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Realized Stock-Market Volatility of the United States and the Presidential Approval Rating

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Abstract: Studying the question of whether macroeconomic predictors play a role in forecasting stock-market volatility has a long and significant tradition in the empirical finance literature. We went beyond the earlier literature in that we studied whether the presidential approval rating can be used as a single-variable substitute in place of standard macroeconomic predictors when forecasting stock-market volatility in the United States (US). Political-economy considerations imply that the presidential approval rating should reflect fluctuations in macroeconomic predictors and, hence, may absorb or even improve on the predictive value for stock-market volatility of the latter. We studied whether the presidential approval rating has predictive value out-of-sample for realized stock-market volatility and, if so, which types of investors benefit from using it.

Keywords: stock-market volatility; macroeconomic predictors; presidential approval rating; forecasting

MSC: 91-08; 91-11; 91B82; 91B84

JEL Classification: C32; C53; G10; G17

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1. Introduction

In recent research, Gupta et al. [1] inter alia point out the importance of the presidential approval rating in predicting the stock-market volatility of the United States (US) in an in-sample context. Because US stock-market volatility is widely accepted to be driven by macroeconomic predictors (see, for example, [2–7]), this result is not surprising, especially in light of the fact that the results of much significant empirical research have shown the presidential approval rating to contain information on the state of the economy [8–12].

The theoretical channels through which the presidential approval rating is linked to stock-market volatility can be elaborated as follows. First, the classic present-value model of asset prices [13,14] implies that stock-market volatility depends on the volatility of cash flows and the discount factor. Given that macroeconomic developments affect the volatility of variables that reflect future cash flows by generating economic uncertainty [15] and the discount factor [16], one can hypothesize a (negative) relationship between the information about the state of the economy reflected in the presidential approval rating and stock-market volatility. Second, Fauvelle-Aymar and Stegmaier [17] show for the US that the presidential approval rating is positively associated with stock-market returns. Such a positive association may reflect a wealth effect, with consumers feeling richer and more confident when stock prices are increasing. At the same time, stock-market returns are closely linked to the so-called “leverage effect” [18]. According to the leverage effect, when stock prices decline, firms become more leveraged because their debt-to-equity ratio rises, which causes the leverage of their capital structures to rise (and the financial state of companies to deteriorate) and, as a result, the systematic risk of common stocks, i.e., the volatility, increases. In other words, again as with the present-value model, the leverage effect predicts a negative association between presidential popularity and stock-market volatility.

Against the backdrop of these theoretical channels, and realizing that in-sample predictability does not necessarily translate into out-of-sample forecasting gains, we compared the forecasting prowess of the presidential approval rating with that of a wide array of macroeconomic predictors used in the literature involving US stock-market volatility (several researchers have argued that an ultimate test of a predictive model with regard to the econometric methodologies and the predictor variables used is its forecasting performance; see [19–21]). This is indeed an important exercise not only from a statistical perspective but also from the point of view of academic research because it yields a hint as to whether the presidential approval rating can provide academics and investors with a single-variable substitute for a large number of macroeconomic predictors as state variables, in case the former performs equally well or even outperforms the latter. In addition, as pointed out by Poon and Granger [22] and Rapach et al. [23], stock-market volatility is a key component of asset valuation, hedging, and portfolio-optimization models. As a result, inaccurate forecasts of stock-market volatility may lead to pricing errors in financial markets, over- or under-hedged investments, and incorrect capital-budgeting decisions, with substantial implications for earnings and cash flows. Moreover, forecasting stock-market volatility is crucial not only for investors and corporate decision-makers but also for policymakers in their assessment of financial fundamentals and investor confidence, while designing appropriate policy responses to minimize the adverse repercussions of financial vulnerability on the macroeconomy. In this regard, it should be noted that the volatility of financial markets and, hence, the uncertainty surrounding it have been a major concern for policymakers since the Global Financial Crisis of 2007–2009, which has been followed by a row of crises, including the European sovereign debt crisis, the "Brexit", the US–China trade war, the COVID-19 pandemic, and the recent Russia–Ukraine war. Naturally, accurate forecasting of stock-market volatility is likely to act as an input into policy decisions that ensures adverse macroeconomic impacts to large negative financial shocks.

Specifically speaking, we forecast the monthly realized volatility (RV), which is captured by the sum of squared returns of the S&P 500 over a month (following Andersen and Bollerslev [24]), which provided us with an observable and unconditional metric of volatility (unlike in the case of the popular generalized autoregressive conditional heteroscedastic and stochastic volatility models), which is otherwise a latent process. We conducted our empirical analysis using a predictive regression framework over the monthly period of 1960:07 to 2022:12, whereby we compared the performance of the presidential approval rating with eight latent factors summarizing the information contained in a large dataset of macroeconomic and financial variables and six metrics of associated uncertainties of these variables. Importantly, we used an asymmetric loss function to evaluate the potential forecasting gains from using the presidential approval rating as a predictor of stock-market volatility. An asymmetric loss function captures the possibility that the loss investors incur in the case of an overprediction of stock-market volatility differs from the loss they incur in the case of an underprediction of the same (absolute) magnitude. An asymmetric loss function, which nests as special cases the popular symmetric quadratic and absolute loss functions commonly studied in the literature studying the drivers of US stock-market volatility, is a natural candidate to evaluate forecasts 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 [25].

To the best of our knowledge, we are the first to forecast the RV of the US stock market based on the presidential approval rating and compare its performance with a large array of macroeconomic predictors by relying on an asymmetric loss function based on data that span six decades involving 12 presidents, with six each from the Democratic and

Republican parties, which, in turn, renders it possible to capture alternative positions of these two parties towards the stock market [26,27]. In the process, we add to the large literature on forecasting stock-market volatility of the US based on macroeconomic and financial predictors (for detailed reviews, see, for example, [28–30]), but now considering the role of presidential politics.

Our research can be considered to add to the literature on the nexus between stock-market movements and the presidential approval rating from the perspective of the second moment of stock-market returns (that is, the realized volatility, RV). In this regard, a related paper is that of Chen et al. [31], who construct a monthly presidential economic approval rating (PEAR) index for the sample period from 1981 to 2019 by averaging ratings on the president's handling of the economy across various national polls. Chen et al. [31] find that the PEAR index affects stock returns in a cross-section of the US. More specifically, the empirical results show that, in the cross-section and on a risk-adjusted basis, stocks with high betas to changes in the PEAR index underperform significantly those with low betas by 1.00% per month in the future. Chen et al. [31] find the resulting low PEAR beta premium to persist for up to one year, being present in various sub-samples and even in other G7 countries. Staying with stock returns, Gupta et al. [1] analyze whether presidential approval ratings can predict the S&P 500 returns over the monthly period of 1941:07 to 2018:04 using a dynamic conditional correlation multivariate generalized autoregressive conditional heteroscedasticity (DCC-MGARCH) model. The authors show that the standard linear Granger causality test fails to detect evidence of predictability because the underlying linear model is misspecified due to structural breaks and nonlinearity. However, when they apply the DCC-MGARCH model, which is robust to such misspecifications, in 69 percent of the sample period, presidential approval ratings strongly predict the S&P 500 stock returns.

To sum up, researchers in the earlier literature have used the presidential approval rating as a predictor of the first moment of stock-market returns, but not stock-market volatility, and given the importance of the latter from the perspective of portfolio decisions of investors, we forecast RV. We organize the remainder of our paper as follows. In Section 2, we describe the data we use in our empirical analysis. In Section 3, we describe our methods. In Section 4, we report our empirical results. In Section 5, we conclude.

2. Data

As stated in the introductory section, we considered the sum of squared daily log-returns of the S&P 500 index to compute the realized stock-market volatility estimates (RV) for each month in our sample, with the data derived from the historical data segment of Yahoo! Finance. The address of the corresponding internet page is as follows: https://finance.yahoo.com/quote/%5EGSPC/history?p=%5EGSPC (accessed on 1 April 2023).

For the sake of clarity, it should be noted that we used RV to measure the realized variance of stock-market returns, while some researchers use the term stock-market volatility as a synonym for the standard deviation of stock-market returns.

The data on the presidential approval rating are based on surveys conducted by Gallup, which in turn are compiled by Professor Gerhard Peters and Professor John T. Woolley as part of the American Presidency Project. An approval rating, commonly expressed in percentage terms, informs about the proportion of respondents to an opinion poll who approve of, for example, a politician or a party program, in our case the US president in office when the poll was conducted. While several national polls inform about public approval of the president, the Gallup poll has the advantage that it has been based over the years on the same approval question: "Do you approve or disapprove of the way [enter president name] is handling his job as president?" (the data were publicly available for download from the following internet page: http://www.presidency.ucsb.edu/data/popularity.php (accessed on 1 April 2023). The data start in 1941:07 (President Franklin D. Roosevelt) and, at the time of writing of this paper, end in 2023:02 (President Joseph Robinette Biden Jr.). The data are available monthly in general, but also weekly at times, and have missing observations intermittently. When available weekly, we took the average over the weeks of the month to convert the presidential approval rating into monthly data, and we interpolated the missing data linearly, like Fauvelle-Aymar and Stegmaier [17].

We now turn our attention to a detailed discussion of our macroeconomic predictors. In this regard, it is important to realize that several macroeconomic variables have been used in the empirical finance literature as predictors of stock-market returns and stock-market volatility. In order to capture a broad base of macroeconomic variables, we, therefore, used 8 factors derived from the 134 macroeconomic variables of Ludvigson and Ng [32,33]. The factors were available for download from the following internet page: https://www.sydneyludvigson.com/data-and-appendixes (accessed on 1 April 2023). Including these factors gave us the advantage of capturing broad categories of aggregate and regional macroeconomic time series (namely, real output and income, employment and hours, real retail, manufacturing and sales data, international trade, consumer spending, housing starts, housing building permits, inventories and inventory sales ratios, orders and unfilled orders, compensation and labor costs, capacity utilization measures, price indexes, interest rates and interest rate spreads, stock-market indicators, and foreign-exchange measures). In addition, we used the macroeconomic uncertainty (MU) and financial uncertainty (FU) measures developed by Jurado et al. [34] and Ludvigson et al. [35], which, in turn, are the average time-varying variance in the unpredictable component of 134 macroeconomic and 148 financial time-series, respectively. In other words, the MU and FU predictors are constructed to capture the average volatility in the shocks to the factors that summarize the real and financial conditions. The MU and FU indexes were available for download from the following internet page: https://www.sydneyludvigson.com/macro-and-financial-uncertainty-indexes (accessed on 1 April 2023) (note that the same 134 variables are used in computing the factors used as predictors and the metric of macroeconomic uncertainty). The metrics that we used are the broadest measures of macroeconomic and financial uncertainties currently available for the US. The uncertainty indexes were available for three forecasting horizons of 1, 3, and 12 months ahead. In sum, we considered 14 variables (8 factors and 3 MUs and FUs each) as our macroeconomic predictors.

Based on the data availability of the macro factors at the time of writing this paper, our data sample covered the period of 1960:07 to 2022:12. We plot in Figure 1 the natural logarithm of realized volatility, the corresponding autocorrelation function, and the natural logarithm of the presidential approval rating. In Table 1, we report summary statistics of the data.

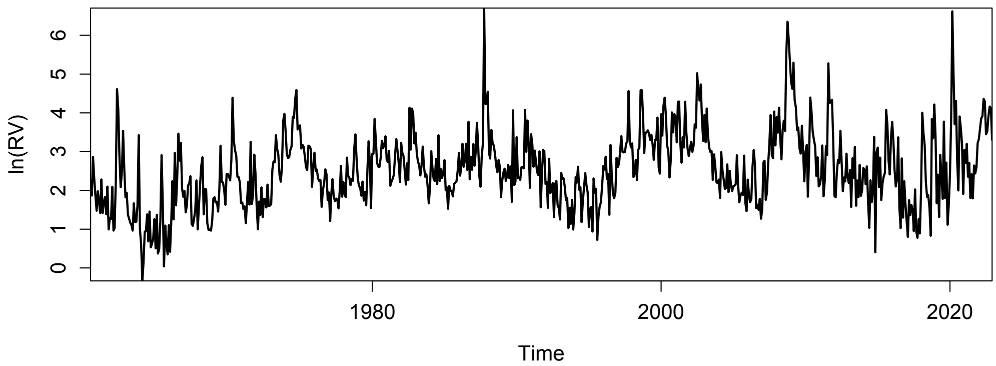


Figure 1. *Cont.*

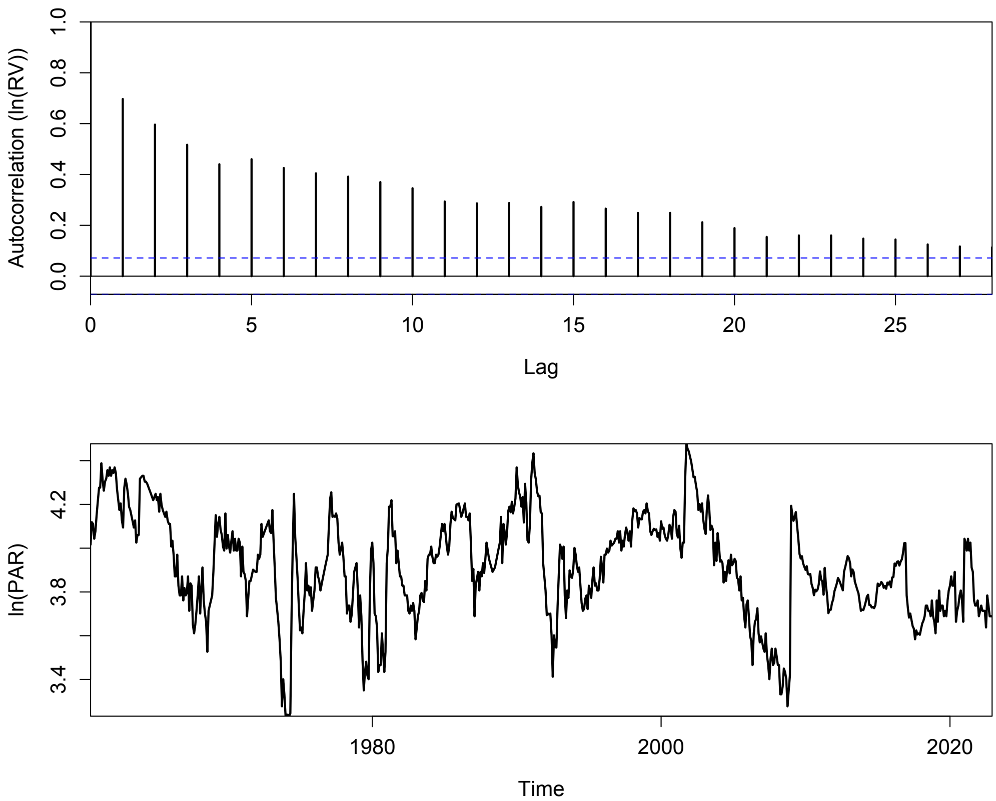


Figure 1. RV, its autocorrelation function, and PAR. RV = realized volatility. ACF = autocorrelation function. PAR = presidential approval rating.

Table 1. Summary statistics.

Variable	Minimum	Mean	Median	Maximum	Std. Dev.
RV	−0.3342	2.5312	2.4277	6.7017	0.9616
F1	−1.2677	−0.0025	−0.0439	2.2000	0.3939
F2	−1.3317	0.0002	0.0039	1.4519	0.2682
F3	−1.4702	0.0004	0.0089	1.2412	0.2612
F4	−1.0588	0.0005	−0.0044	0.9315	0.2294
F5	−0.8510	−0.0001	−0.0196	1.2255	0.2100
F6	−0.7028	−0.0003	0.0031	0.6766	0.1990
F7	−1.2655	0.0001	0.0105	0.4835	0.1737
F8	−0.7008	0.0013	−0.0047	0.4821	0.1538
MU1	0.5270	0.6536	0.6252	1.2166	0.1060
MU3	0.6527	0.7911	0.7611	1.2797	0.1079
MU12	0.7996	0.9171	0.9012	1.1773	0.0713
FU1	0.5948	0.9071	0.8833	1.5499	0.1679
FU3	0.6871	0.9469	0.9307	1.4237	0.1332
FU12	0.8831	0.9870	0.9843	1.1343	0.0485
PAR	3.2321	3.9157	3.9120	4.4773	0.2305

RV = realized volatility (natural logarithm). PAR = presidential approval rating (natural logarithm). $F_j, j = 1, \ldots, 8$ = macroeconomic factors. $MU_j, FU_j, j = 1, 3, 12$ = macroeconomic and financial uncertainties.

3. Methods

Our baseline forecasting model for stock-market volatility, RV_{t+h}, at forecast horizon h was given by the following equation:

$$RV_{t+h} = \beta_0 + \beta_1 RV_t + \beta_2 \text{MACRO}_t + \beta_3 \text{PAR}_t + \eta_{t+h}, \tag{1}$$

where $\beta_j, j = 1, 2, 3, 4$ are coefficients (and in the case of the macroeconomic variables, a vector of coefficients) to be estimated, η_{t+h} is the usual disturbance term, MACRO_t is a vector of macroeconomic variables (8 factors and 6 uncertainties), and PAR_t is the presidential approval rating. As for the forecast horizon, we set $h = 1, 3, 6, 12$ months ahead. As our dependent variable, we used the average realized volatility over the relevant forecast horizon when we studied a forecast horizon with $h > 1$.

The model given in Equation (1) is a standard long-horizon prediction model used in our empirical analysis to generate out-of-sample forecasts, which has a deep-rooted historical background in forecasting asset-market movements (see, for example, the detailed discussions in Campbell and Shiller [36,37], and more recently, Welch and Goyal [38] and Rapach et al. [39]). The model can be estimated using the ordinary least-squares technique, which is robust even under non-Gaussian errors. Moreover, the model features *RV* as a predictor on the right-hand side and, thereby, contains a catch-all predictor variable that accounts for effects on the realized volatility not already captured by the macroeconomic variables. Such a catch-all variable, which also accounts for the persistence of realized volatility, helps to trace out the incremental predictive value of the PAR predictor. In a way, the three groups of predictor variables on the right-hand side of Equation (1) can be thought of as representing a parsimonious forecasting model that accounts for the influence on the realized volatility of (i) macroeconomic factors (MACRO), (ii) the political "climate" (PAR), and (iii) other factors that can be interpreted to represent volatility clustering and other financial-market dynamics. Other advantages of the model are that similar models have been widely studied in various contexts in empirical finance and that its simple linear structure implies that the empirical results that we report in our research do not hinge on the specific assumed functional forms or the numerical values assigned to the (hyper-)parameters of a more complicated statistical model. At the same time, however, the model given in Equation (1) can be extended easily to a quantile-regression model. The quantile-regression model retains the simple linear structure of the model given in Equation (1) for any given quantile of realized volatility and, at the same time, renders it possible to add an element of non-linearity to our empirical research strategy in that the coefficients, β_j, of the forecasting model are allowed to vary across the different quantiles of the conditional distribution of realized volatility. Looking at just the conditional mean of *RV* may "hide" interesting characteristics as it can lead us to conclude that a predictor(s) has poor predictive performance, while it is actually valuable for predicting certain parts of the distribution of volatility, especially since business-cycle fluctuations are likely to induce the slope coefficient(s) associated with the predictor(s) to vary across quantiles [40].

It is important to note that, on the one hand, unlike in the case of the Markov-switching and the smooth-threshold models, we did not need to specify the number of regimes of *RV* in an ad hoc fashion with the quantile model. On the other hand, the quantile approach has the added advantage over non- or semi-parametric models and neural networks that we could study each point of the conditional distribution characterizing the existing nature of the volatility in the stock market. At the same time, because the quantile-regression approach sheds light on the entire conditional distribution, which captures various states of the stock market, it adds an inherent time-varying facet to the estimation process.

For our forecasting experiment, we used 50–75% of the data for estimation of the forecasting model and the remaining proportion for testing the forecasting performance of the models. In order to mitigate peaks in the realized volatility and to bring the data closer to a normal distribution, we studied the natural logarithm of the realized volatility as our dependent variable, but to evaluate forecasts we converted it back to anti-logs, where we added the usual Jensen-Ito term. We also used the natural logarithm of the presidential approval rating in our baseline setting, so that the coefficient β_3 can be interpreted as an elasticity.

We also studied forecasting models featuring (i) the natural logarithm of the square root of *RV* and (ii) the anti-log of the presidential approval rating, with qualitatively similar results. In addition, we studied an extension where we used a recursive estimation window to estimate the forecasting models, where we used a training period to initialize the estimations and then extended the estimation window step-by-step until we reached the end of the sample period. The results of these various extensions can be found at the end of the paper (Appendix A).

The general model given in Equation (1) nests several special forecasting models of interest. Setting $\beta_2 = \beta_3 = 0$ gives a pure autoregressive model (AR model). Setting $\beta_2 = 0$ excludes the macroeconomic variables and gives an autoregressive model extended to include the presidential (economic) approval rating (AR-PAR model). Finally, setting $\beta_3 = 0$ gives an autoregressive model extended to include the macroeconomic variables (AR-MAC model).

In order to evaluate the performance of the forecasting models, we considered the possibility that an investor may have an asymmetric loss function, that is, that an underestimation of RV does not cause exactly the same loss as an overestimation of the same absolute size. In this regard, we considered an asymmetric loss function proposed by Elliott et al. [41,42]. The loss function is given by $\mathcal{L}(k,\alpha) = [\alpha + (1-2\alpha)\mathbf{1}(fe < 0)]|fe|^k$, where fe denotes the forecast error and $\mathbf{1}$ denotes the indicator function. The parameter $k = 1,2$ governs whether the loss function is a quasi-linear or a squared function of the forecast error, while the parameter $\alpha \in (0,1)$ governs the asymmetry of the loss function. A symmetric quadratic loss function is obtained as a special case for $k = 2, \alpha = 0.5$, while $k = 1, \alpha = 0.5$ gives a symmetric loss function that is increasing in the absolute forecast error. In the general case, setting $\alpha > 0.5$ ($\alpha < 0.5$) implies that the loss from underestimating (overestimating) the realized volatility exceeds the loss from an overestimation (underestimation) of the same absolute magnitude.

A comparison of forecasts from a benchmark and a rival model then can be undertaken in terms of the following out-of-sample statistic, $R^k(\alpha) = 1 - \sum \mathcal{L}(k,\alpha)_R / \sum \mathcal{L}(k,\alpha)_B$, where $B =$ the benchmark model, and $R =$ a rival model. When one observes $R^k(\alpha) > 0$, the rival model outperforms the benchmark model, and vice versa. For $k = 2, \alpha = 0.5$, this statistic is the familiar out-of-sample R^2 statistic, $R^2 = 1 - \sum fe_R^2 / \sum fe_B^2$, which evaluates the forecasting performance by comparing the sum of squared forecast errors implied by two models. For $k = 1, \alpha = 0.5$, in turn, one obtains $R^1 = 1 - \sum |fe_R| / \sum |fe_B|$, a statistic that compares the forecasting performance of a rival and a benchmark model in terms of the sum of their absolute forecast errors.

Finally, it should be noted that $\mathcal{L}(1,\alpha)$ simply is the conventional check function used to estimate a quantile-regression model, where α denotes the quantile being studied. As an extension, we, therefore, also estimated the forecasting model given in Equation (1) as a quantile-regression model and then used the $R^1(\alpha)$ statistic to compare a benchmark with a rival forecasting model.

We used the R language and environment for statistical computing [43] for our empirical analysis.

4. Empirical Results

4.1. Baseline Results

We summarize our results in Figure 2 (for $R^1(\alpha)$) and Figure 3 (for $R^1(\alpha)$). The vertical axis of these two figures displays the number of in-sample estimation data. As this number increases, the proportion of estimation data increases from 50% to 75%. The horizontal axis displays the asymmetry parameter, α.

We studied the results for the $R^k(\alpha)$ criterion for three different combinations of rival and benchmark models. First, we compared a pure autoregressive benchmark model with an autoregressive rival model extended to include the macroeconomic variables (AR/AR-MAC). Second, we compared a pure autoregressive benchmark model with an autoregressive rival model extended to include the presidential approving rating (AR/AR-PAR). Third, we compared an autoregressive benchmark model extended to include the macroeconomic variables with an autoregressive rival model extended to include the presidential approving rating (AR-MAC/AR-PAR).

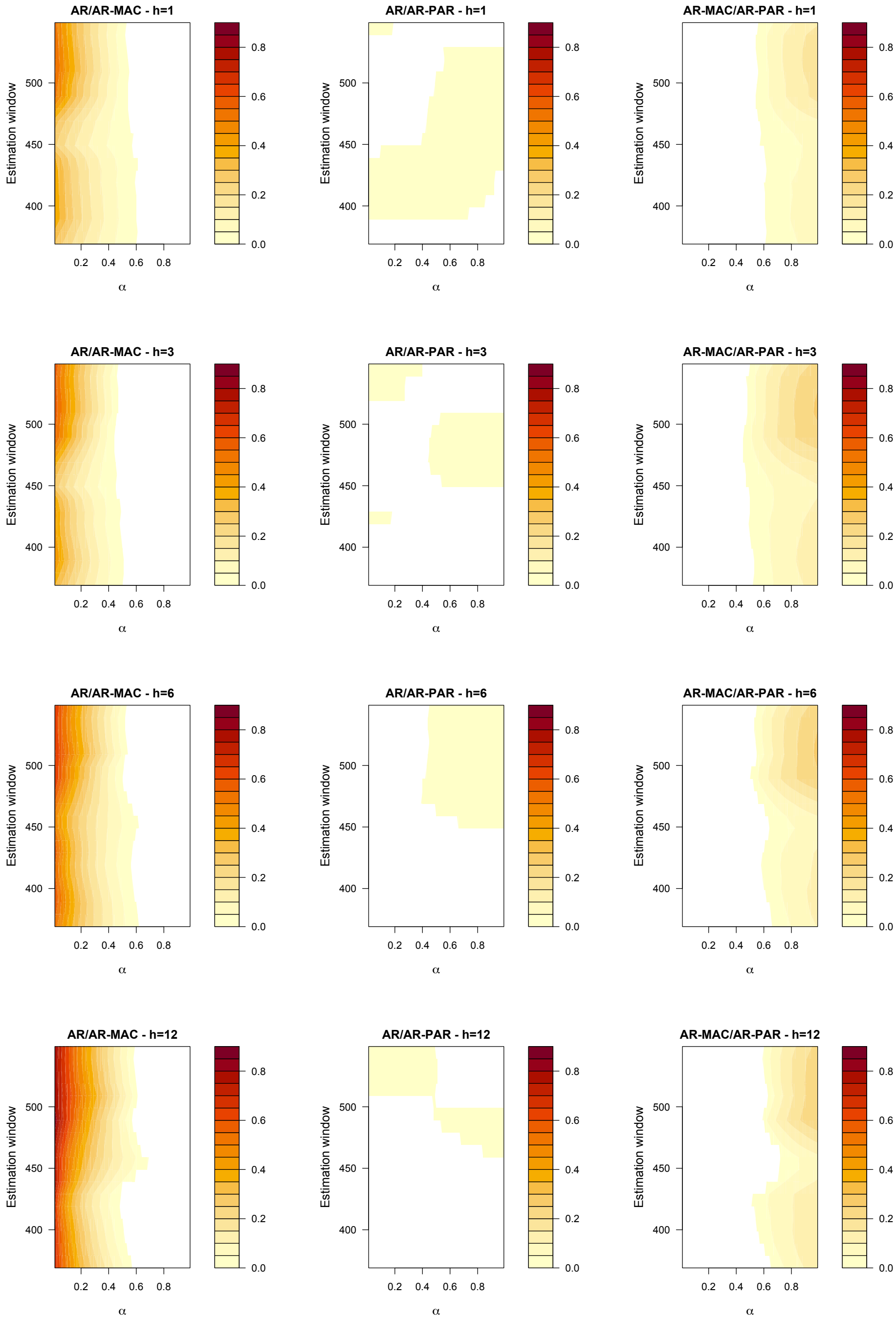


Figure 2. Results for $R^1(\alpha)$. h = forecast horizon. Estimation period = training period (in months) used for the estimation of the forecasting models (ranges from 50% to 75% of the data). The white region indicates combinations of the asymmetry parameter and the estimation window for which the benchmark model outperforms the rival model.

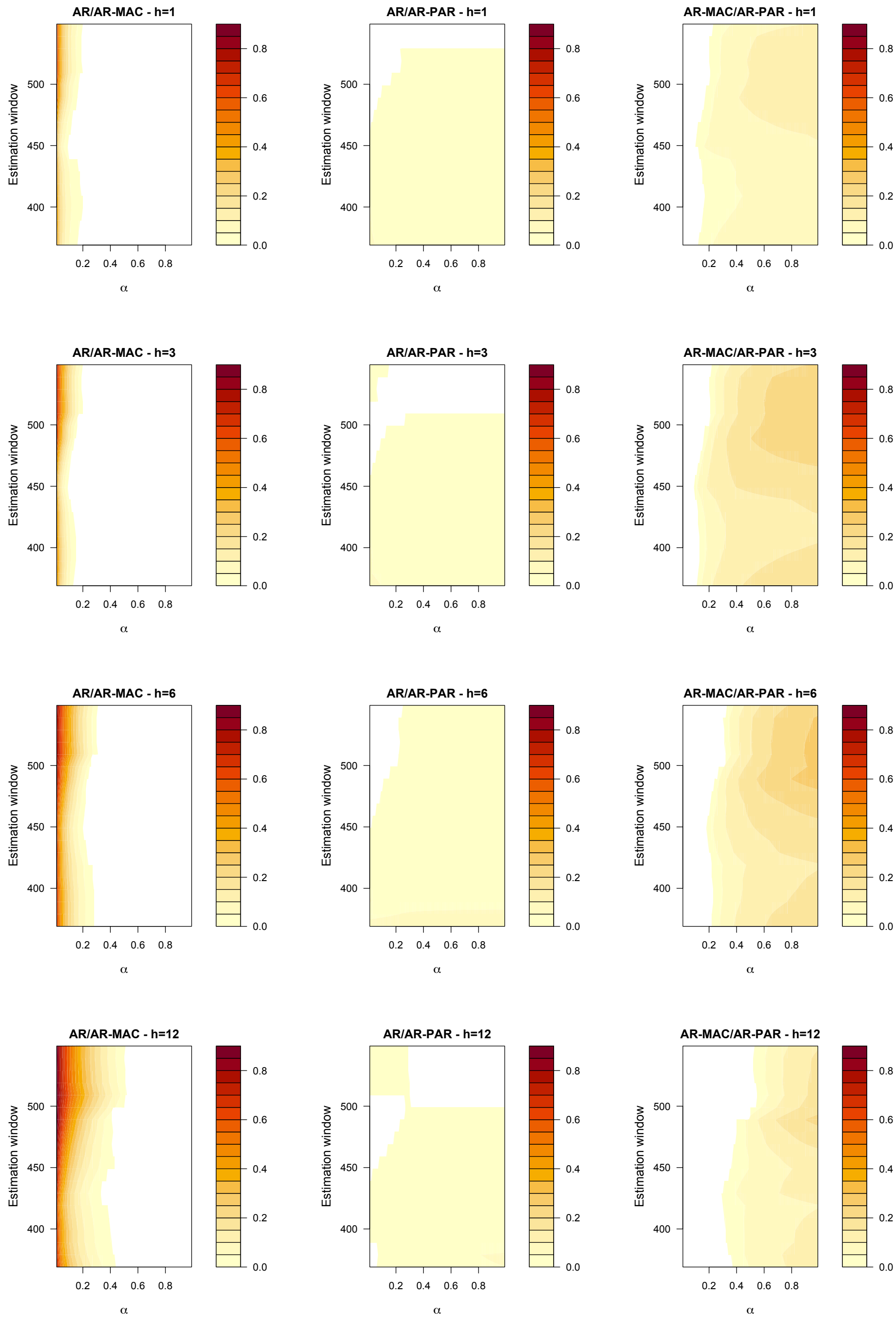


Figure 3. Results for $R^2(\alpha)$. h = forecast horizon. Estimation period = training period (in months) used for the estimation of the forecasting models (ranges from 50% to 75% of the data). The white region indicates combinations of the asymmetry parameter and the estimation window for which the benchmark model outperforms the rival model.

The results showed that the AR-MAC model tends to outperform the AR model when an investor faces a larger loss in the case of an overestimation of RV than in the case of an underestimation of the same absolute size. The performance of the AR-PAR model relative to the AR model, in turn, depended on the loss function being studied. When we used the $R^1(\alpha)$ criterion, the AR-PAR outperformed the AR model for several model configurations when the loss from an underestimation exceeded that of a corresponding overestimation of RV, but for $h = 1$ and some of the shorter estimation windows also in the opposite case. When we studied the $R^2(\alpha)$ criterion, the AR-PAR model performed better than the AR model for all admissible α parameters when the proportion of in-sample data was not too large. As a consequence, when we combined the results for the AR-MAC and the AR-PAR model, the latter turned out to be the better forecasting model for an investor who suffers from a larger loss from an underestimation of RV rather than from an overestimation of the same size (for both the $R^1(\alpha)$ and the $R^2(\alpha)$ criteria). When we focused on the loss function with $k = 2$, even an investor whose loss function exhibits a shape parameter $\alpha < 0.5$ benefited from using the presidential approval rating rather than the macroeconomic variables to predict RV.

We used the modified Diebold and Mariano [44] test as suggested by Harvey et al. [45] to study whether the differences in accuracy across the AR-MAC and AR-PAR forecasts are statistically significant. We found several significant test results (not reported for reasons of space) for combinations of the asymmetry parameter and the estimation window, where an underestimation of RV is costlier than an overestimation of the same absolute size. For the $R^1(\alpha)$ criterion, the regions of significant test results (asymmetry parameter−estimation) became smaller when we moved from the short to the intermediate and long forecast horizons, whereas the test results for the $R^2(\alpha)$ criterion were significant only in the case of the short forecast horizon.

In Figures A1 and A2, we plot the results we obtained when we not only considered PAR as a predictor but also included in the AR-PAR model an extra predictor that we computed as the product of PAR with the number of months a president was in office (where we let the data start with the beginning of the presidency of John F. Kennedy). In doing so, we accounted in a stylized way for a potential presidential-cycle effect. The results show that accounting for such an interaction effect somewhat widens (mainly for the $R^1(\alpha)$ criterion) the range of combinations of the window lengths and the asymmetry parameter for which the AR-PAR model performs somewhat better than the AR model, but on balance leaves the results of a comparison of the AR-MAC model with the AR-PAR model qualitatively unaffected.

4.2. An Extension Based on Historical Data

Next, we extended our analysis by using long-range historical data, which date back to 1941:07, i.e., the starting point of the presidential approval rating. However, the macroeconomic variables, based on data availability, and in line with the literature, are a smaller set, and included three variables, namely the seasonally-adjusted Consumer Price Index (CPI)-based month-on-month inflation rate, the month-on-month growth rate of the seasonally-adjusted industrial production, and the three-month Treasury bill rate. The raw data for these three variables were sourced from the FRED database of the Federal Reserve Bank of St. Louis.

We summarize our results for the long-range historical data in Figures 4 and 5. When we considered the $R^1(\alpha)$ criterion, we observed that the AR-MAC model performed better than the AR model when an overestimation of RV outweighed an underestimation of the same absolute size. The AR-PAR model, in turn, unfolded its strength relative to the pure AR model mainly when the loss from an underestimation outweighed the loss from a corresponding overestimation and, as in Figure 2, also in the opposite case when we studied some of the shorter estimation windows in the case of $h = 1$. As a result, the AR-PAR model performed relatively better than the AR-MAC model (or, in some cases, relatively less poorly than the pure AR model) when α took on a value in the upper half of its admissible range. For the $R^2(\alpha)$ criterion, in turn, the AR-MAC model performed worse than the pure AR model for most combinations of the shape parameter, α, and the estimation window. The AR-PAR model, in contrast, outperformed the pure AR model for most combinations of the shape parameter, α, and the estimation window and, hence, the AR-PAR model also performed better than the AR-MAC model when the numerical value of the shape parameter, α, was not too small.

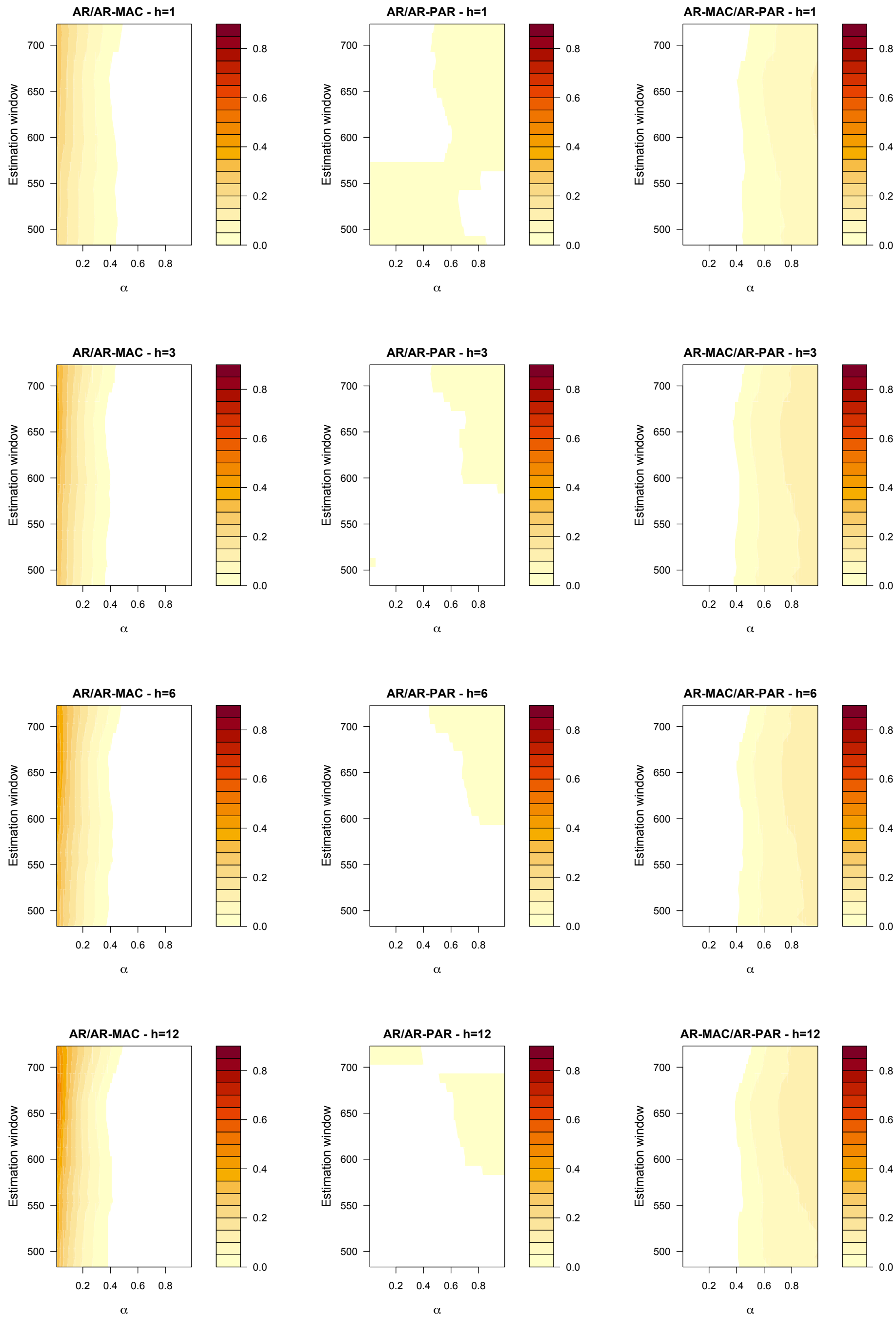


Figure 4. Results for $R^1(\alpha)$ (historical data). h = forecast horizon. Estimation period = training period (in months) used for the estimation of the forecasting models (ranges from 50% to 75% of the data). The white region indicates combinations of the asymmetry parameter and the estimation window for which the benchmark model outperforms the rival model.

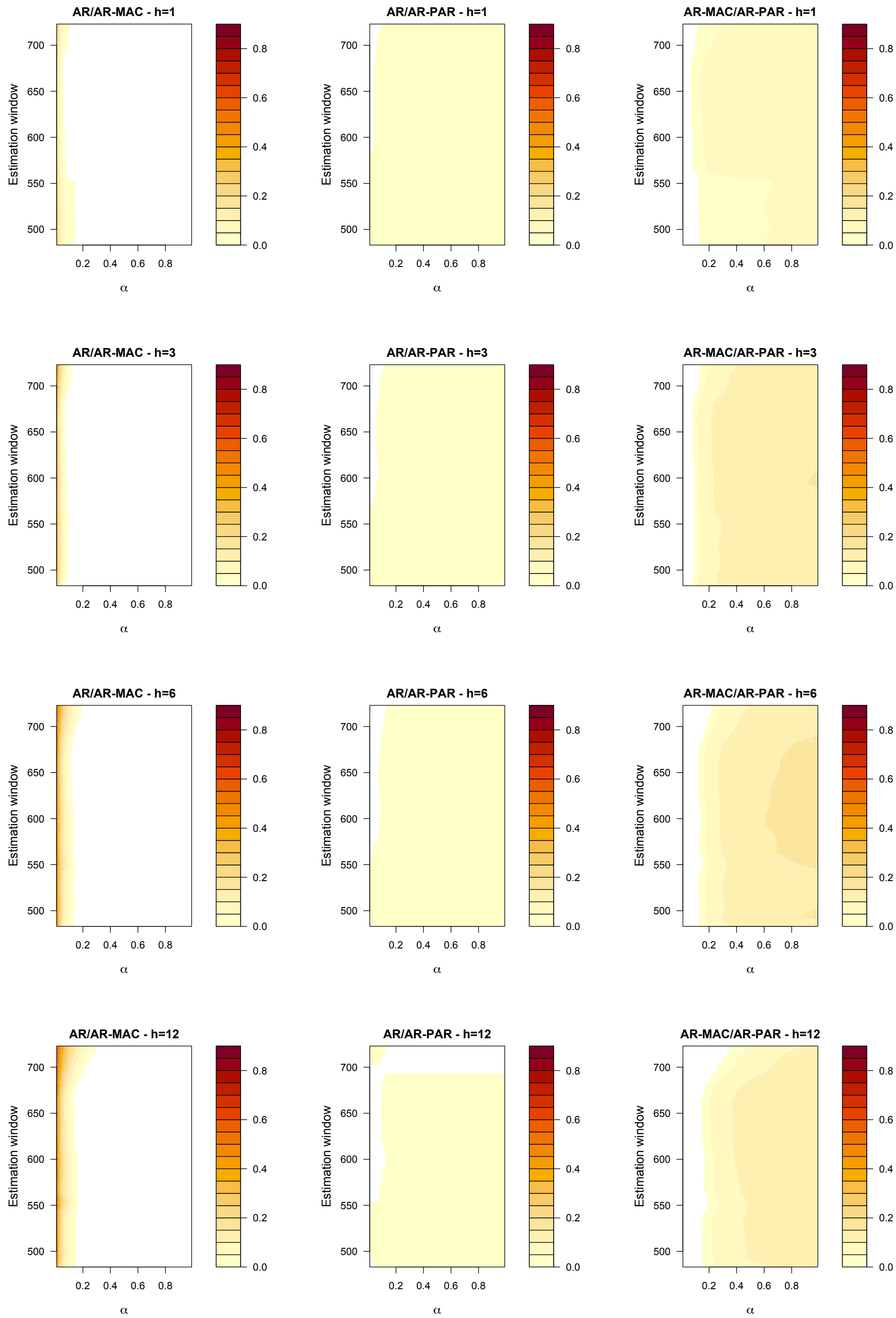


Figure 5. Results for $R^2(\alpha)$ (historical data). h = forecast horizon. Estimation period = training period (in months) used for the estimation of the forecasting models (ranges from 50% to 75% of the data). The white region indicates combinations of the asymmetry parameter and the estimation window for which the benchmark model outperforms the rival model.

4.3. A Comparison of PAR and PEAR

As pointed out earlier, recently, in order to measure public opinion on the president's handling of the economy and to relate it to stock-market returns, Chen et al. [31] constructed a PEAR (i.e., presidential economic approval rating) index by using various national polls. The underlying data were obtained from Roper iPoll at the Roper Center for Public Opinion. Data on the PEAR index were available for download from the following internet page: https://www3.nd.edu/~zda/ (accessed on 1 April 2023). Over the common sample period of 1981:04 to 2022:12, PAR and PEAR were significantly positively correlated (with a coefficient of 0.66). Notwithstanding, it is interesting to compare the PAR with the PEAR index in some more detail.

We summarize the results of a direct comparison of the AR-PAR (the rival) and AR-PEAR (the benchmark) forecasting models in Figure 6. Given the significantly positive correlation between PAR and PEAR, both forecasting models did not differ much in terms of the $R^1(\alpha)$ and the $R^2(\alpha)$ criteria for a broad array of combinations of the estimation window and the asymmetry parameter. For the $R^1(\alpha)$ criterion, we found that the AR-PAR model performed better than the AR-PEAR model for virtually all estimation windows when $\alpha < 0.7\tilde{0}.8$. The AR-PEAR model gained ground relative to the AR-PAR model when the forecast horizon increased. For the $R^2(\alpha)$ criterion, in turn, we found that the AR-PAR model performed better than the AR-PEAR model for $h = 1$ when α settled in the lower part of its admissible range (with the boundaries of this range depending on the length of the estimation window). For the longer forecast horizons, the AR-PAR model performed better for the short and intermediate estimation windows, while the AR-PEAR model was the forecasting model of choice for the long estimation windows.

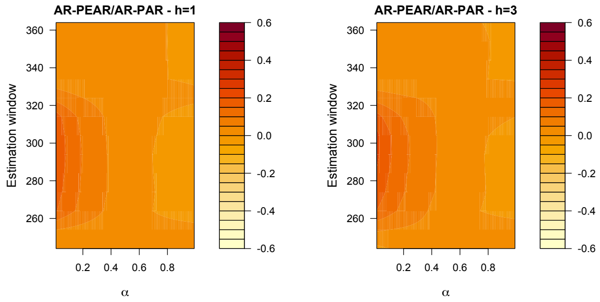
In any event, our focus on PAR allowed us to study volatility forecasting over a longer sample period (in fact, in the case of the historical data that we studied in Section 4.2, a much longer sample period) and more economic cycles and presidencies.

4.4. Extensions Based on Quantile Regressions

Figure 7 plots the forecasting results that we obtained when we estimated Equation (1) as a quantile-regression model (on data for the sample period 1960:07 to 2022:12). In line with the check function underlying the quantile-regression model, we used the $R^1(\alpha)$ criterion to shed light on the forecasting performance of the models. The AR-MAC model tended to perform better than the AR model mainly in the region where $\alpha < 0.5$ when the forecasting horizon increased. For the AR-PAR model, in turn, we observed that the regions where it outperformed the AR model were scattered throughout the figures, where the array of combinations of the estimation window and the asymmetry parameter for which the AR-PAR model was the preferred forecasting model showed a tendency to increase in the forecast horizon. Finally, when we directly compared the AR-MAC with the AR-PAR model, we observed that the latter clearly dominated the former as the asymmetry parameter, α, increased. This result is not surprising given that this is the parameter region where the AR-MAC model clearly was inferior to the AR model and the AR-PAR model, while it did not unambiguously dominate the AR model (as indicated by the white areas in the figures), outperformed the AR model for some combinations of the estimation window and the asymmetry parameter.

In order to investigate the question of quantile-based predictability in some more detail, we utilized, as part of a preliminary investigation, the bivariate k-th order nonparametric causality-in-quantiles test of Balcilar et al. [46], which allowed us to uncover in-sample predictability from PAR or PEAR for both returns and squared returns (i.e., volatility) over the quantiles of the distributions. When we applied this test to the US, the rest of the G7 (Canada, France, Germany, Italy, Japan, and the United Kingdom (UK)) countries, and Switzerland, as well as the BRICS (Brazil, Russia, India, China, and South Africa) bloc, we found evidence of quantile-based predictability for both returns and volatility, though the effect was stronger for the latter, as can be observed from Tables A1 and A2 (Appendix A). This evidence provided us with an alternative motivation to focus on volatility rather than returns for the US. Note that, just like the US, stock log-returns data, derived from Global Financial Data, were available for all countries from 1941:07, barring Brazil, China, and Russia, for which the data started from 1954:02, 1993:01, and 1995:01, respectively.

Panel A: $R^1(\alpha)$



Panel B: $R^2(\alpha)$

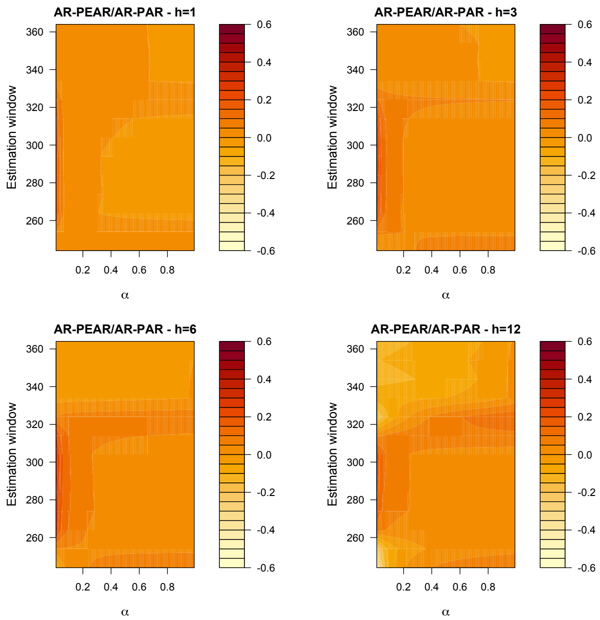


Figure 6. A comparison of PAR and PEAR. h = forecast horizon. Estimation period = training period (in months) used for the estimation of the forecasting models (ranges from 50% to 75% of the data).

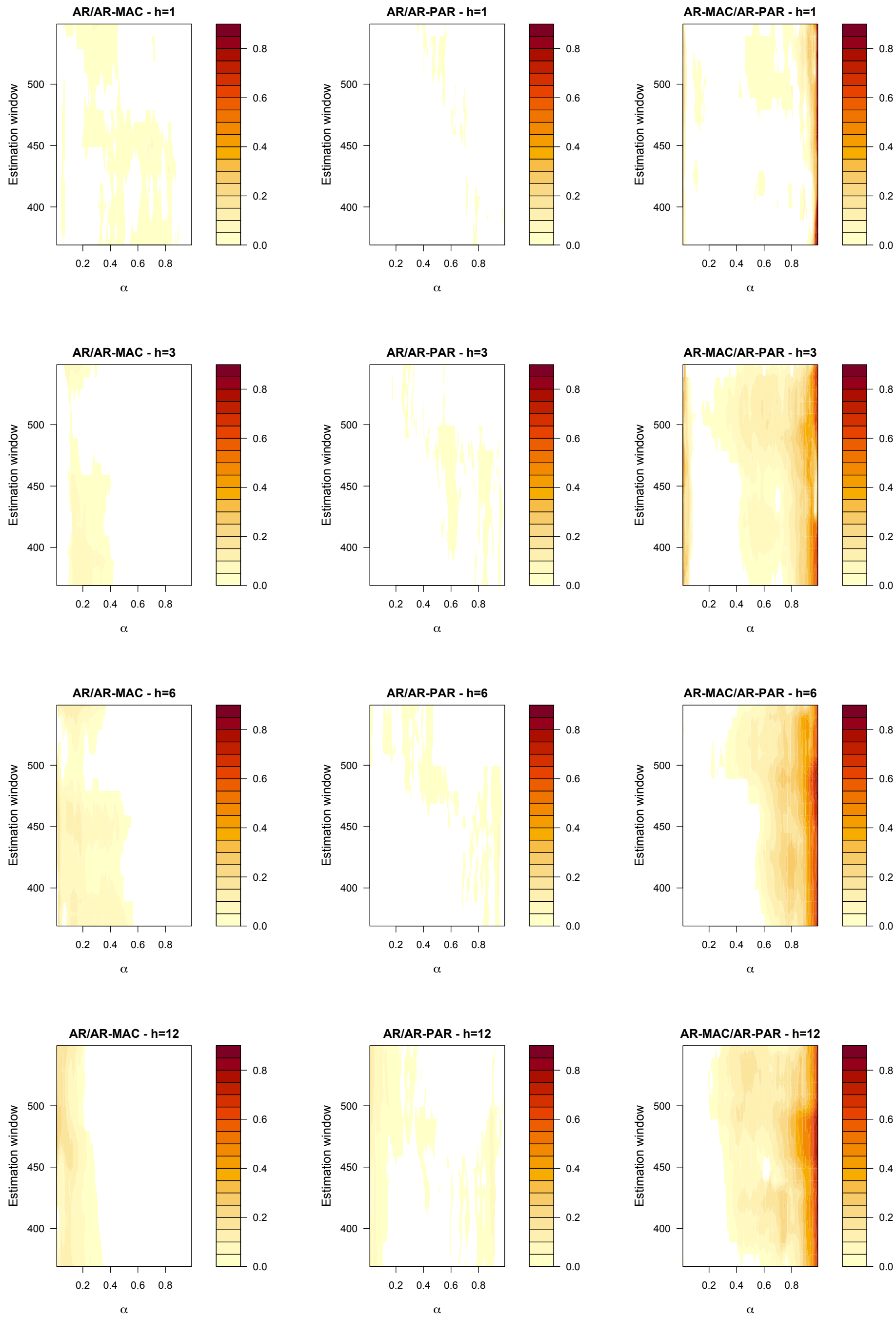


Figure 7. Quantile-regression results ($R^1(\alpha)$). h = forecast horizon. Estimation period = training period (in months) used for the estimation of the forecasting models (ranges from 50% to 75% of the data). The white region indicates combinations of the asymmetry parameter and the estimation window for which the benchmark model outperforms the rival model. Results are based on the natural logarithms of the realizations/forecasts of RV.

4.5. Relation to the Existing Literature

It is interesting to put some perspective into our findings in relation to the earlier literature, keeping in mind that, while many researchers (see the studies cited in Section 1) have related the predictability and/or forecastability of the (realized) volatility of the US stock market with macroeconomic and financial factors, the same cannot be said about PAR and/or PEAR, and that is specifically where we come in. Our idea was to check whether presidential approval can act as a single replacement for multiple macroeconomic and financial predictors in forecasting the US realized stock-market volatility, *RV*. In this regard, we showed that, consistent with the literature (see for example, [4–6,28] among others), macroeconomic variables do indeed carry important predictive information for RV compared to a benchmark model. At the same time, in line with the only available in-sample evidence reported by Gupta et al. [1], we found that PAR outperformed the autoregressive baseline model in forecasting RV, where we showed that it is important to account for the potential asymmetry of an investor's loss function. More importantly, however, we documented that PAR, again depending on the shape of an investor's loss function, can indeed act as the sole predictor that can replace information carried by many macroeconomic predictors in forecasting the US RV due to its better performance. In other words, we could confirm the hypothesis that, since PAR reflects the macroeconomic and financial market conditions, PAR can serve for some groups of investors as a catch-all predictor for RV.

5. Concluding Remarks

Our empirical findings show that, depending on the loss function an investor uses to evaluate under- and overestimations of the realized stock-market volatility, the presidential approval rating is a useful catch-all variable for more standard macroeconomic variables considered in the extant literature as predictors of stock-market volatility. Such a single-variable substitute for a large array of macroeconomic variables results in a parsimonious and easy-to-interpret forecasting model that, in addition, can be readily justified economically by resorting to political-economy considerations (and the results of significant earlier empirical research).

Because stock-market volatility is a reflection of the vulnerability of the financial system, policy authorities can rely on the predictive content of the presidential approval rating to design appropriate fiscal and monetary policy responses in a timely manner to prevent possible negative spillovers on the real economy, which are associated with financial uncertainty [47,48]. At the same time, Chong et al. [8] have highlighted the role of uncertainty in negatively impacting presidential approval ratings, thus implying a feedback effect. In other words, while the presidential approval rating is shown to drive the realized volatility of the US stock market, the latter can also drive the former, giving rise to bi-directional causations and requiring stronger policy interventions to reduce the depth of a recession. Having said this, the US presidential office can also utilize the future path of volatility, which may even be obtained daily based on intraday data, to obtain a better understanding of what can be expected in terms of presidential ratings. Naturally, this can provide ahead-of-time information to undertake policies to reduce forthcoming economic slowdowns by curtailing volatility, and, hence, simultaneously, when viewed from a political-economy perspective, improving the public image and standing of the current president. Better management of the economy, of course, has potential positive implications for the reflection of the incumbent president if it is the first term.

Finally, under the current emphasis on open-source research, the fact that we can obtain favorable results using publicly available data (of presidential approval ratings) in a parsimonious set-up (based on free software) should be of tremendous appeal to academics, as researchers will not have to secure proprietary data on a large number of macroeconomic and financial indicators at exorbitant costs to conduct research on factors driving the equity-market volatility of the US.

Given the importance of US politics for the global financial system [49], as part of future research, it will be interesting to analyze whether the presidential approval rating can be utilized to forecast stock-market return volatility in other advanced and emerging economies, especially in light of the preliminary in-sample predictive evidence reported by us above. In this regard, an associated research question is whether the US presidential approval rating helps to explain the evolution of global stock-market linkages and perhaps even contagion effects. Finally, it is interesting to study other asset markets, whereby the predictive value of the US presidential approval rating for (international) bond risk premia and exchange rates could be investigated as well.

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Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Table A1. Predictability of international stock returns.

Panel A: PAR									
Quantile	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
Canada	1.402	2.108 **	2.994 ***	2.507 **	2.531 **	2.193 **	2.232 **	2.108 **	1.707 *
France	1.152	1.811 *	2.017 **	2.154 **	2.006 **	2.089 **	1.82 *	2.357 **	1.849 *
Japan	1.817 *	2.199 **	2.78 ***	2.819 ***	2.927 ***	3.028 ***	3.064 ***	2.525 **	2.042 **
Germany	2.644 ***	4.368 ***	5.163 ***	5.249 ***	5.853 ***	6.063 ***	5.573 ***	4.779 ***	3.225 ***
Italy	1.648 *	2.407 **	3.082 ***	3.203 ***	3.097 ***	2.759 ***	2.992 ***	3.545 ***	2.24 **
US	1.316	2.181 **	2.46 **	2.318 **	2.566 **	2.441 **	2.188 **	2.353 **	1.884 *
UK	1.696 *	2.557 **	2.558 **	2.9 ***	3.486 ***	3.514 ***	2.976 ***	2.818 ***	1.402
Switzerland	1.771 *	1.762 *	2.088 **	2.571 **	2.755 ***	3.218 ***	3.542 ***	2.963 ***	1.803 *
Panel B: PEAR									
Quantile	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
Canada	1.292	1.319	1.847 *	2.39 **	2.393 **	1.977 **	1.719 *	1.226	1.866 *
France	1.513	1.787 *	2.116 **	1.862 *	2.498 **	2.246 **	2.834 ***	2.711 ***	1.492
Japan	1.343	2.093 **	2.094 **	2.031 **	1.858 *	1.893 *	1.663 *	1.451	1.199
Germany	1.247	1.433	1.306	1.818 *	1.684 *	1.962 **	2.39 **	1.973 **	1.934 *
Italy	1.009	1.01	1.141	1.242	1.508	1.449	2.624 ***	2.811 ***	1.658 *
US	1.076	1.676 *	1.991 **	1.684 *	2.145 **	2.264 **	2.007 **	1.516	1.398
UK	1.203	2.258 **	1.919 *	1.768 *	2.548 **	2.712 ***	2.924 ***	2.972 ***	1.233
Switzerland	1.377	1.424	2.185 **	2.892 ***	2.401 **	2.945 ***	2.137 **	2.005 **	1.411

Note: ***, **, and * indicate rejection of the null hypothesis of non-Granger causality at the 1%, 5%, and 10% levels of significance, respectively, i.e., critical values of 2.575, 1.96, and 1.645 for the standard normal test statistic, from presidential approval rating (PAR) or presidential economic approval rating (PEAR) to stock returns for a particular quantile.

Table A2. Predictability of international stock return volatility (squared returns).

Panel A: PAR									
Quantile	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
Canada	5.177 ***	6.789 ***	7.959 ***	8.647 ***	8.871 ***	8.709 ***	8.213 ***	6.860 ***	5.247 ***
France	5.483 ***	7.812 ***	8.300 ***	8.667 ***	8.234 ***	8.069 ***	7.794 ***	6.547 ***	4.848 ***
Japan	5.485 ***	7.351 ***	8.820 ***	9.851 ***	9.671 ***	9.033 ***	8.752 ***	7.779 ***	5.446 ***
Germany	6.541 ***	8.528 ***	9.589 ***	10.21 ***	10.67 ***	10.44 ***	9.787 ***	8.435 ***	6.268 ***
Italy	5.222 ***	7.163 ***	8.332 ***	9.020 ***	9.381 ***	8.751 ***	8.231 ***	7.261 ***	5.484 ***
US	5.359 ***	6.668 ***	7.806 ***	8.251 ***	8.874 ***	8.685 ***	8.507 ***	7.187 ***	4.969 ***
UK	5.423 ***	7.762 ***	8.704 ***	9.134 ***	9.256 ***	9.114 ***	8.516 ***	7.580 ***	5.664 ***
Switzerland	5.077 ***	6.799 ***	7.961 ***	8.752 ***	9.011 ***	8.949 ***	8.244 ***	7.246 ***	5.307 ***
Panel B: PEAR									
Quantile	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
Canada	3.679 ***	4.859 ***	5.784 ***	6.134 ***	5.943 ***	5.806 ***	5.617 ***	4.950 ***	3.819 ***
France	3.750 ***	5.024 ***	6.260 ***	6.285 ***	6.556 ***	6.128 ***	5.516 ***	5.094 ***	3.701 ***
Japan	3.497 ***	4.854 ***	5.503 ***	5.735 ***	5.866 ***	5.910 ***	5.570 ***	5.143 ***	3.584 ***
Germany	3.983 ***	5.217 ***	6.128 ***	6.914 ***	6.893 ***	6.843 ***	6.267 ***	5.277 ***	3.716 ***
Italy	3.861 ***	4.894 ***	5.365 ***	5.744 ***	5.947 ***	5.887 ***	5.876 ***	5.227 ***	3.968 ***
US	3.874 ***	5.287 ***	5.744 ***	6.228 ***	6.091 ***	5.865 ***	5.543 ***	5.184 ***	3.579 ***
UK	4.203 ***	5.858 ***	6.194 ***	6.692 ***	6.543 ***	6.338 ***	6.021 ***	5.288 ***	3.676 ***
Switzerland	3.454 ***	5.167 ***	6.309 ***	6.345 ***	6.871 ***	6.594 ***	6.078 ***	5.042 ***	3.496 ***

Note: *** indicates rejection of the null hypothesis of non-Granger causality at the 1% level of significance, i.e., critical value of 2.575 for the standard normal test statistic, from presidential approval rating (PAR) or presidential economic approval rating (PEAR) to squared stock returns (volatility) for a particular quantile.

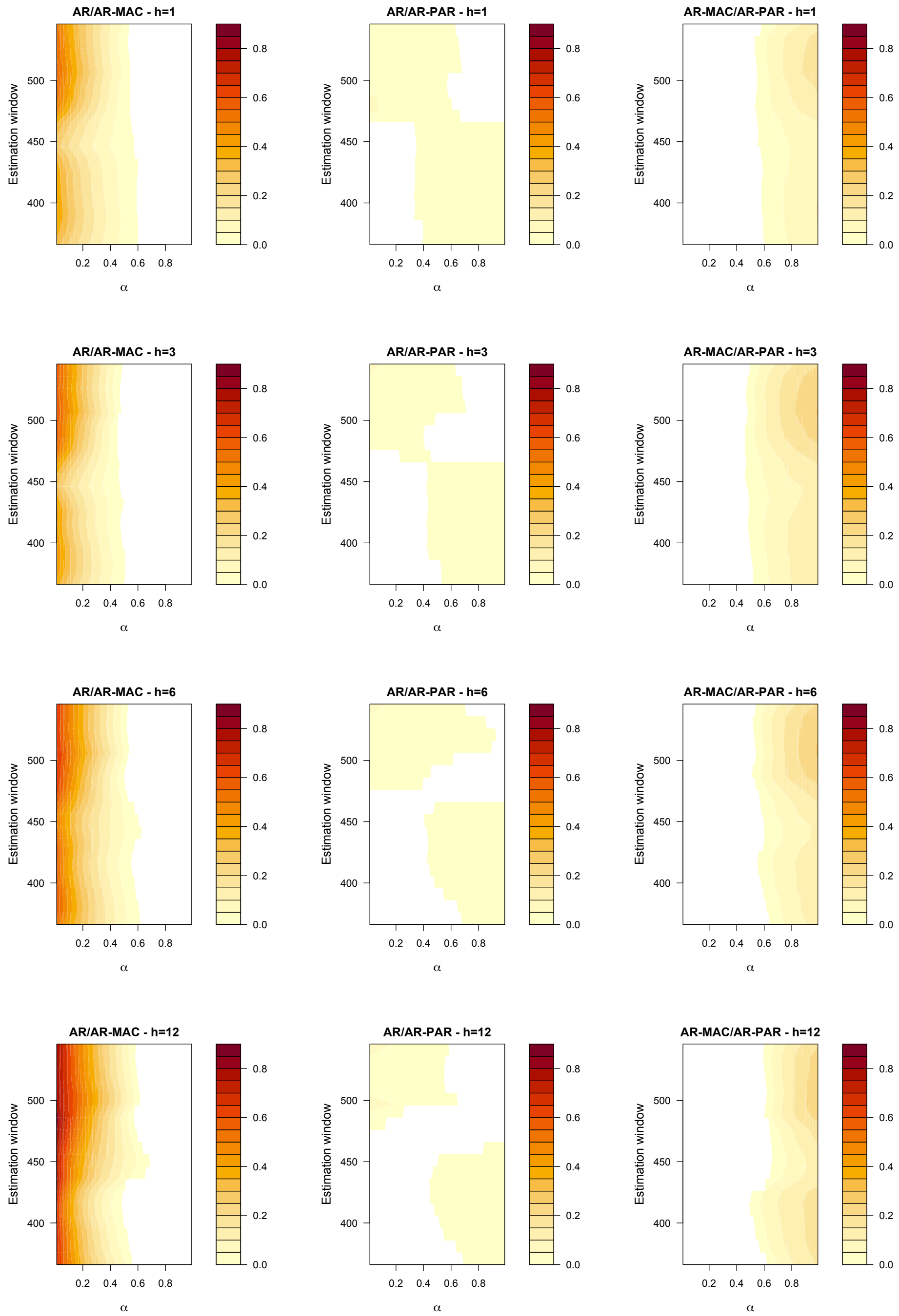

Figure A1. Results for $R^1(\alpha)$ (PAR interacting with months in office). h = forecast horizon. Estimation period = training period (in months) used for the estimation of the forecasting models (ranges from 50% to 75% of the data). The white region indicates combinations of the asymmetry parameter and the estimation window for which the benchmark model outperforms the rival model.

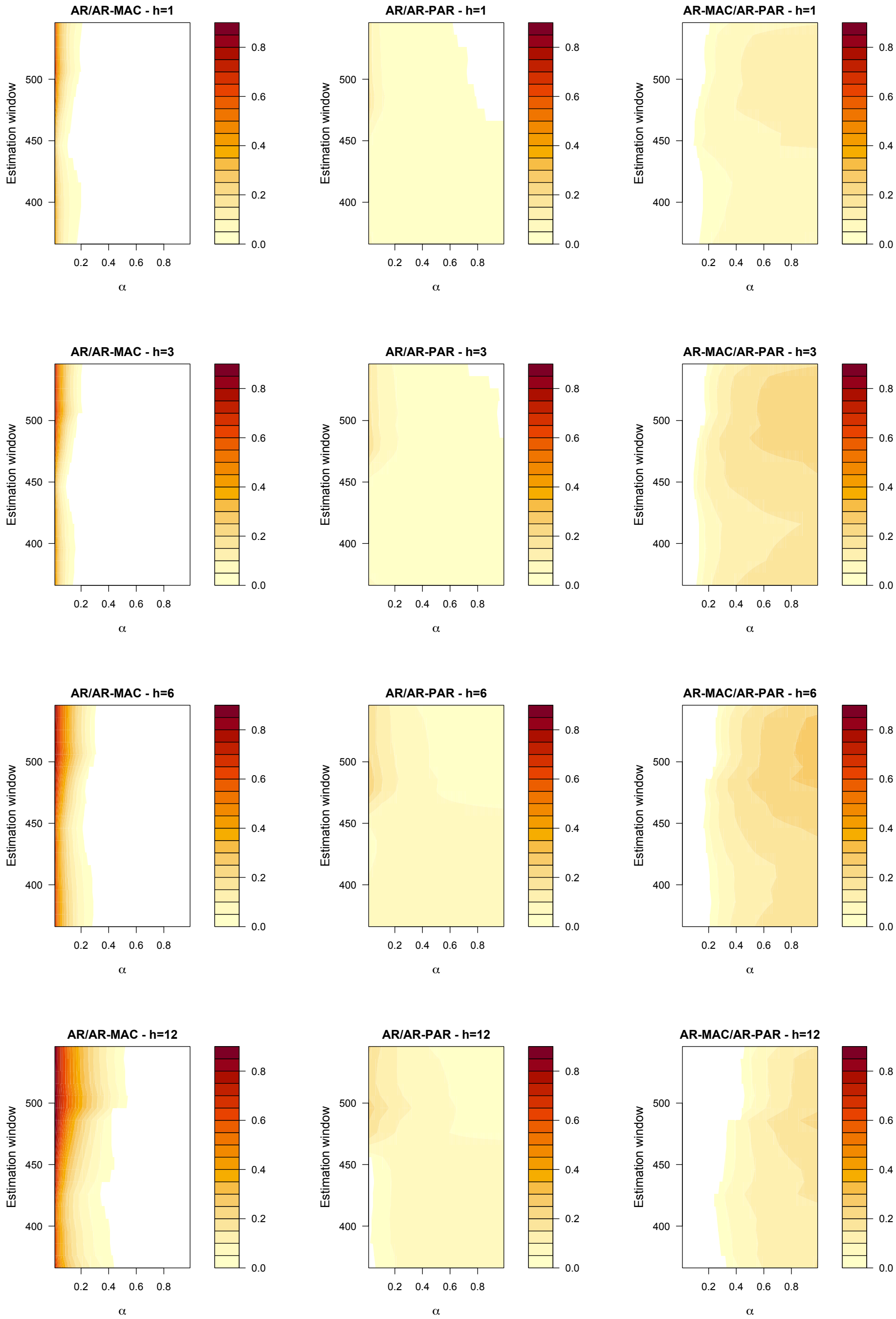

Figure A2. Results for $R^2(\alpha)$ (PAR interacting with months in office). h = forecast horizon. Estimation period = training period (in months) used for the estimation of the forecasting models (ranges from 50% to 75% of the data). The white region indicates combinations of the asymmetry parameter and the estimation window for which the benchmark model outperforms the rival model.

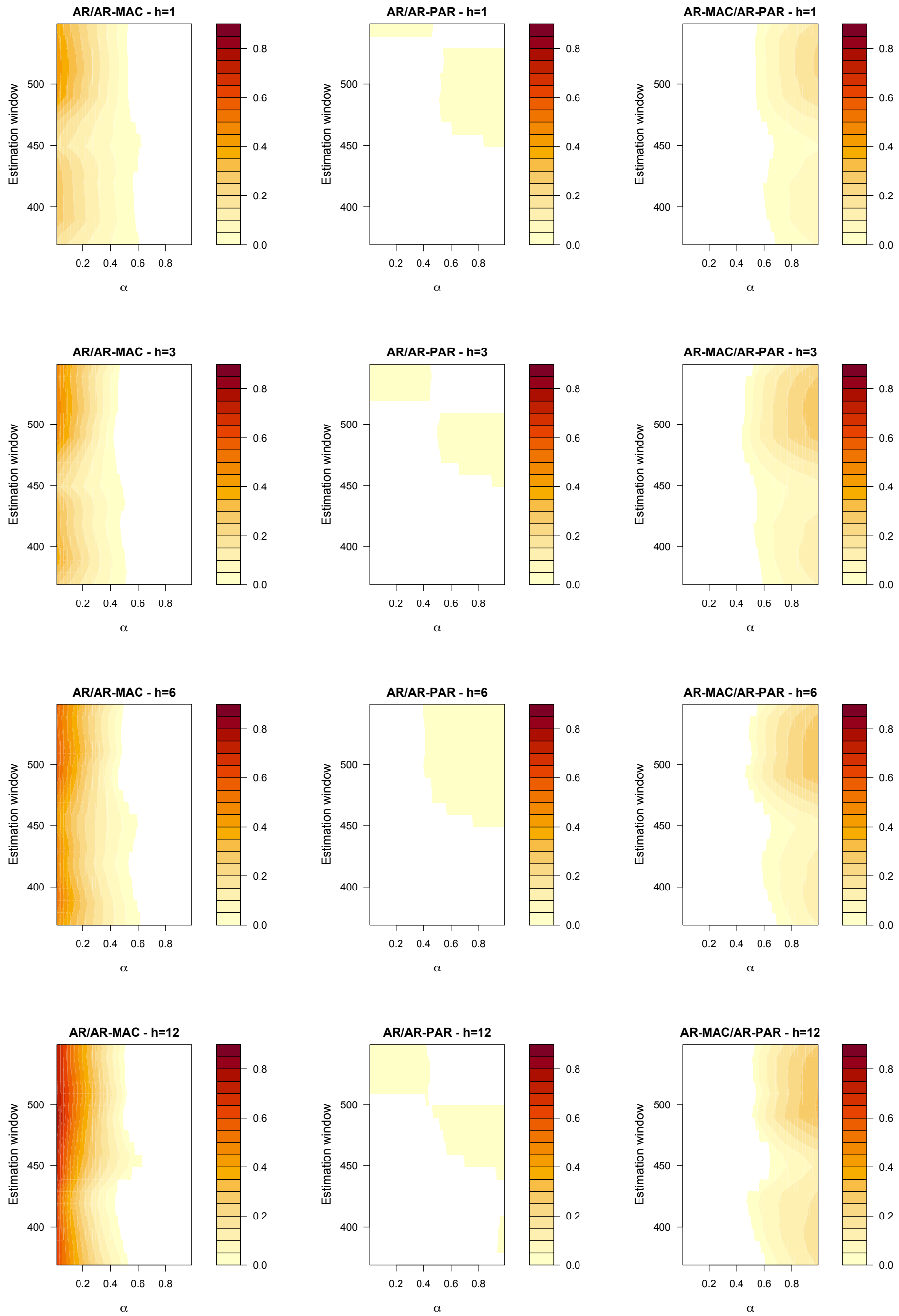

Figure A3. Results for $R^1(\alpha)$ (natural logarithm of the square root of RV). h = forecast horizon. Estimation period = training period (in months) used for the estimation of the forecasting models (ranges from 50% to 75% of the data). The white region indicates combinations of the asymmetry parameter and the estimation window for which the benchmark model outperforms the rival model.

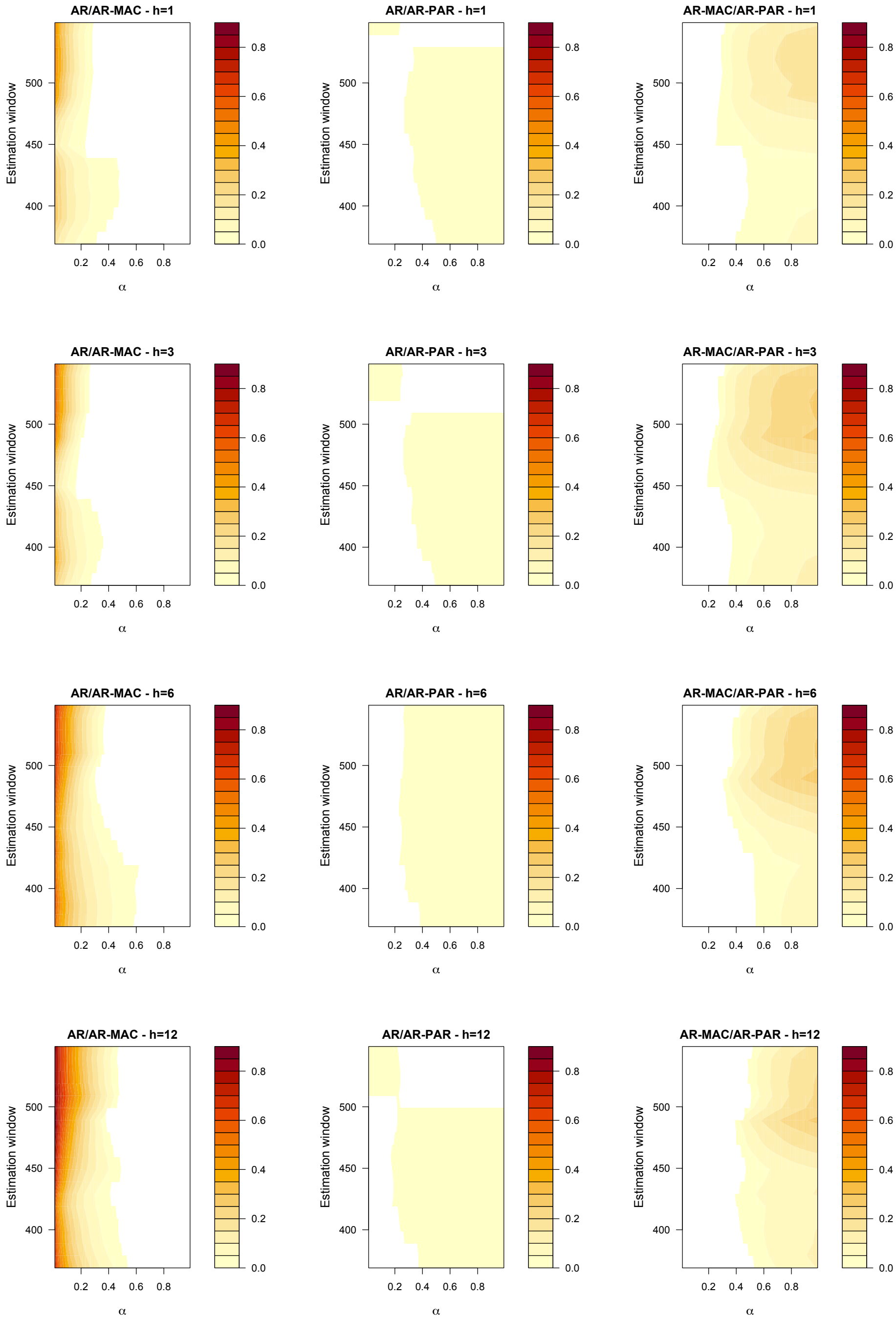

Figure A4. Results for $R^2(\alpha)$ (natural logarithm of the square root of RV). h = forecast horizon. Estimation period = training period (in months) used for the estimation of the forecasting models (ranges from 50% to 75% of the data). The white region indicates combinations of the asymmetry parameter and the estimation window for which the benchmark model outperforms the rival model.

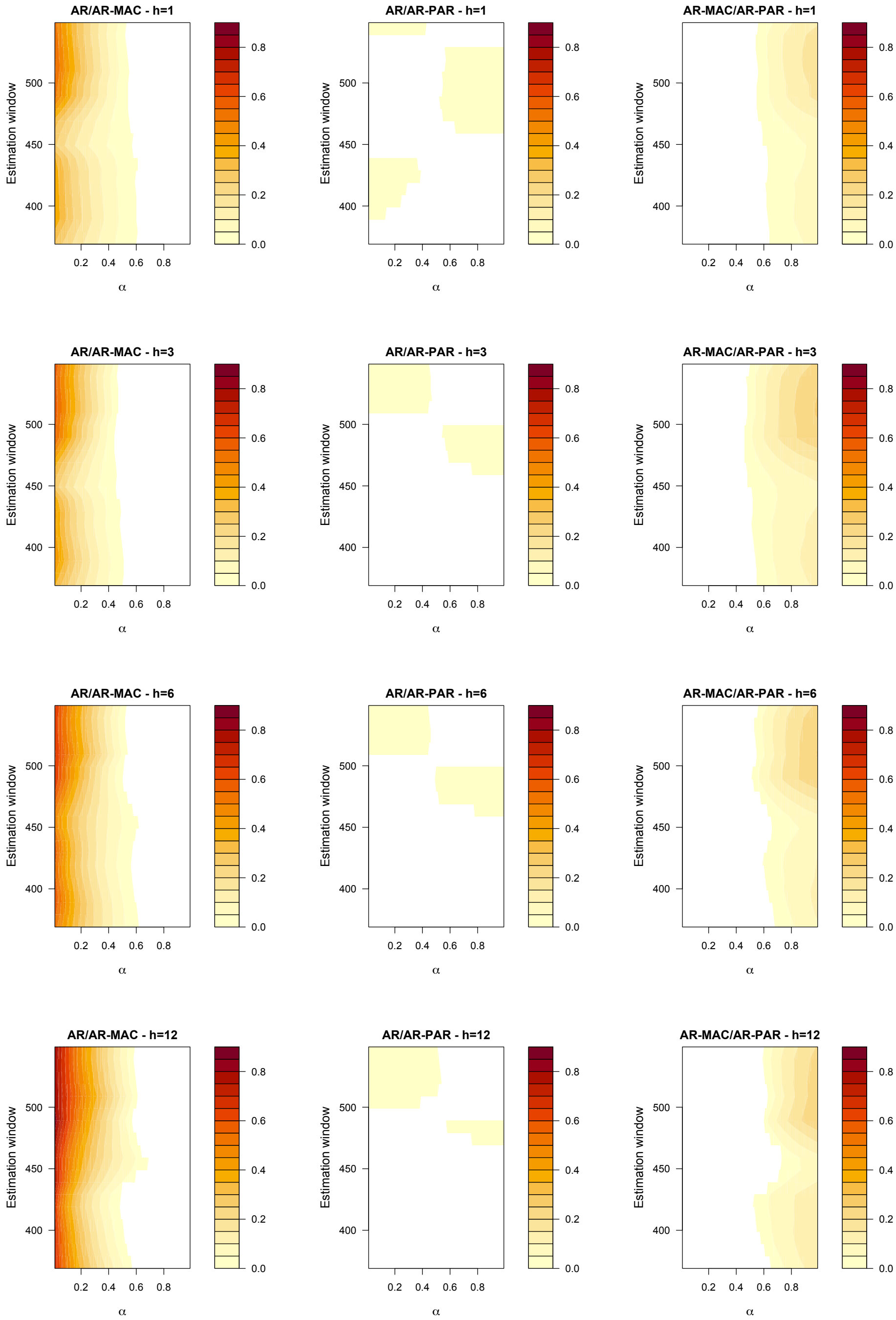

Figure A5. Results for $R^1(\alpha)$ (anti-log of PAR). h = forecast horizon. Estimation period = training period (in months) used for the estimation of the forecasting models (ranges from 50% to 75% of the data). The white region indicates combinations of the asymmetry parameter and the estimation window for which the benchmark model outperforms the rival model.

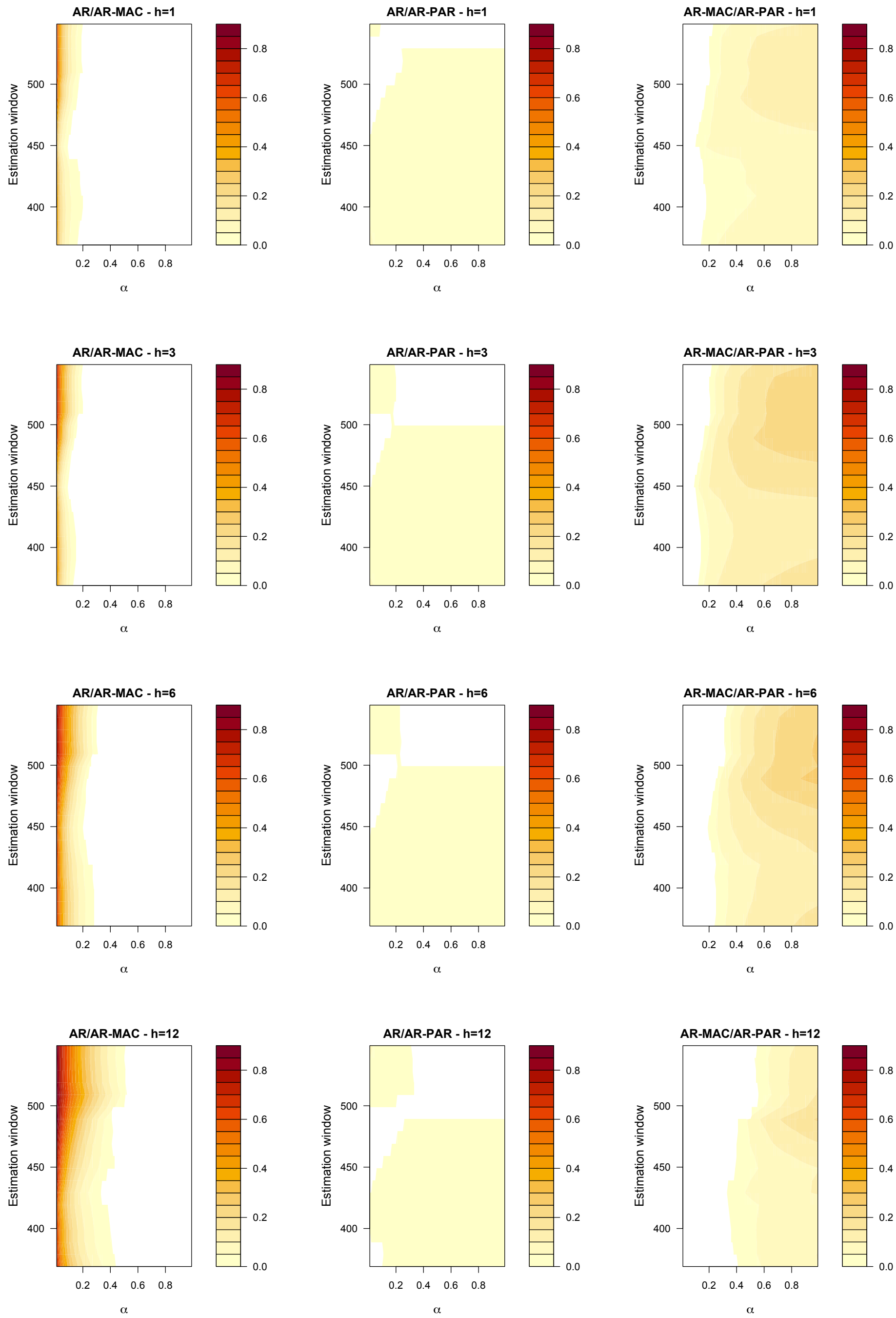

Figure A6. Results for $R^2(\alpha)$ (anti-log of PAR). h = forecast horizon. Estimation period = training period (in months) used for the estimation of the forecasting models (ranges from 50% to 75% of the data). The white region indicates combinations of the asymmetry parameter and the estimation window for which the benchmark model outperforms the rival model.

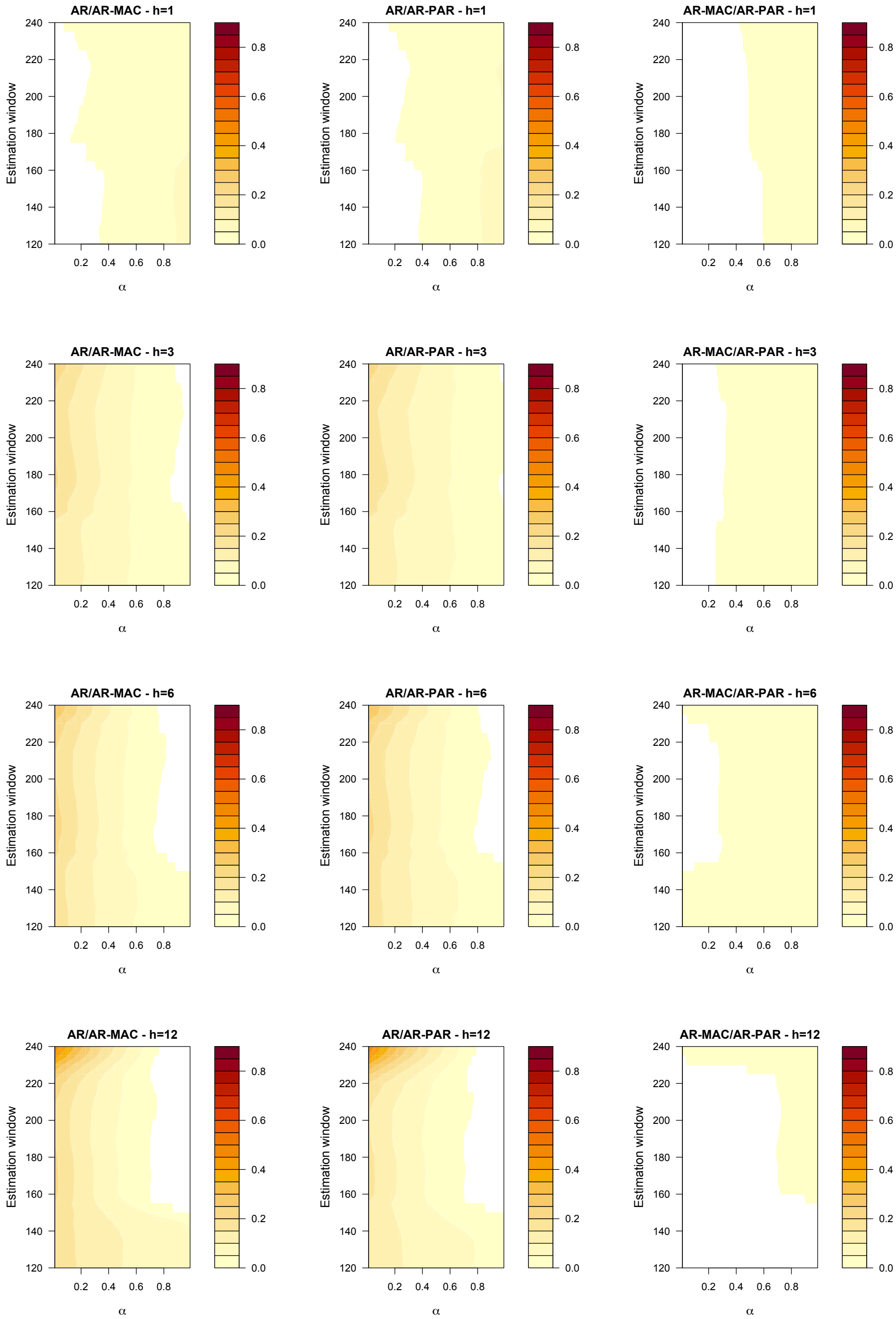

Figure A7. Results for $R^1(\alpha)$ (recursive-estimation window). h = forecast horizon. Estimation period = training period (in months) used for the estimation of the forecasting models (expands step-by-step in a recursive way until the end of the sample period is reached). The white region indicates combinations of the asymmetry parameter and the estimation window for which the benchmark model outperforms the rival model.

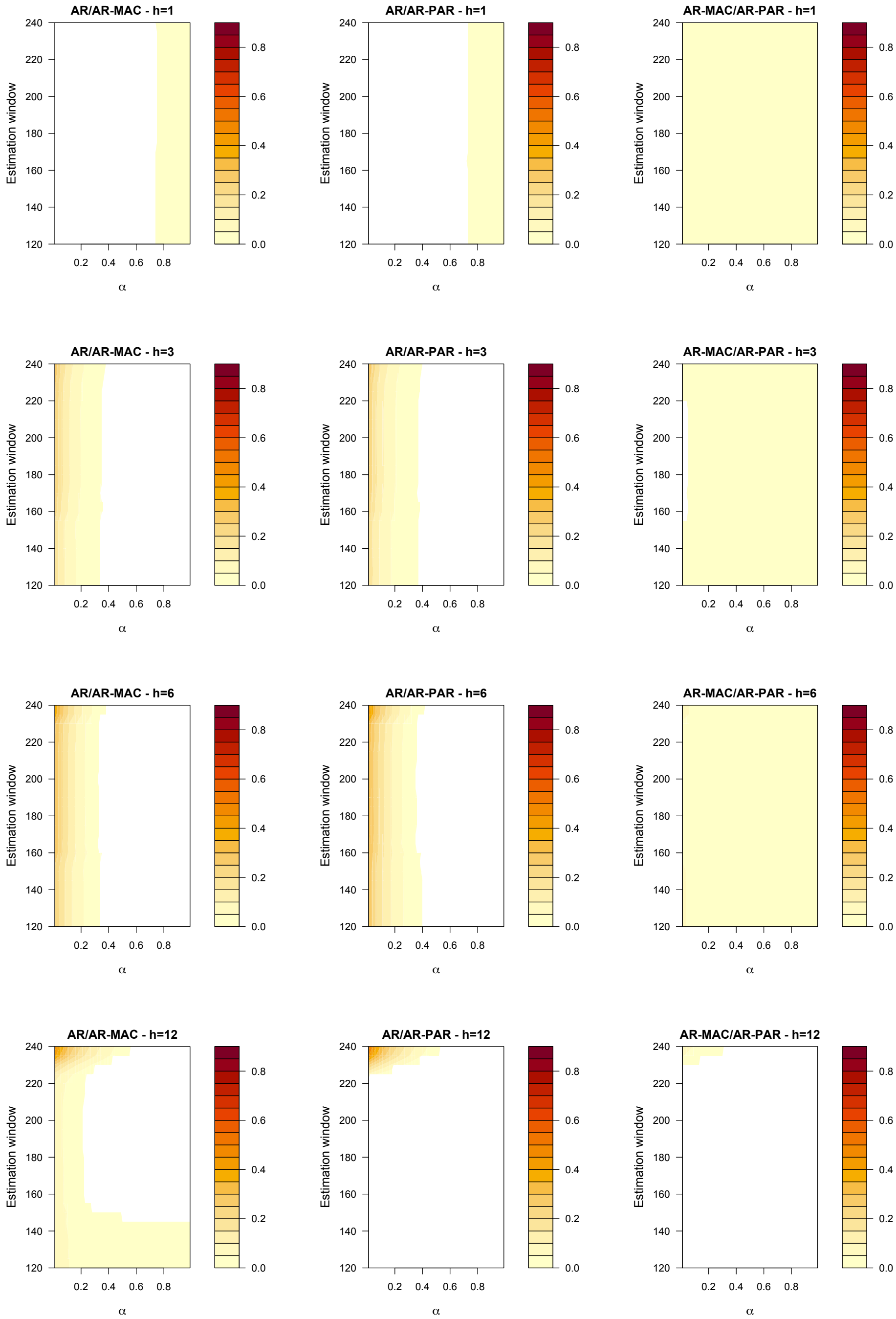

Figure A8. Results for $R^2(\alpha)$(recursive-estimation window). h = forecast horizon. Estimation period = training period (in months) used for the estimation of the forecasting models (expands step-by-step in a recursive way until the end of the sample period is reached). The white region indicates combinations of the asymmetry parameter and the estimation window for which the benchmark model outperforms the rival model.

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