derived by Barndorff-Nielsen and Shephard (2004). Accordingly, the realized variance converges into a discontinuous (jump) and a permanent component,

$$\lim_{M\to\infty}RV_t=\int_{t-1}^{t}\sigma^2(s)ds+\sum_{j=1}^{N_t}k_{t,j}^2, \tag{6}$$

where N_t is the number of jumps within day t and $k_{t,j}$ is the jump size. Equation (6) makes clear that RV_t is a consistent estimator of the jump contribution plus the integrated variance $\int_{t-1}^{t}\sigma^2(s)ds$. Using the asymptotic properties, Barndorff-Nielsen and Shephard, Barndorff-Nielsen and Shephard ((2004), (2006)) show that

$$\lim_{M\to\infty}BV_t=\int_{t-1}^{t}\sigma^2(s)ds, \tag{7}$$

where BV_t is the daily realized bipolar variation defined as

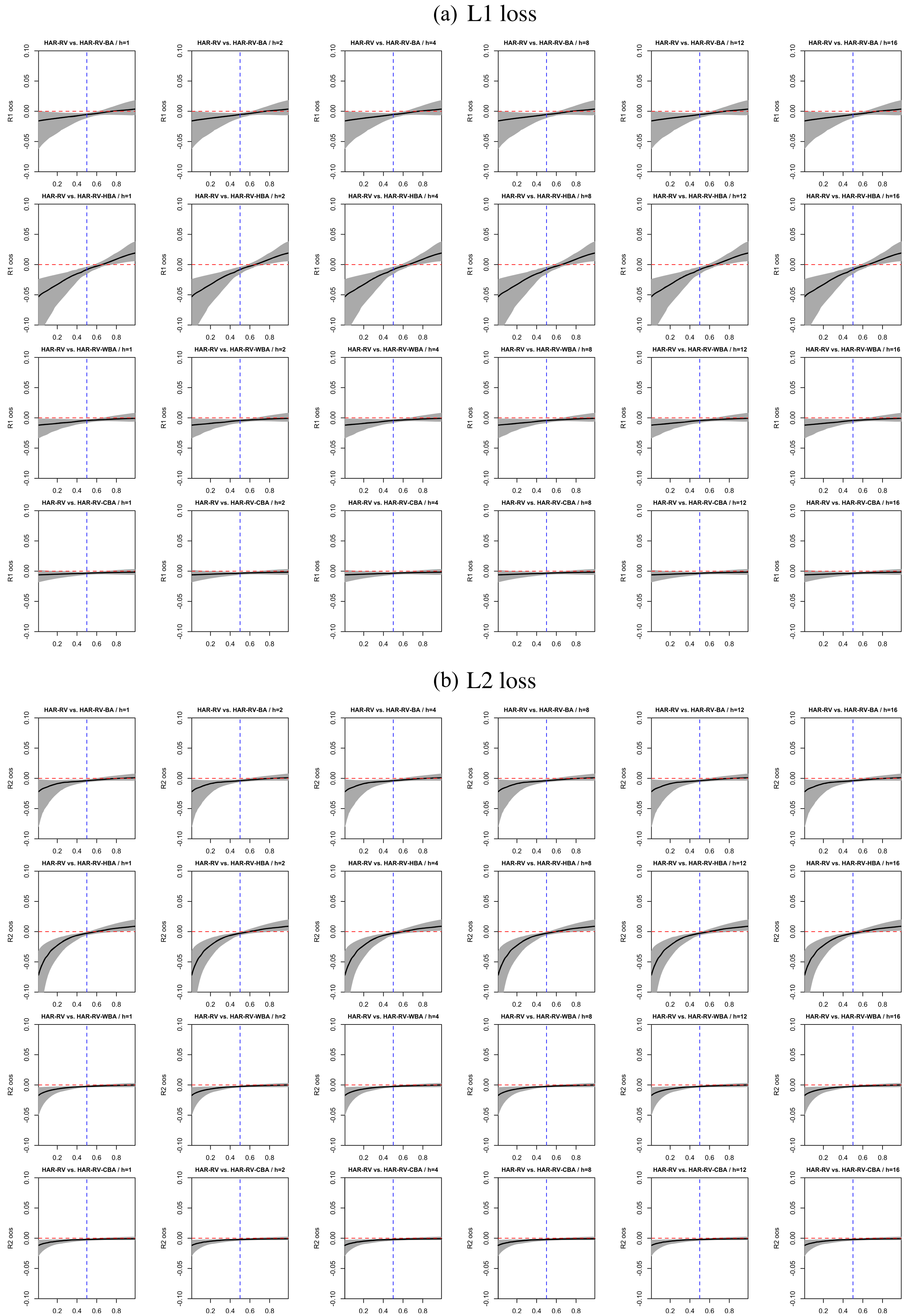

FIGURE 1 Legend on next page.

FIGURE 1 Baseline results. (a) L1 loss. (b) L2 loss. Benchmark: HAR-RV model (with RV, biweekly RV, and monthly RV). Rival: The model features (the surprise component of) state-level BA (or of CBA, HBA, WBA) as an additional predictor. R1 (R2) >0: rival model outperforms the benchmark model. Solid lines: median. Gray area: interquartile range across states. Dashed vertical line: Symmetric loss function. CBA, BAs from a corporation; HAR-RV, heterogeneous autoregressive realized volatility; HBA, high-propensity business applications; WBA, business applications with planned wages.

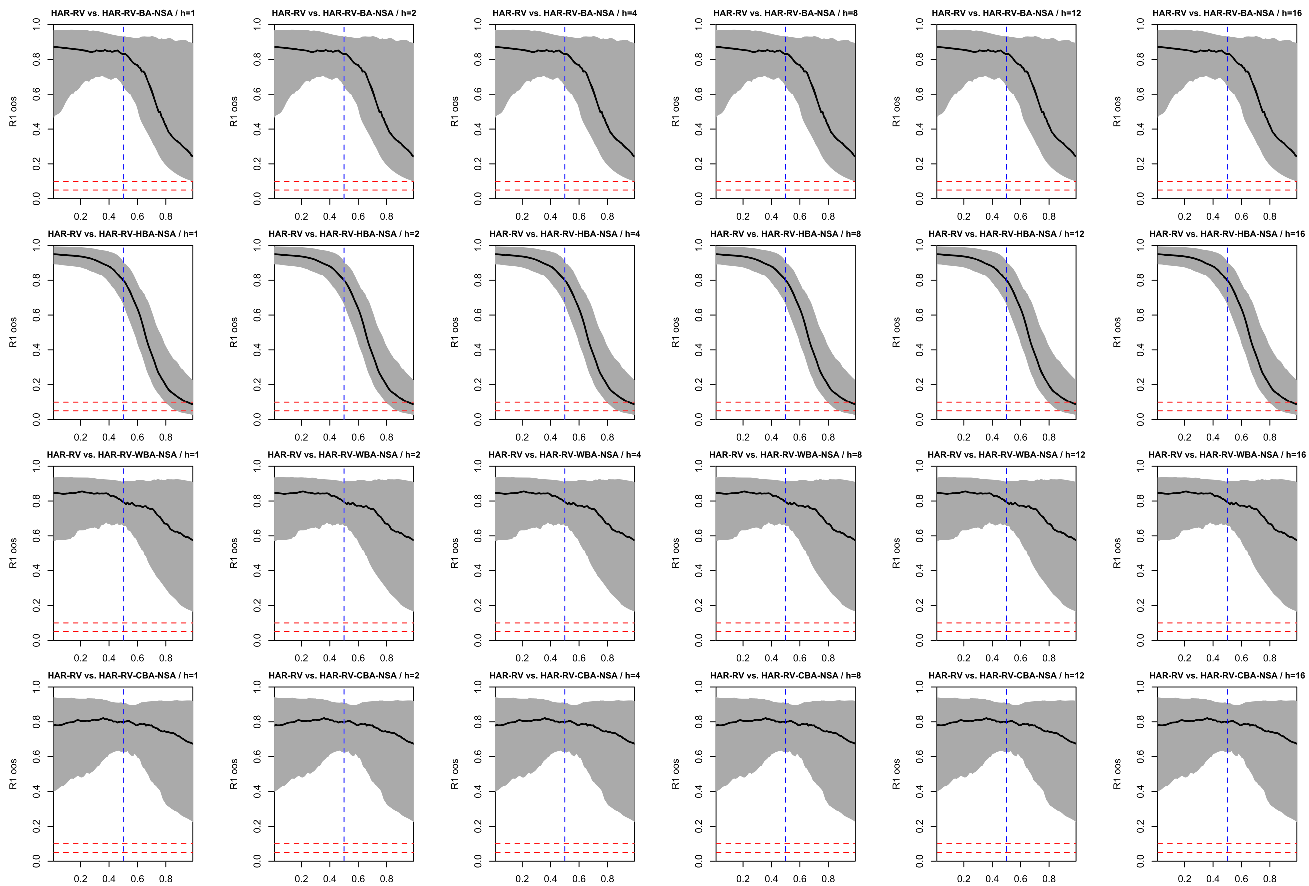

FIGURE 2 Test results. Benchmark: HAR-RV model (with RV, biweekly RV, and monthly RV). Rival: The model features (the surprise component of) state-level BA (or of CBA, HBA, WBA) as an additional predictor. R1 >0 and R2 >0: rival model outperforms the benchmark model. Solid lines: median. Gray area: interquartile range across states. Dashed vertical line: Symmetric loss function. CBA, BAs from a corporation; HAR-RV, heterogeneous autoregressive realized volatility; HBA, high-propensity business applications; WBA, business applications with planned wages.

$$BV_t = \mu_1^{-2}\left(\frac{M}{M-1}\right)\sum_{i=2}^{M}|r_{t,i-1}||r_{i,t}| = \frac{\pi}{2}\sum_{i=2}^{M}|r_{t,i-1}||r_{i,t}|, \quad (8)$$

where

$$\mu_a = E(|Z|^a), Z \sim N(0,1), a > 0. \quad (9)$$

We define the consistent estimator of the pure daily jump contribution using the continuous component of realized variance to get

$$J_t = RV_t - BV_t \quad (10)$$

We test the significance of the jumps using the formal test estimator proposed by Barndorff-Nielsen and Shephard (2006). To this end, we use the following test statistic:

$$JT_t = \frac{RV_t - BV_t}{(v_{bb} - v_{qq})\frac{1}{N}QP_t}, \quad (11)$$

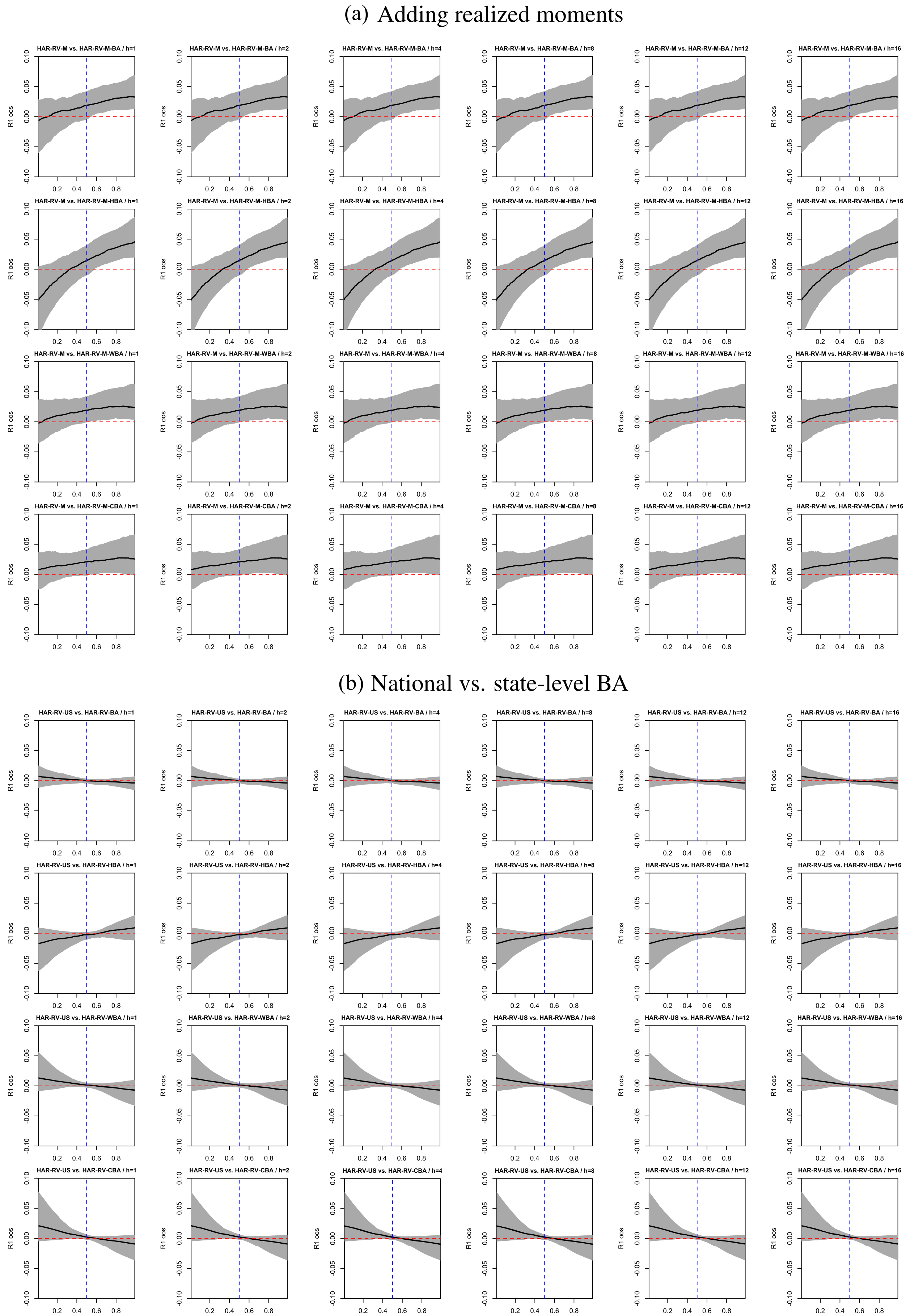

FIGURE 3 Legend on next page.

FIGURE 3 Extensions. (a) Adding realized moments. (b) National versus state-level BA. Benchmark: HAR-RV model (with RV, biweekly RV, and monthly RV) including realized moments (Panel a) / HAR-RV-model (with RV, biweekly RV, and monthly RV) including national BA (Panel b). Rival: The model features (the surprise component of) state-level BA (or of CBA, HBA, WBA) state-level BA as an alternative predictor. R1 >0 and R2 >0: rival model outperforms the benchmark model. Solid lines: median. Gray area: interquartile range across states. Dashed vertical line: Symmetric loss function. CBA, BAs from a corporation; HAR-RV, heterogeneous autoregressive realized volatility; HBA, high-propensity business applications; WBA, business applications with planned wages.

where $v_{bb} = \left(\frac{\pi}{2}\right) + \pi - 3$ and $v_{qq} = 2$ and QP_t is the daily Tri-Power Quarticity:

$$TP_t = M\frac{M}{M-2}\left(\frac{\Gamma(0.5)}{2^{2/3}\Gamma(7/6)}\right)\sum_{i=3}^{M}|r_{t,i}|^{4/3}|r_{t,i-1}|^{4/3}|r_{t,i-2}|^{4/3}, \tag{12}$$

which converges to

$$TP_t \to \int_{t-1}^{t}\sigma^4(s)ds, \tag{13}$$

even in the presence of jumps. For each $t, JT_t \sim N(0,1)$ as $M \to \infty$.

Equation (10) shows that the jump contribution to RV_t is nonnegative, and to avoid obtaining negative empirical contributions, we redefine the jump measure as (see Zhou & Zhu, 2012):

$$RJ_t = \max(RV_t - BV_t; 0). \tag{14}$$

The weekly jump contribution is obtained as average over the trading week (Monday to Friday) of the daily jump contribution.

Lastly, we consider the Hill tail risk estimator (Hill, 1975). We consider $X_{t,i}$ the set of reordered intraday returns $r_{t,i}$ in such a way that

$$X_{t,i} \geq X_{t,j} \text{ for } i < j. \tag{15}$$

We compute the (daily) Hill positive tail risk estimator (our predictor TR_u) as

$$H_t^{up} = \frac{1}{k}\sum_{j=1}^{k}\ln(X_{t,i}) - \ln(X_{t,k}) \tag{16}$$

and the (daily) negative tail risk estimator (our predictor TR_d) as

$$H_t^{down} = \frac{1}{k}\sum_{j=n-k}^{n}\ln(X_{t,i}) - \ln(X_{t,n-k}), \tag{17}$$

where k is the observation denoting the chosen α tail interval. We compute the weekly tail risk as usual by averaging the daily tail risk over the Monday–Friday trading week.

4 | EMPIRICAL RESULTS

We present our baseline results in Figure 1.[8] The benchmark model is the HAR-RV model, and we compare it with a rival model that includes, as an additional predictor, either the surprise component of BA or one of the surprise components of the series HBA, WBA, CBA. The $R^k, k = 1,2$ statistic is plotted as a function of the asymmetry parameter, α. The state-level results are summarized by plotting the median of the R^k statistic (solid line) and the respective interquartile range (gray area). Two key findings emerge. First, the forecasting gains from using BA (or one of the other series) to predict RV tend to increase with the asymmetry parameter, indicating that this predictor is relatively more beneficial for forecasters who suffer greater losses from underprediction of RV than for forecasters who incur greater losses from overprediction. Second, this tendency is stronger for HBA than for BA or the other two BA-based predictors. The results (p-values) of the (modified) Diebold-Mariano test, which are summarized in Figure 2, support this finding, as the test results for HBA become stronger for the cross-section of states when the asymmetry parameter increases. While this strengthening of the test results can also be observed to a lesser extent for the surprise components of BA and the other two BA-based predictors, it is most pronounced for HBA.

We further report the results of two extensions in Figures 3 and 4. The first extension uses the HAR-RV-M model as the benchmark, which includes the various realized moments as additional predictors. The results are qualitatively similar to the baseline scenario, but overall, the tendency of the R^k statistic to increase in the asymmetry parameter is stronger than in the baseline scenario, and the cross-sectional dispersion of the results is larger. In the second extension, we employ the HAR-RV-US model as the benchmark, which features the national BA series as an additional predictor.[9] The R^k

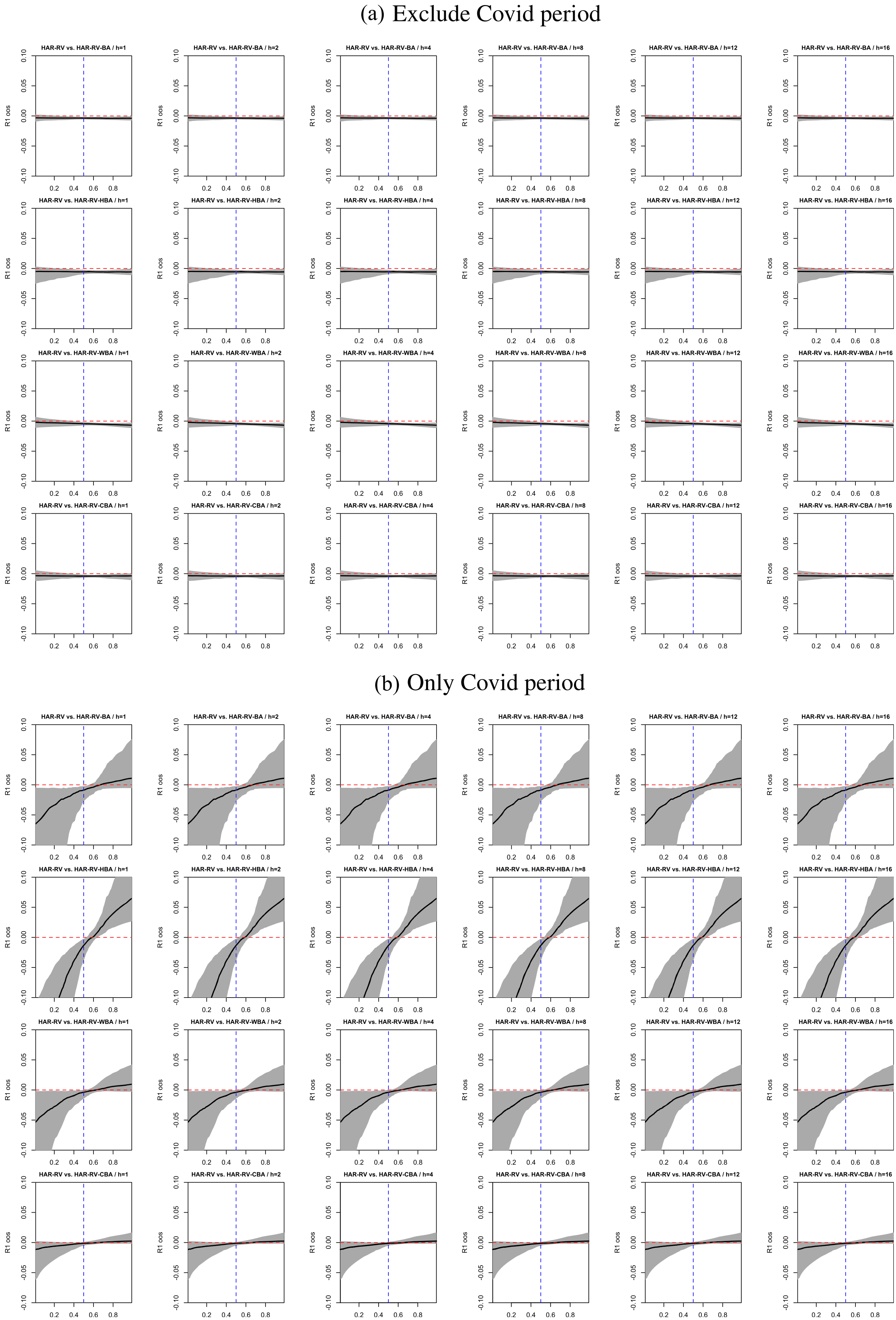

FIGURE 4 Legend on next page.

FIGURE 4 The influence of the Covid pandemic. (a) Exclude Covid period. (b) Only Covid period. Benchmark: HAR-RV model (with RV, biweekly RV, and monthly RV). Rival: The model features the surprise component of) state-level BA (or of CBA, HBA, WBA) as an additional predictor. R1 >0 and R2 >0: rival model outperforms the benchmark model. Solid lines: median. Gray area: interquartile range across states. Dashed vertical line: Symmetric loss function. The pre-COVID-19 period comprises the first 380 forecasts of the out-of-sample forecasting period, while the COVID-19 period comprises the remaining forecasts. CBA, BAs from a corporation; HAR-RV, heterogeneous autoregressive realized volatility; HBA, high-propensity business applications; WBA, business applications with planned wages.

statistic increases in the asymmetry parameter for HBA, while it shows a tendency to decrease for BA and the other two BA-based predictors. Hence, the results for HBA remain robust when compared to the national BA series, whereas the pattern of the weaker baseline results for BA, WBA, and CBA changes.

Notably, our sample period includes the time of the COVID-19 period. In Figure 4, we compare the pre-COVID-19 period with the COVID-19 period. The pre-COVID-19 period comprises the first 380 forecasts of the out-of-sample forecasting period, while the COVID-19 period comprises the remaining forecasts. We find that the COVID-19 period significantly influences our baseline results. The COVID period led to major economic disruptions and a substantial increase in RV. Underestimation of this significant increase in RV results in relatively large losses when the asymmetry parameter, α, is such that $\alpha > 0.5$. This effect is particularly pronounced in the case of HBA, but it is also visible for BA, WBA, and, to a lesser extent, for CBA.

5 | CONCLUDING REMARKS

We have analyzed, using high-frequency data for the period from September, 2011 to October, 2021, the predictive value of (the surprise component of) state-level BAs, which we have used as a proxy of state-level investor sentiment, for the state-level realized US stock-market volatility. Our main empirical result shows that BAs, taking into account that users of forecasts have preferences that can be described in terms of an asymmetric loss function, tend to have predictive value in several states, mainly when users of forecasts incur a larger loss in case of an underestimation of state-level realized volatility than in case of an overestimation of the same absolute size. This result is robust and applies to good and bad realized volatility as well and continues to hold to the inclusion of realized moments (realized skewness, realized kurtosis, realized tail risks) as control variables in the forecasting model. Accounting for (the surprise component of) national BA, in turn, weakens the predictive value of state-level BAs (and also reverses the role of the shape of the loss function relative to the baseline scenario), but not for HBA (that is, high-propensity BAs), for which our results continued to be relatively strong. We also have documented that the COVID-19 period is a major driver of our results in that it had a profound effect on the evidence of a predictive value of BAs for state-level realized volatility.

Naturally, our results are important to investors, portfolio managers, and other market participants, especially for those market participants whose preferences are asymmetric in the forecast error. An asymmetric loss function may reflect, for example, behavioral biases, but it also easily arises in case investors implement certain option-trading strategies. In addition, our results, when combined with a mixed-frequency models, may be useful to improve the accuracy of low-frequency predictions of state-level real-activity variables, which is of obvious importance for policymakers who seek to use, especially in periods of large realized stock-market volatility, the predictive content of BAs to design appropriate local fiscal responses in a timely manner to smooth regional real economic fluctuations.

In light of the recent focus on “climate finance” and the fact that behavior of climate risks is highly heterogenous across the US states (Gil-Alana et al., 2022), as part of future research, it is interesting to conduct a similar regional analysis of forecasting of state-level RVs based on metrics of climate-related uncertainties. Such a question is relevant because climate change has been shown to impact a composite of economic indicators and persistence of the process of uncertainty across the US states (Sheng et al., 2022a, 2022b) and, hence, is likely to contain predictive information for the movements of the local equity markets. Moreover, while our focus in this paper has been only volatility, further investigation of the role of BAs could deal with the other moments of state-level stock returns, such as realized skewness and kurtosis, jumps, and tail risks. Even stock returns could be investigated, contingent on the availability of other wider controls in line with the literature. In this regard, it is important to point out that our econometric approach is based on the linear HAR-RV model, but it has been shown that volatility could also be linked to its predictors, including behavioral factors, in a nonlinear fashion (Gupta et al., 2023), which is a possible limitation of our work. Hence, in future research, it is interesting to utilize nonlinear forecasting approaches, for example, quantile regression extensions of the HAR-RV model, which will also allow the entire conditional distribution of *RV* to be studied and, in this process, the role of an asymmetric loss function to be re-examined.

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DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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ENDNOTES

[1] For the impact of noise trading on the volatility of financial market prices, see also, for example, Lux (1997).

[2] Traditionally, two approaches have been followed to measure investor sentiment (Bathia et al., 2016). First, it is captured by various market-based measures (e.g., trading volume, closed-end fund discount, initial public offering [IPO] first-day returns, IPO volume, option implied volatilities (VIX), or mutual fund flows) acting as proxies for investor sentiment, while survey-based indexes (such as AAII Investor Sentiment Survey, University of Michigan Consumer Sentiment Index, the UBS/GALLUP Index for Investor Optimism, or investment newsletters) comprise the second approach. More recently, measures of investor sentiment have been obtained using daily Internet search data or social media platforms (i.e., Facebook and Twitter) by focusing on particular "economic" keywords that reflect investors' sentiment towards economic developments.

[3] In order to keep the notation as simple as possible, we do not introduce a separate abbreviation for the realized volatility, but merely emphasize that we consider the realized volatility to estimate our forecasting model (Equation (3)) and to evaluate forecasts (see Sections 4).

[4] https://www.census.gov/econ/bfs/csv/bfs_state_apps_weekly_nsa.csv.

[5] An EIN, also known as a Federal Tax Identification Number, is used to identify a business entity. EINs are IDs used by business entities for tax purposes.

[6] Similar to BA, the data for CBA, HBA, and WBA are available at: https://www.census.gov/econ/bfs/csv/bfs_state_apps_weekly_nsa.csv. For the relevant definitions, see the following internet page: https://www.census.gov/econ/bfs/definitions.html.

[7] Upon conducting a comprehensive analysis of the raw data, we identified periods (a small fraction of the data for most states) during which the data exhibit more or less a straight trend. This trend is likely to indicate that Bloomberg stopped producing the indices during those periods and, in retrospect, interpolated the resulting gap in the data. We keep those "gap periods" in the sample in order to avoid data gaps, and because their effect for the forecast error is of minor importance. We carried out additional robustness checks to verify that removing the data for the gap periods does not change our results in any substantive way. The results of these robustness checks are not reported for the sake of brevity, but they are available upon request from the authors.

[8] For our empirical analysis, we use the R language and environment for statistical computing (R Core Team, 2023). Qualitatively similar results for good and bad *RV* can be found in Figure A1 at the end of our paper (Appendix).

[9] The national values of BA are available for download from: https://www.census.gov/econ/bfs/csv/bfs_us_apps_weekly_nsa.csv.

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APPENDIX A

TABLE A1 Descriptive statistics.

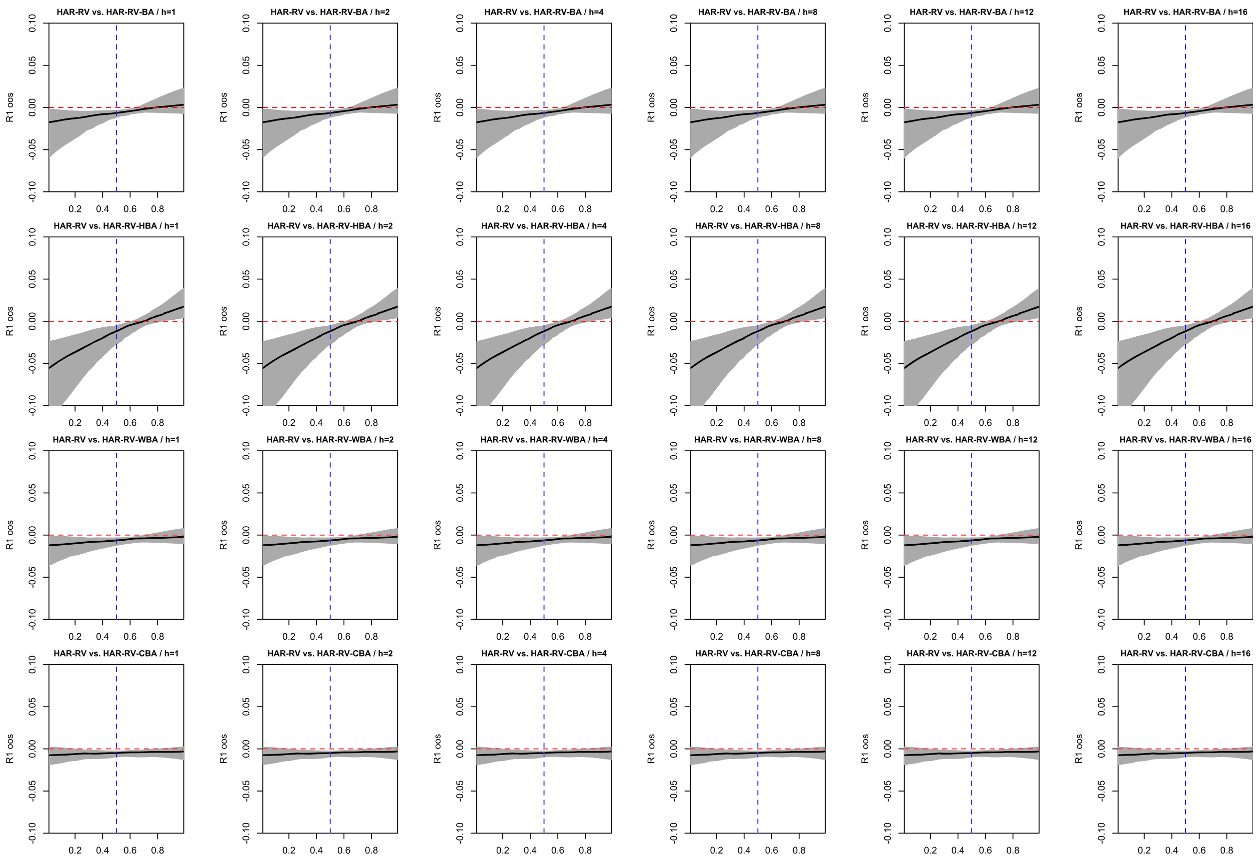
State name	Start date	End date	Observations
Alabama	14/9/2011	22/10/2021	216432
Alaska	09/9/2011	22/10/2021	216676
Arizona	13/9/2011	22/10/2021	216434
Arkansas	14/9/2011	22/10/2021	216433
California	13/9/2011	22/10/2021	216519
Colorado	13/9/2011	22/10/2021	216120
Connecticut	15/9/2011	22/10/2021	215984
Delaware	15/9/2011	22/10/2021	215984
Florida	14/9/2011	22/10/2021	216280
Georgia	14/9/2011	22/10/2021	216215
Hawaii	15/9/2011	22/10/2021	216108
Idaho	13/9/2011	22/10/2021	216298
Illinois	14/9/2011	22/10/2021	216131
Indiana	15/9/2011	22/10/2021	216040
Iowa	14/9/2011	22/10/2021	216299
Kansas	13/9/2011	22/10/2021	216415
Kentucky	15/9/2011	22/10/2021	216210
Louisiana	14/9/2011	22/10/2021	216295
Maine	15/9/2011	22/10/2021	216125
Maryland	15/9/2011	22/10/2021	216033
Massachusetts	15/9/2011	22/10/2021	216106
Michigan	14/9/2011	22/10/2021	216130
Minnesota	13/9/2011	22/10/2021	216466
Mississippi	14/9/2011	22/10/2021	216040
Missouri	14/9/2011	22/10/2021	216201
Montana	13/9/2011	22/10/2021	216405
Nebraska	13/9/2011	22/10/2021	216347
Nevada	13/9/2011	22/10/2021	216337
New Hampshire	15/9/2011	22/10/2021	216033
New Jersey	21/9/2011	22/10/2021	215706
New Mexico	13/9/2011	22/10/2021	216233
New York	19/8/2011	22/10/2021	217318
North Carolina	14/9/2011	22/10/2021	216092
North Dakota	13/9/2011	22/10/2021	216139
Ohio	15/9/2011	22/10/2021	216264
Oklahoma	14/9/2011	22/10/2021	216350
Oregon	13/9/2011	22/10/2021	216179
Pennsylvania	14/9/2011	22/10/2021	216118
Rhode Island	15/9/2011	22/10/2021	216323
South Carolina	15/9/2011	22/10/2021	216340
South Dakota	13/9/2011	22/10/2021	216480

(Continues)

TABLE A1 (Continued)

State name	Start date	End date	Observations
Tennessee	14/9/2011	22/10/2021	216344
Texas	09/9/2011	22/10/2021	216604
Utah	13/9/2011	22/10/2021	216516
Vermont	15/9/2011	22/10/2021	216041
Virginia	15/9/2011	22/10/2021	216348
Washington	14/9/2011	22/10/2021	216085
West Virginia	15/9/2011	22/10/2021	216254
Wisconsin	14/9/2011	22/10/2021	216349
Wyoming	13/9/2011	22/10/2021	216308

(a) Bad *RV*



(b) Good *RV*

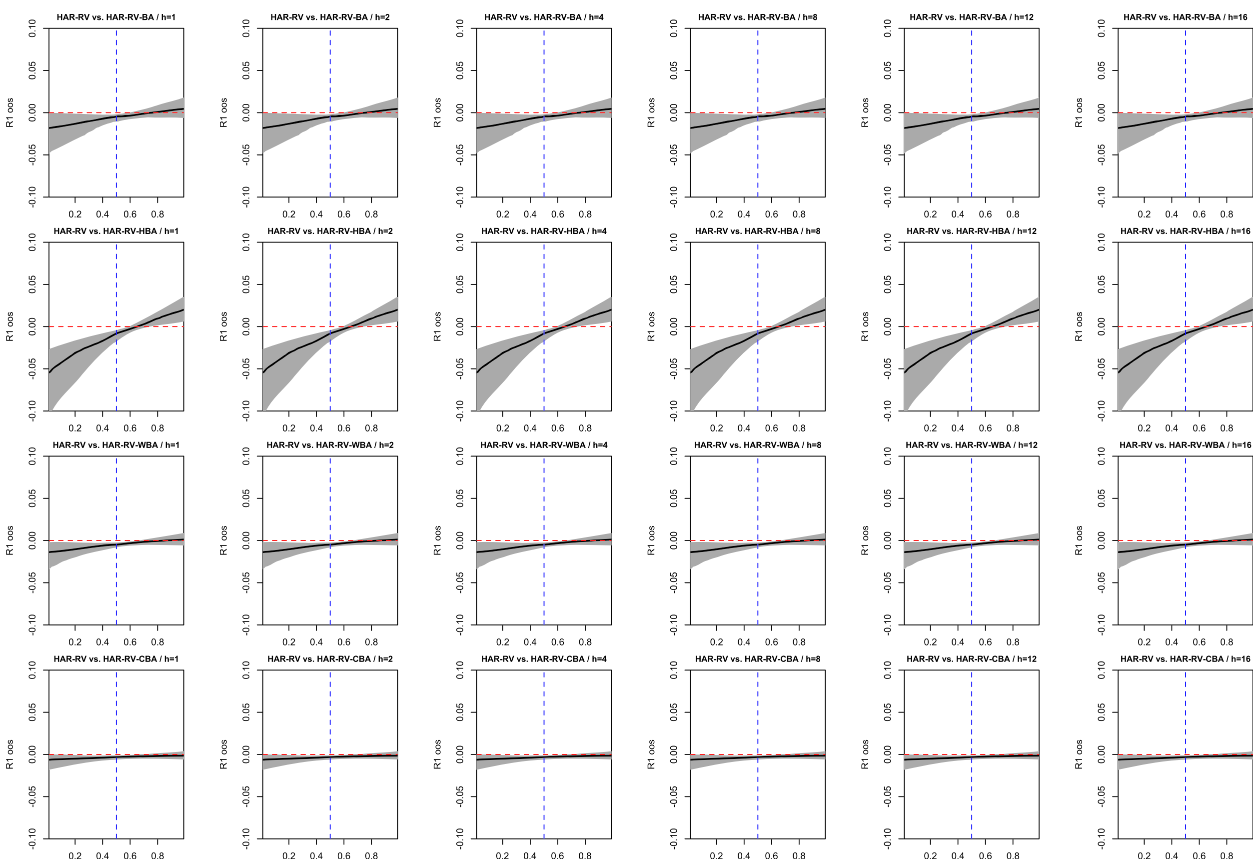


FIGURE A1 Legend on next page.

FIGURE A1 Bad and good RV. (a) Bad RV. (b) Good RV. Benchmark: HAR-RV model (with RV, biweekly RV, and monthly RV). Rival: The model features the surprise component of) state-level BA (or of CBA, HBA, WBA) as an additional predictor. R1 >0 and R2 >0: rival model outperforms the benchmark model. Solid lines: median. Gray area: interquartile range across states. Dashed vertical line: Symmetric loss function. CBA, BAs from a corporation; HAR-RV, heterogeneous autoregressive realized volatility; HBA, high-propensity business applications; WBA, business applications with planned wages.