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Do Shortages Forecast Aggregate and Sectoral U.S. Stock Market Realized Variance? Evidence from a Century of Data

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Abstract

Recent global economic and political events have made clear that shortages are a key factor driving macroeconomic and financial market developments. Against this backdrop, we studied the forecasting value of shortages for monthly U.S. stock market realized variance (RV) at the aggregate and sectoral level using data spanning the period 1900–2024 and 1926–2023 (for most sectors), respectively. To this end, we considered linear and non-linear statistical learning estimators. When we used linear estimators (OLS and shrinkage estimators), we did not find evidence that aggregate and disaggregate shortage indexes have predictive value for subsequent market or sectoral RVs. In contrast, when we used random forests, a nonlinear nonparametric estimator, we detected that aggregate and disaggregate shortage indexes improve forecast accuracy of market and sectoral RVs after controlling for realized moments (realized leverage, realized skewness, realized kurtosis, realized tail risks). We then decomposed RV into a high, medium, and low frequency component and found that the shortages indexes are correlated mainly with the medium and low frequencies of RV.

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1 Introduction

Following the COVID-19 pandemic, which resulted in severe supply chain constraints and an associated adverse impact on international trade, recent studies, in line with the earlier work of Lamont (1997), have attempted derive metrics aiming to capture and quantify such disruptions (Benigno et al., 2022; Kliesen and Werner, 2022; Pitschner, 2022; Smirnyagin and Tsyvinski, 2022; Chen and Houle, 2023; Soto, 2023; Bai et al., 2024; Burriel et al., 2024; Caldara et al., 2024; Bernanke and Blanchard, forthcoming), and then utilized them to shed light on the associated impact on the macroeconomy (see, for example, the above-mentioned studies and, Finck and Tillmann (2022), Diaz et al. (2023), Asadollah et al. (2024), Ascari et al. (2024), Tillmann (2024)). In general, this rapidly growing strand of research highlights that global supply shortages are associated with lower output and that they also play an important part in driving inflation.

At the same time, building on the works of Hendricks and Singhal (2003, 2005a, b), and Baghersad and Zobel (2021) based on pre-COVID-19 data associated with supply chain disruptions and diminished financial performance (such as shareholder value, equity risk and value, revenue, operating income, and returns on sales), recent research by Smirnyagin and Tsyvinski (2022), Burriel et al. (2024) and Ginn (2024) indicates that, besides the adverse outcomes on the macroeconomy, supply chain disruptions are also likely to have a negative effect on equity market returns. We build on this line of research dealing with the link between supply chain disruptions and stock markets by analyzing the role of newspapers artcles-based indexes of shortages, developed by Caldara et al. (2024), in forecasting the monthly variances of aggregate and sectoral stock market returns of the United States (U.S.) using data covering 1900 to 2024 and 1926 to 2023. Given that the variance of stock market returns is a key input for portfolio and hedging decisions, and that accurate forecasts are critical for the effectiveness of portfolio and risk management strategies as well as the pricing of derivative securities (Poon and Granger, 2003; Rapach et al., 2008), such an exercise should be of pertinent importance to investors, beyond its academic value. Moreover, by studying the longest possible sample of data available for shortages, we are able to avoid any sample-selection-bias, and track, in a robust manner, the historical effects on variance predictability due to events such as major coal mines strikes during the turn of the 20th century, two World Wars, the Suez Crisis in 1956, the oil shocks during 1970s, the Iraqi invasion of Kuwait in 1990, besides the recent COVID-19 pandemic.

From an econometric perspective, rather than relying on model-based estimates of conditional variance (such as, generalized autoregressive conditional heteroskedasticity (GARCH) and stochastic volatility (SV) models), we utilize a model-free approach by computing monthly realized variances as the sum of daily squared returns over a month (Andersen and Bollerslev, 1998), which, in turn, serves as our dependent variable at the aggregate and sectoral level. Furthermore, though the focus is on shortages originating in labor, materials, goods, and energy, and an overall index of these markets, we control for the role of realized moments (i.e., realized leverage, realized skewness, realized kurtosis, realized lower and upper tail risks) in our predictive regression models, given widespread evidence of their importance (Mei et al., 2017; Zhang et al., 2021; Bonato et al., 2023). As this results in inflating the number of predictors in our model, besides using the standard ordinary least squares (OLS) estimator, we rely on linear and nonlinear machine-learning approaches (allowing us to accommodate likely regime changes over our long data span), to conduct our forecasting experiment in a parsimonious setup.

At this stage, it is important to discuss the theoretical basis of our analysis by realizing that metrics of supply-side constraints tend to act as "catch-all" empirical proxies for rare disasters (Smirnyagin and Tsyvinski, 2022) associated with not only strikes and price controls but also, generally, capturing geopolitical risks, natural (climate-related) disasters, pandemics, and even trade wars (Burriel et al., 2024; Caldara et al., 2024). Given this, we derive our empirical predictive link from shortages to between realized stock market variances from the studies of Wachter (2013) and Tsai and Wachter (2015). These papers develop theoretical models in which aggregate consumption in general follows a low-volatility normal distribution, but there exists a positive probability of events that cause, so-called, far-out-in-the-left-tail realizations of consumption and output. To put differently, these models capture the risk associated with rare disaster events. The possibility of such an extreme outcome not only substantially reduces stock returns and raises the equity premium (Barro, 2006; 2009), but also produces high stock-market volatility due to the time-variation in the probability of such a disaster. We expect this channel to work in our context of shortages via the so-called "leverage effect" (Black, 1976),[1] given the above mentioned evidence of the negative effects of supply-side constraints on stock returns.

[1]Increases in debt-to-asset ratios, i.e., leverage, due to extreme supply chain pressures during the coronavirus outbreak has been empirically confirmed by Hupka (2022).

To the best of our knowledge, we are the first to analyze the forecasting ability of shortages for overall and sectoral stock returns variance of the U.S., spanning (nearly) a century of data using linear and nonlinear predictive models. The only other related study in this regard is the (working) paper of Bouri et al. (2024), who provide evidence of in-sample predictability for volatility of the agggregate U.S. stock market due to shortages indexes in a nonparametric set-up, but as is quite well-discussed (Rapach and Zhou, 2022; Goyal et al., 2024), in-sample predictability of stock price movements does not necessarily translate into out-of-sample forecasting gains, with the latter being a relatively more robust test of predictability. In the process, we add to the enormous strand of literature that offers a wide-array of linear and nonlinear models in univariate and multivariate settings to model and forecast aggregate and sectoral U.S. stock market volatility (see, Salisu et al. (2022, 2024a, b), and Segnon et al. (2024) for detailed reviews). In order to get to our empirical findings, we organize the rest of the paper as follows. In Section 2, we provide a description of the data we use in our study, while we outline in Section 3 our methods. In Section 4, we present our empirical results. In Section 5, we conclude.

2 The Data

In order to obtain our monthly realized moments, involving realized variance, RV, as well as our predictors (which we discuss in detail below), of the aggregate U.S. stock market, we utilize the log-returns of the Dow Jones Industrial Average (DJIA) derived from Global Financial Data.[2] The DJIA returns are computed

[2]See the following internet page: https://globalfinancialdata.com/.

from 2nd January, 1900, so as to correspond to the starting date of the shortages indexes. In order to derive the realized metrics for the 49 sectors considered, we rely on the Data Library of Professor Kenneth R. French.[3] In general, barring the Fabricated Products, Precious Metals (Gold), Defense (Guns), Healthcare, Business Supplies (Paper), Personal Services, Rubber and Plastic Products, Candy and Soda (Soda), Computer Software, the daily sectoral-level data starts from 1 July, 1926.

As far as our dependent variable is concerned, we use the classical estimator of RV, i.e., the sum of squared daily returns (Andersen and Bollerslev, 1998), given as

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

where $r_{t,i}$ denotes the daily $M \times 1$ return vector, and $i = 1, ..., M$ is the number of daily returns over month t. We report summary statistics of the aggregate and sectoral RV data in Table A1 at the end of the paper (Appendix).

Turning now to our main predictors, i.e., the shortage indexes, which, in turn, are monthly newspapers-based indicator that measures the intensity of shortages of materials, goods, labor, and energy in the U.S., with the individual indexes (for energy, food, industry, and labor shortages) adding up to the overall index.[4] Caldara et al. (2024) describe how they construct these indexes from a sample of approximately 20,000 news articles per month, staring in 1900 (until recent months) encompassing about 25 million articles over the entire sample,

[3]The data is available for download from the following internet page: https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

[4]The data can be downloaded from the following internet page: https://www.matteoiacoviello.com/shortages.html.

published in six major U.S. newspapers: The Boston Globe, The Chicago Tribune, The Los Angeles Times, The New York Times, The Wall Street Journal, and The Washington Post. For every month in the sample period, the shortage indexes count the number of articles that discuss energy, food, industry, or labor shortages. Given the long sample period and the broad text corpus that Caldara et al. (2024) consider in their research, their shortage indexes cover a very long historical epoch involving many domestic as well as global events.

We plot the shortages indexes in Figure A1 at the end of the paper (Appendix). The figure makes clear that the shortage indexes are generally much higher during periods of increased economic turmoil, such as the World Wars and the 1970s oil crises (energy), with it also spiking during the COVID-19 pandemic, when the overall shortage index reached its highest level in the last 40 years. However, there are some other past peaks, especially associated with the World Wars I and II, and the oil crises, which are of comparable or larger size. Finally, there is also considerable variation across the shortages subindexes, implying that it is interesting to use not only the overall shortage index, but also the sub-indexes in our forecasting experiment.

Another group of predictors, at the aggregate- and industry-level, consists of the daily-data-based realized moments that have been widely studied in the literature on the modeling of realized volatility: 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

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

and RKU as

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

where the scaling by $(M)^{1/2}$ and M turns the statistics into the corresponding monthly skewness and kurtosis values.

Last, we consider the Hill tail risk estimator (Hill, 1975), to derive our realized upside and downside tail risks. Let $X_{t,i}$ the set of reordered daily returns on month t, $r_{t,i}$ in such a way that :

$$X_{t,i} \geq X_{t,j} \text{ for } i < j. \tag{4}$$

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

$$H_t^{up} = \frac{1}{k}\sum_{j=1}^{k} \ln(X_{t,i}) - \ln(X_{t,k}) \tag{5}$$

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

$$H_t^{down} = \frac{1}{k}\sum_{j=n-k}^{n} \ln(X_{t,i}) - \ln(X_{t,n-k}) \tag{6}$$

where k is the observation denoting the chosen α tail interval.

Based on data availability of the variables under consideration at the time of writing of this paper, our aggregate-level analysis covers January, 1900 to

May, 2024, while the coverage of the sectoral exercise involves July, 1926 to September, 2023 (see Table A1 for details).

3 Methods

3.1 Forecasting Models

We start with a simple linear forecasting model, which we always estimate by the ordinary least squaress (OLS) technique, given by the following equation:

$$RV_{s,t+h} = \beta_0 + \beta_1 RV_{s,t} + u_{s,t+h}, \tag{7}$$

where $RV_{s,t+h}$ denotes the average realized variance of sector s over the forecast horizon, h, computed using data for the periods $t+1, ..., t+h$, and $u_{s,t+h}$ denotes the sectoral disturbance term. The coefficients to be estimated are given by β_0 and β_1. As for the forecast horizon, h, we consider in our forecasting experiment one, three, and six months (that is, we set $h = 1, 3, 6$).

In order to inspect the robustness of our OLS results, and to bring the data closer to normality, we also consider in some specifications the realized volatility (that is, the square-root of the realized variance) and the natural log of the realized volatility.

We next expand Equation (7) to include a vector of sectoral realized moments, $MO_{s,t}$ as control variables as well as the overall shortage index, $SALL_t$, and a vector, $SSUB_t$, of the four different shortage subindexes (that is, energy, food, industry, and labor; see Section 2 for details). In this way, we obtain the following forecasting models:

$$RV_{s,t+h} = \beta_0 + \beta_1 RV_{s,t} + \beta_2 MO_{s,t} + u_{s,t+h}, \tag{8}$$

$$RV_{s,t+h} = \beta_0 + \beta_1 RV_{s,t} + \beta_2 MO_{s,t} + \beta_3 SALL_t + u_{s,t+h}, \tag{9}$$

$$RV_{s,t+h} = \beta_0 + \beta_1 RV_{s,t} + \beta_2 MO_{s,t} + \beta_3 SSUB_t + u_{s,t+h}, \tag{10}$$

where β_2 and β_3 now denote appropriately dimensioned vectors of coefficients to be estimated. The moments vector, $MO_{s,t}$, contains the sectoral realized leverage, the sectoral realized kurtosis, the sectoral realized skewness, and the sectoral realized lower and upper tail risks.

As a further extension, we include a vector of realized market moments, MM_t, in our sectoral forecasting models. The resulting forecasting models are given by

$$RV_{s,t+h} = \beta_0 + \beta_1 RV_{s,t} + \beta_2 MO_{s,t} + \beta_3 MM_t + u_{s,t+h}, \tag{11}$$

$$RV_{s,t+h} = \beta_0 + \beta_1 RV_{s,t} + \beta_2 MO_{s,t} + \beta_3 MM_t + \beta_4 SALL_t + u_{s,t+h}, \tag{12}$$

$$RV_{s,t+h} = \beta_0 + \beta_1 RV_{s,t} + \beta_2 MO_{s,t} + \beta_3 MM_t + \beta_4 SSUB_t + u_{s,t+h}, \tag{13}$$

where the vector of market moments contains the same moments as the vector of sectoral moments, MO_t, but now measured for the aggregate market.

We also estimate our forecasting models for the aggregate marke,t $RV_{m,t}$. In this case, we consider the following forecasting models:

$$RV_{m,t+h} = \beta_0 + \beta_1 RV_{m,t} + u_{m,t+h}, \tag{14}$$

$$RV_{m,t+h} = \beta_0 + \beta_1 RV_{m,t} + \beta_2 MM_{m,t} + u_{m,t+h}, \tag{15}$$

$$RV_{m,t+h} = \beta_0 + \beta_1 RV_{m,t} + \beta_2 MM_{m,t} + \beta_3 SALL_t + u_{m,t+h}, \tag{16}$$

$$RV_{m,t+h} = \beta_0 + \beta_1 RV_{ms,t} + \beta_2 MM_{m,t} + \beta_3 SSUB_t + u_{m,t+h}, \tag{17}$$

In order to estimate our various forecasting models, and to set up our out-of-sample forecasting experiment, we split up the sample period into various training and test windows. The shortest training window that we consider comprises the first 50% of the data, while the longest training window comprises 75% of the data. We vary the length of the training window between these two extreme cases in steps of 5 percentage points, so that we study in total six different training windows. The remaining data are the test data that we use to compute out-of-sample forecasts of RV.

3.2 Estimation Methods

We estimate our forecasting models by means of standard linear and non-linear estimators. As for a straightforward linear estimator, we already mentioned the OLS technique. The OLS technique, however, may not be the best choice given that (leaving the simple AR benchmark model aside) our forecasting models feature various predictors. Hence, in order to obtain parsimonious forecasting models, we estimate our forecasting models by means of standard shrinkage estimators. Specifically, we consider the Lasso estimator (Tibshirani, 1996), an elastic net, and a Ridge regression estimator.[5] The shrinkage estimators obtain as special cases of the following penalized forecasting model:

$$\sum_{t=1}^{T} \left(RV_{z,t+h} - \beta_0 - \beta_1 RV_{z,t} - \beta_2 X_{z,t}\right)^2 + \lambda \left(\alpha ||\beta||_1 + (1-\alpha)||\beta||_2^2/2\right), \tag{18}$$

where $z = \{s, m\}$, and T denotes the number of observations available for estimating the forecasting model, and $X_{s,t}$ denotes a vector of control variables. Depending on the forecasting model that we study (and on whether we study a sector or the aggregate market), this vector includes some or all elements of $(MO_{s,t}, MM_t, SALL_t, SSUB_t)$. It follows from Equation (18) that we do not penalize the intercept and the AR coefficient. The parameter, α, governs the choice of the shrinkage estimator. For the Lasso, we set $\alpha = 1$ so that the vector of coefficients, β, is penalized under the $L1$-norm. For the Ridge regression estimator, we set $\alpha = 0$ so that the vector of coefficients, β, is penalized under the $L2$-norm. Finally, an elastic net estimator obtains for $\alpha \in (0, 1)$. We set $\alpha = 0.5$.

As a popular off-the-shelf non-linear estimator, we use random forests (see Breiman, 2001). Random forests have the advantages that they account in a fully data-driven way for nonlinear patterns in the data, potential interaction effects between the predictors, and the non-negative domain of RV. A random forest consists of many individual regression trees, T. A regression tree, in turn, consists of a root and several nodes and branches, which partition the space of the predictors into in a binary way into non-overlapping regions (see, Breiman et al. (1984)). The regions are computed in a recursive top-down way by applying

[5] Our description of the shrinkage estimators and random forests is rather compact. For a more detailed exposition as well as a comprehensive list of further references, an interested reader is referred to the textbook by Hastie et al. (2009).

a search-and-split algorithm that helps to find the regions-specific means, $\bar{RV}$ of RV so as to minimize the sum of squared errors. Formally, in the simple case of only two regions, the algorithm searches over all combinations of a predictor and a corresponding splitting point, (s, p), and the resulting regions, $R_1(s, p) = \{x_s | x_s \leq p\}$ and $R_2(s, p) = \{x_s | x_s > p\}$, to obtain an optimal combination, $\{s^*, p^*\}$, that solves the following minimization problem (deleting for notational simplicity the time index, the index for the forecast horizon, and the sector/market index):

$$\min_{s,p} \left\{ \min_{\bar{RV}_{r,1}} \sum_{P_s \in R_1(s,p)} (RV_r - \overline{RV}_{r,1})^2 + \min_{\bar{RV}_{r,2}} \sum_{P_s \in R_2(s,p)} (RV_r - \overline{RV}_{r,2})^2 \right\} \quad \rightarrow \{s^*, p^*\}, \quad (19)$$

where $P_s \in R_i(s, p), i = 1, 2$ expresses that predictor P belongs to region R_i, given (s, p), the index, r, denotes that a realization of RV belongs to the region being studied, and $\{s^*, p^*\}$ denotes the optimal combination

While the two regions, R_1 and R_2, already form a rudimentary regression tree, we next can apply the search-and-split algorithm to both regions so as to get a slightly larger regression tree. Upon recursively applying the search-and-split algorithm to the ensuing branches of the regression tree, we obtain a finer and finer partitioning of the predictor space and, thereby, increasingly finer forecasts of RV once we trickle down the tree new data on the predictors. Tree growing stops once a preset maximum number of terminal nodes is reached or the terminal regions have a minimum number of observations. A forecast of RV can then be computed by applying the following formula:

$$T\left(\mathbf{x}_i, \{R_l\}_1^L\right) = \sum_{l=1}^{L} \overline{RV}_l \mathbf{1}(\mathbf{x}_i \in R_l), \quad (20)$$

where L denotes the number of regions, $\mathbb{1}$ denotes the indicator function, and $\mathbf{x}_i$ denotes the data on the predictors used for forecasting.

While a large regression tree renders it possible to compute granular forecasts of RV, it is clear that its complex hierarchical tree structure easily gives rise to an overfitting and data-sensitivity problem, ultimately deteriorating forecasting performance. One technique to overcome the overfitting problem is to grow a random forest. A random forest consists of an ensemble of many regression trees which is built in three steps:

1. Compute a large number of bootstrap samples by resampling from the data.

2. Grow a random regression tree on every bootstrap sample. A random regression tree is grown using a random subset of the predictors for splitting, which dampens the effect of influential predictors on tree building.

3. Combine the large number of random regression trees to form a random forest and compute a forecast of RV by averaging across the individual random regression trees. Averaging stabilizes the resulting forecasts.

3.3 Computational Issues

We use the R language and environment for statistical computing (R Core Team, 2023) to set up our forecasting experiment.

For implementation of the shrinkage estimators, we rely on the R add-on package "glmnet" (Friedman et al. 2010, Tay et al., 2023). We choose the penalty parameter, λ, by 10-fold cross-validation, where we use the value of the shrinkage parameter that minimizes the average cross-validated error.

As for random forests, we use the R add-on package "randomForestSRC" (Ishwaran and Kogalur, 2023) to estimate our forecasting models. Our random forests consist of 1,000 individual regression trees. We bootstrap the data by sampling with replacement.[6]

4 Empirical Results

4.1 Linear Models

Figure 1 depicts the market-level results for three forecast horizons, $h = 1, 3, 6$, of estimating our forecasting models by OLS. The horizontal axis shows the proportion of the data we use to estimate our models (that is, the training window). The vertical axis shows either the root-mean-squared forecast error (RMSFE) or the mean-absolute forecast error (MAFE) ratio, where a ratio that exceeds unity indicates that the rival model performs better than the benchmark model. The panels in the first row depict the the RMSFE ratio for RV, while the panels in the second row depict the corresponding MAFE ratios. The panels in the third and fourth row depict the MAFE ratio for $\sqrt{RV}$ and $\ln \sqrt{RV}$. Three results can be taken home from the figure. First, the results for RV,$\sqrt{RV}$, and $\ln \sqrt{RV}$ do not differ much, while the differences between the benchmark and extended models tends to be somewhat more pronounced when we use the MAFE rather than the RMSFE ratio. Second, the AR model extended to include the market moments (AR-MM model) clearly outperforms the AR benchmark model, especially at the

[6]For the other "hyperparameters", we use the default values recommended by the authors of the package. We refer an interested reader for details to the extensive documentation of the package.

short and intermediate forecast horizons. Third, the AR-MM model extended to include the overall shortage index (AR-MM-SALL model) and the AR-MM model that features the shortage subindexes (AR-MM-SSUB model) produce forecasts whose accuracy is close or slightly better than the accuracy of the benchmark (AR or AR-MM) forecasts, or the extended models perform worse than the respective benchmark model.

– Figure 1 about here. –

We summarize the sectoral OLS results in Figure 2. In order to summarize graphically the sectoral results in a condensed but informative way, we plot in Figure 2 the cross-sectoral median of the MAFE ratio (solid line), the cross-sectional inter-quartile range (shaded areas), and we plot, on the horizontal axis, not only information on the training window (numbers in the upper row) but also the proportion of sectors for which the MAFE ratio is larger than unity (numbers in the lower row).

The sectoral results corroborate the results we obtain at the market level. The AR model extended to include the sectoral moments ("own" moments, OM) tends to outperform the AR benchmark model for the majority of sectors. When we compare the AR-OM model with an AR-OM-MM model that features, in addition to the sectoral moments, the corresponding market moments, than the AR-OM model performs better for many sectors than the AR-OM-MM model. Finally, adding either the overall shortage index or the corresponding shortage subindexes to the AR-OM model or the AR-OM-MM model improves forecasting performance only for a few sectors but, when evaluated in the cross-section of sectors, deteriorates forecasting performance relative to the more parsimonious

AR-OM and AR-OM-MM models.

The latter result perhaps is not too surprising as one would expect that a parsimonious model exhibits a better and more robust forecasting performance than a complex model that features several predictors. We, therefore, present in Figure 3 results at the market level for the Lasso estimator, while we document in Figure 4 the corresponding sectoral results for the Lasso estimator.[7] Figure 3 makes clear that the Lasso results at the market level closely resemble the corresponding OLS results. At the sectoral level, the performance of the relatively complex AR-OM-MM and AR-OR-MM-SSUB models tends to improve somewhat, mainly at the short and intermediate forecast horizons, as the shaded areas shift upward a bit and the proportion of sectors for which the MAFE ratio exceeds unity increases. In the cross-section, however, only the AR-OM model (and perhaps the AR-OM-MM model) tend to perform better than their respective (AR and AR-OM) benchmark models.

– Figures 3 and 4 about here. –

4.2 Random Forests

We next turn to random forests. Figure 5 depicts the results at the market level. When we study the RMSFE ratio, the AR-MM model clearly outperforms the AR model. Moreover, the performance of the AR-MM-SALL and AR-MM-SSUB relative to the AR-MM model tends to improve as the forecast horizon increases. For

[7] Results for the elastic net and the Ridge regression estimators, two popular variants of the Lasso estimator, are qualitatively similar. We report results for an elastic net at the end of the paper in Figures A2 and A3. The complete set of results for the shrinkage estimators is not reported to save journal space, but is available from the authors upon reasonable request.

the MAFE ratio, the results for the models that feature the shortage predictors are even stronger than for the RMSFE ratio. Both the AR-MM-SALL model and the AR-MM-SSUB model outperform the AR-MM benchmark model at all three forecast horizons, and for almost all training windows, where the performance advantage of the shortage models tends to strengthen in the length of the forecast horizon, especially as far as the AR-MM-SSUB model is concerned.

– Figures 5 and 6 about here. –

The sectoral random-forest (MAFE) results that we summarize in Figure 6 corroborate the results for market RV. The AR-OM model outperforms the AR benchmark model for approximately one-third of the sectors, while the AR-OM-SALL and AR-OM-SSUB models dominate the AR-OM model for several sectors, in case of the AR-OM-SALL model in about 60% of the sectors. The dominance of the AR-OM-SALL and AR-OM-SSUB models tends to strengthen at the sectoral level when the forecast horizon increases. The results are similar when we control for market moments and compare the AR-OM-MM-SALL and AR-OM-MM-SSUB models with the AR-OM-MM benchmark model.

Given the relatively good performance of the shortage models in case we use random forests, it is interesting to ask whether the differences in performance across models are statistically significant. Given the highly complex and nonlinear structure of random forests, which complicates statistical testing, we present results for two alternative tests: the Clark and West (CW, 2007) test for nested models and the Diebold and Mariano (DM, 1995), as modified by Harvey et al. (1997).[8]

[8]The modified DM-test is computed as DM-modified $= ((n + 1 - 2h + n^{-1}h(h-1))/n)^{1/2}\times$ DM,

– Figure 7 about here. –

We summarize in Figure 7 the test results (p-values) for market RV. The test results are in line with the results for the RMSFE and MAFE ratios that we document in Figure 5. The AR-MM model significantly outperforms the AR benchmark model for most training windows when we study the CW test, and for the DM test for $h = 1$ and occasionally also for $h = 6$ when we consider a squared-error loss function. Under an absolute-error loss function, in contrast, the DM test results for the AR-MM model forecasts are all insignificant, while the test results for the AR-MM-SALL and the AR-MM-SSUB models are highly significant for most training windows at all three forecast horizons. Under a squared-error loss function, the DM test yields significant results for these two models only for $h = 6$ and only when we consider some of the short training windows. For the CW test, in turn, the test results for the AR-MM-SSUB model are statistically significant for $h = 3$ for many training windows, and for both the AR-MM-SALL model and the AR-MM-SSUB model for all training windows at $h = 6$. In sum, while the test results are not necessarily uniform across both tests and loss functions, which is not surprising given the complex structure of random forests, the test results, together with the results documented in Figure 5, clearly provide signs that the shortage indexes have predictive value for subsequent market RV.

We plot the corresponding test results at the sectoral level (for the CW test only) in Figure 8. As in the case of the market RV, the AR-OM model performs significantly better than the AR benchmark model. The results for the AR-OM-MM model are less strong in this regard. While we observe considerable cross-

where n = number of forecast errors. See the R add-on package "forecast" (Hyndman et al., 2023; Hyndman and Khandakar, 2008).

sectional variation in the p-values, the proportion of sectors for which the AR-OM-SALL and AR-OM-SSUB models significantly outperform the AR-OM model, in turn, increases in the forecast horizon, and this effect is stronger for the AR-OM-SSUB model than for the AR-OM-SALL model. A similar picture emerges when we compare the AR-OM-MM-SALL and AR-OM-MM-SSUB models with the AR-OM-MM model.

– Figure 8 about here. –

When we compare the results for random forests with the results for the linear estimators, it is clear that the evidence that the shortage indexes contribute to forecasting performance is stronger for random forests than for the linear estimators, which, in turn, should not come as a surprise, given the widespread evidence of a nonlinear relationship between RV and its predictors in the literature (see, for example, Lyócsa and Stašek (2021) and Gupta et al. (2023) for detailed discussions). Given the relative superior performance of the random forests approach, therefore, it is interesting to study the marginal effects of a variation in the shortage indexes. We compute the marginal effects, using the full sample of data, by varying the shortage indexes while holding all other predictors fixed at their respective mean value. We plot the marginal effects in Figure 9 for $h = 3$. The marginal effects clearly show a substantial degree of variation across sectors, and they also differ for any given sector substantially across the four shortage subindexes. A close eyeballing of the marginal effects further shows that they tend to exhibit a U-shaped form. Hence, they first tend to decrease at low levels of the shortage indexes, attain a minimum, and then start gradually to increase as the shortage indexes take on larger values. At very large values of the shortage indexes, the marginal effects become flat curves. It is clear that the nonlinear nature of random forests implies that this technique is better suited to capture the marginal effects of the shortage indexes on the sectoral RVs than a linear estimator.

– Figures 9 and 10 about here. –

Bouri et al. (2021) argue, in a different context, that the kind of U-shaped pattern of the marginal effects that we observe in Figures 9 and 10 can be rationalized in terms of the speculative and hedging purposes of traders in different market regimes. Accordingly, when shortages are less of a concern and, thus, uncertainty is low (Ludvigson et al., 2021; Baker et al., 2024), it is most likely that the economy is performing well. In such a regime, trading for speculative purposes is strong, resulting in high values of RV. When the shortage indexes increase, attention of market participants is likely to turn on a broad base to the likelihood of supply-chain disruptions, inducing traders to switch to safe assets (or even "safe haven" investments), and so low trading causes RV decrease.[9] When macroeconomic tensions caused by shortages fully unfold, leading to a very poor current economic performance, expected future returns, however, may increase again, and traders may substitute back from safe-haven assets to stock investments, so that RV starts increasing again.

[9]While shortages are expected to increase leverage and, hence, volatility, recent empirical evidence obtained for the U.S. indicates that leverage may even decrease in the wake of increased supply constrains (see, for example, Ginn and Saadaoui (2024)).

4.3 Frequencies of RV

As an academic exercise, it would be interesting to understand the underlying empirical reason behind the role of shortages in driving future stock market volatility of the U.S., over and above its realized moments. For this purpose, in line with the recent work of Souropanis and Vivian (2023), we use the wavelet approach to decompose RV into its low-, medium-, and high-frequency components. Figure 10 plots the results (p-values) of tests for the statistical significance of the correlations between the three frequency-components of RV with the shortage indexes. We find strong evidence that the shortage indexes are mainly correlated with the medium- and low-frequency components of RV.[10] This finding is in line with our intuition, since shortages proxying for rare disaster events are now known to lower output and higher inflation (as discussed in the introduction) and, thus, convey "bad news" about the state of the macroeconomy (on macro predictors of stock market volatility, see Schwert, 1989; Engle et al., 2013). Hence, shortages are expected to impact the slow-moving components of RV.[11]

[10] We obtain qualitatively similar results (not reported, but available from the authors upon reasonable request) when we correlated the shortage indexes with the lead frequencies at the different forecast horizons.

[11] One would expect that own realized moments exhibit a stronger correlation with the high-frequency component of RV. Results (not reported, but available from the authors upon reasonable request), in fact, showed that this is the case especially for the correlation of the contemporaneous frequencies of RV with realized kurtosis, realized skewness, and upside tail risk.

5 Concluding Remarks

Recent global economic and political events have brought to the forefront that supply-chain disruptions can trigger severe macroeconomic distortions as well as to financial market jitters. It is, therefore, important to deepen our understanding of how exactly shortage-induced economic tensions transmit onto financial markets in general and how they affect asset-price and stock market volatility in particular. Our results for monthly U.S. aggregate and sectoral stock market RV, which are based on data for the 20th century that cover two World Wars, the oil shocks during 1970s, the recent COVID-19 pandemic as well as several other crisis periods, show that shortages tend to improve forecasts of RV once we switch from linear and a non-linear statistical learning estimator (that is random forests), where a wavelet-based analysis has shown that shortages are more strongly correlated with the medium- and low-frequency component of RV

Given that volatility forecasts are used as inputs for optimal asset-allocation decisions, our findings suggest that, depending on the sector under consideration, incorporating the role of shortages, over and above realized moments, in forecasting models of realized variance can help an investor to improve the design of portfolios across various investment horizons. Moreover, given that stock market volatility has historically adversely impacted the real economy of the U.S. (Pierdzioch and Gupta, 2020; Bouri et al., 2024), policymakers would need to monitor supply constraints closely, and design the magnitude and persistence of policies accordingly to ensure that shortages does not lead to volatile stock markets, and further deepen the direct recessionary impact arising due to supply-chain disruptions.

As part of future research, given the availability of supply-chain constraints data for other countries (as recently developed by Burriel et al., 2024), even though for the last two decades only, it is interesting to extend our work to international stock markets, which, in turn, would allow us to generalize our findings. In addition, one could also look at the role of shortages in forecasting commodity returns volatility, given the existing first-moment impact reported by Gozgor et al. (2023).

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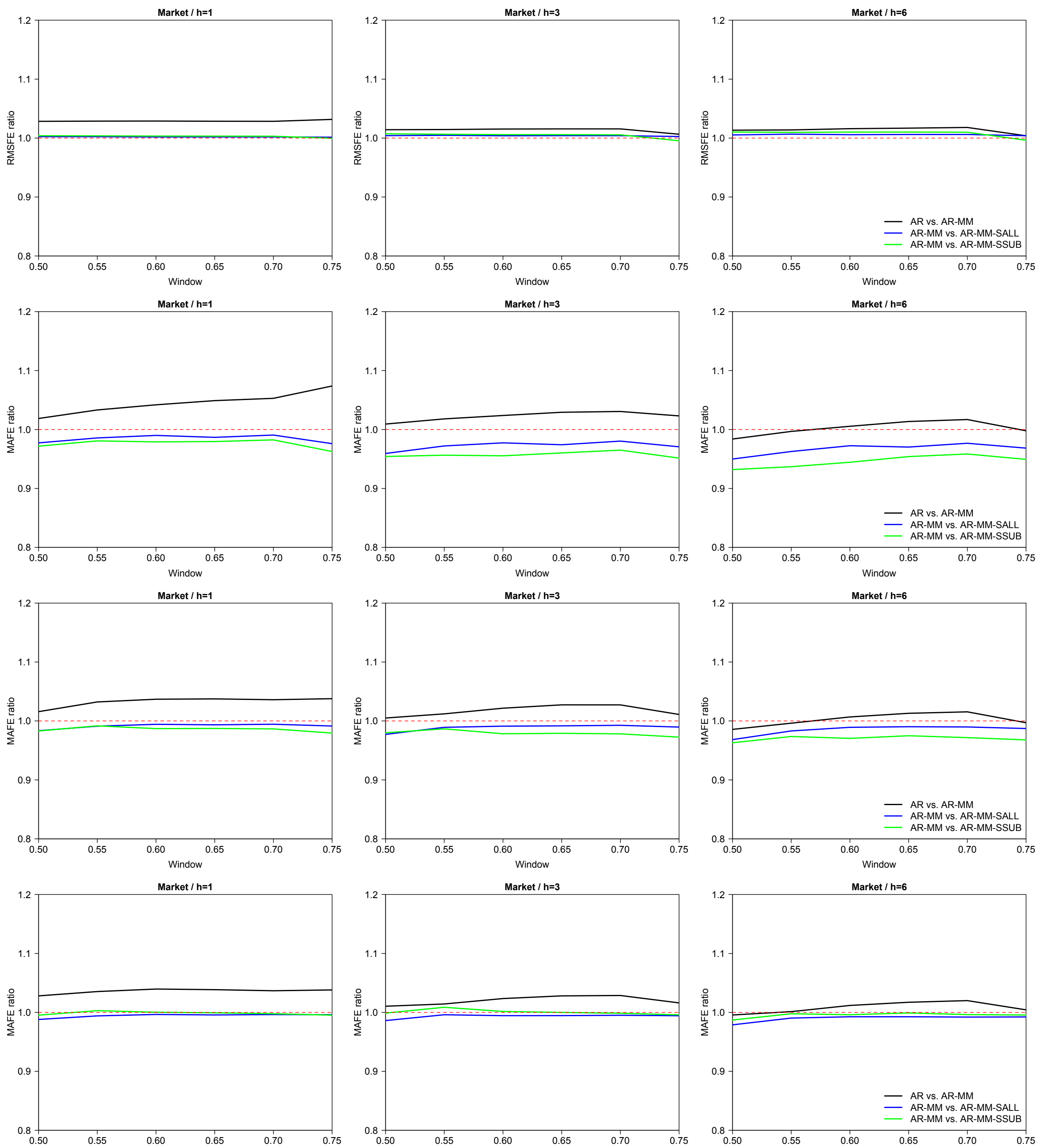
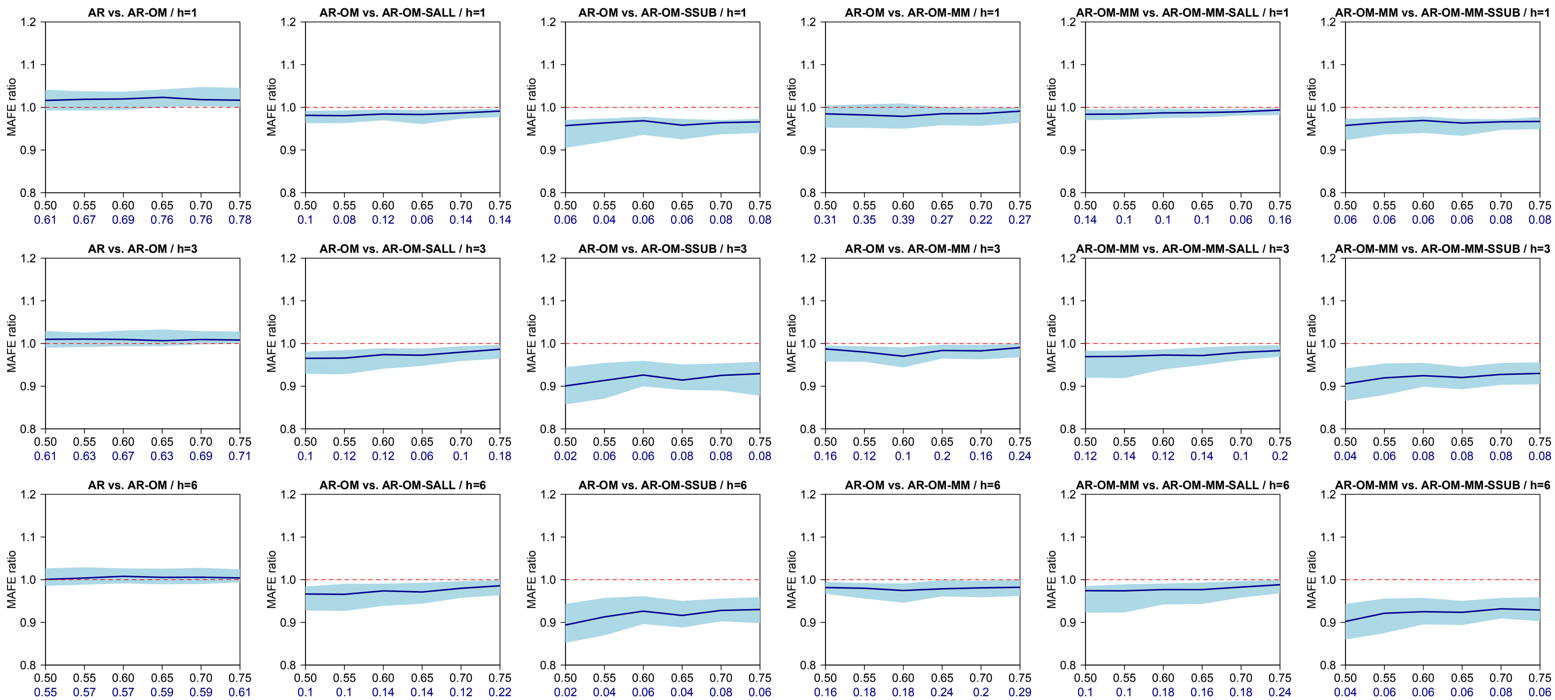
Figure 1: OLS Results at the Market Level



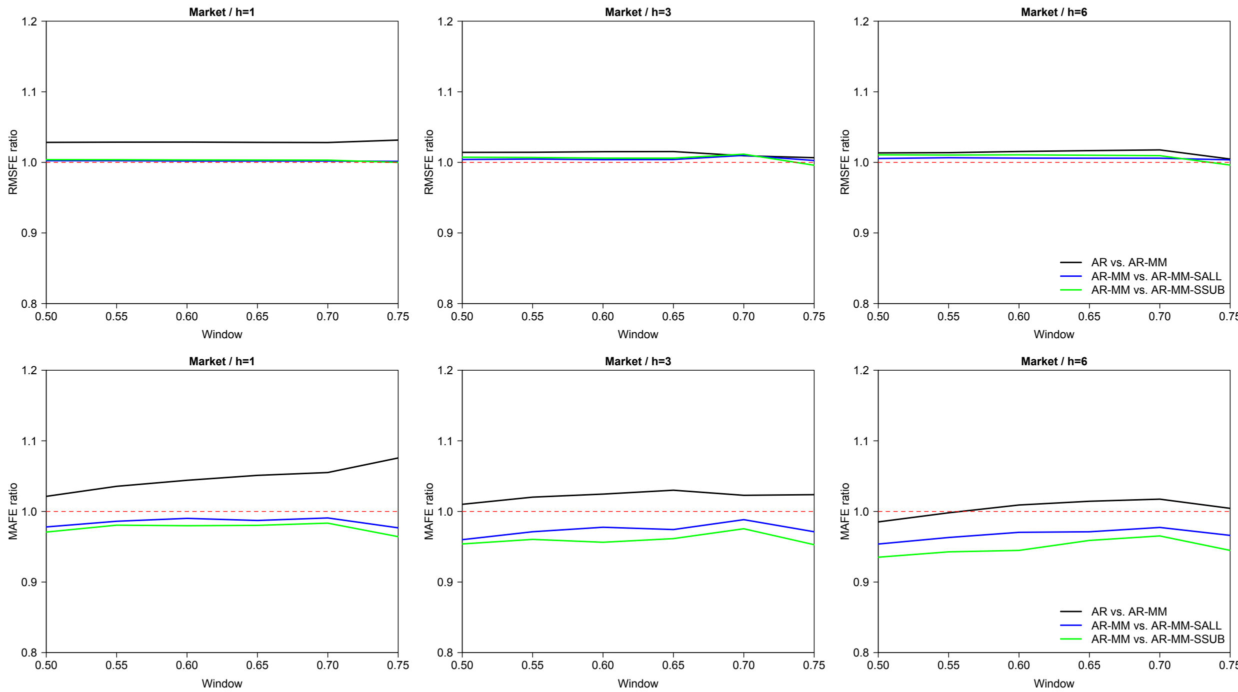
The horizontal axis denotes the length of the estimation (that is, training) window (in percent). A ratio that exceeds unity indicates that the rival model performs better than the benchmark model. The panels in the first (second) row depict the RMSFE (MAFE) ratio for RV. The panels in the third (fourth) depict the MAFE ratio for $\sqrt{RV}$ ($\ln\sqrt{RV}$).

Figure 2: OLS Results at the Sectoral Level



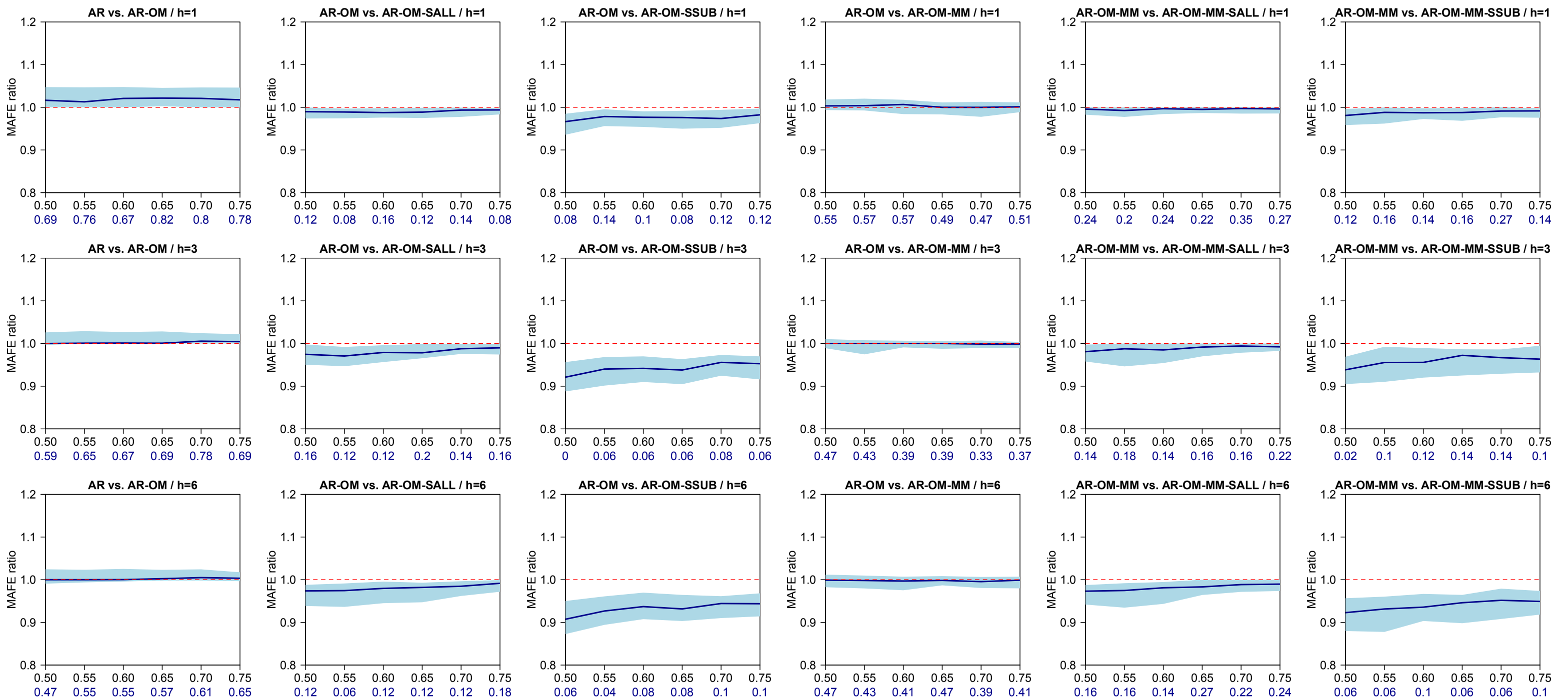
The upper numbers depicted on the horizontal axis denote the length of the estimation (that is, training) window (in percent). The lower numbers depicted on the horizontal axis denote the proportion of sectors for which the ratio exceeds unity (that is, 0.1 means 10%). A ratio that exceeds unity indicates that the rival model performs better than the benchmark model. The solid line denotes the cross-sectoral median. The shaded area denotes the cross-sectoral interquartile range. The results are for RV.

Figure 3: Lasso Results at the Market Level



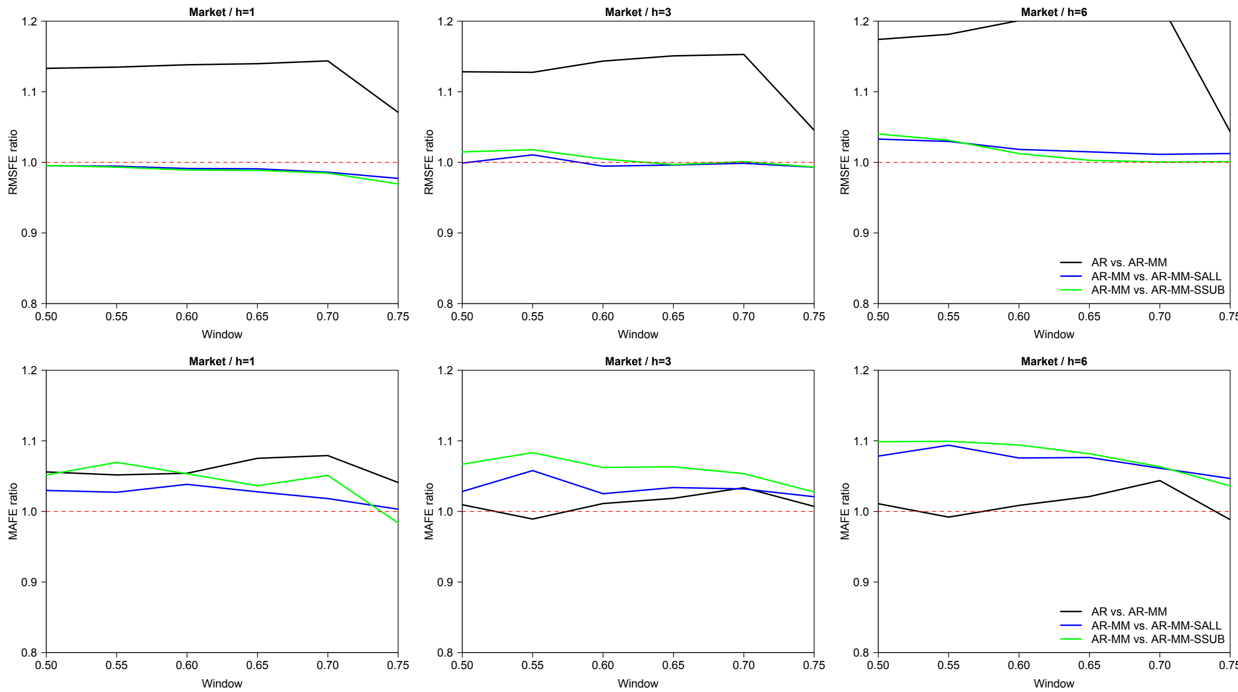
The horizontal axis denotes the length of the estimation (that is, training) window (in percent). A ratio that exceeds unity indicates that the rival model performs better than the benchmark model. The results are for the Lasso estimator and RV.

Figure 4: Lasso Results at the Sectoral Level



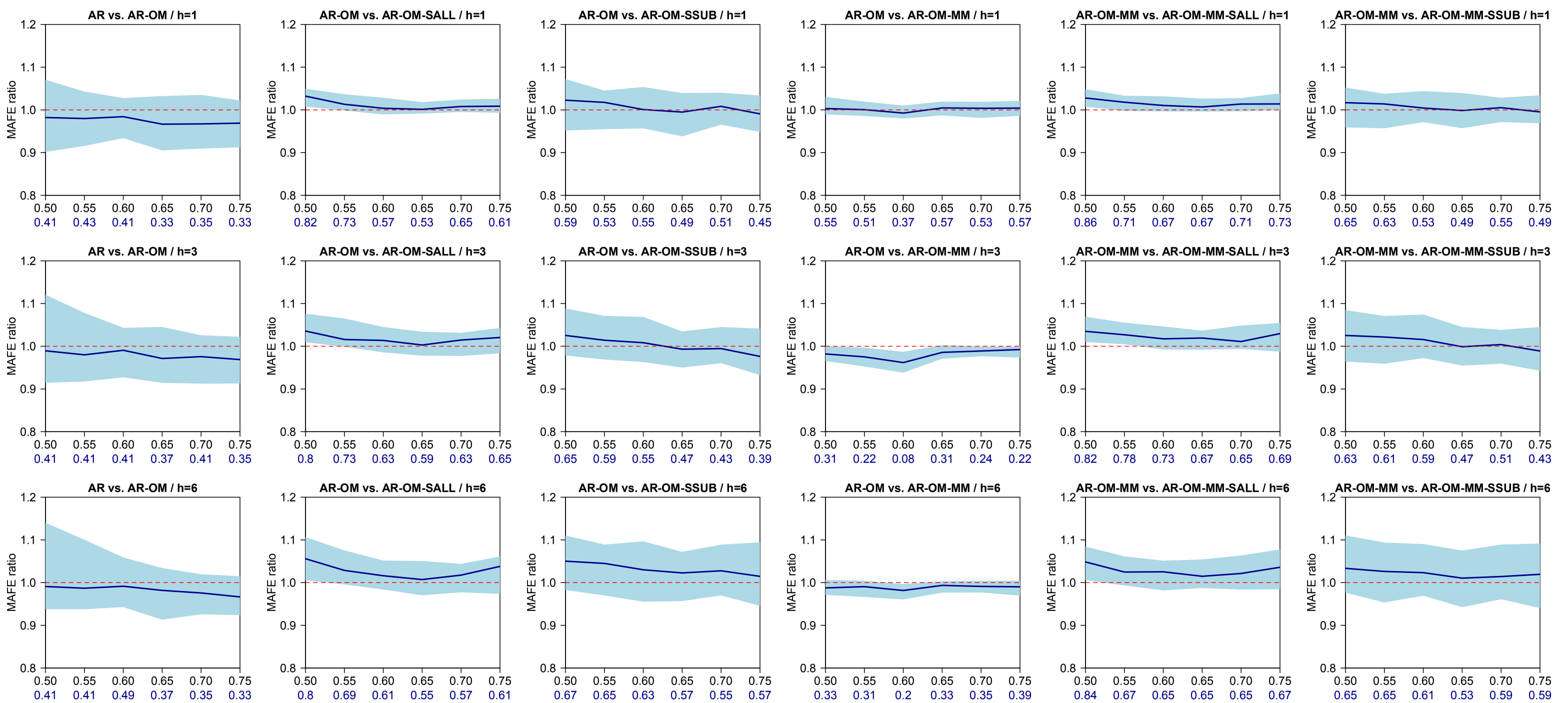
The upper numbers depicted on the horizontal axis denote the length of the estimation (that is, training) window (in percent). The lower numbers depicted on the horizontal axis denote the proportion of sectors for which the ratio exceeds unity (that is, 0.1 means 10%). A ratio that exceeds unity indicates that the rival model performs better than the benchmark model. The solid line denotes the cross-sectoral median. The shaded area denotes the cross-sectoral interquartile range. The results are for RV.

Figure 5: Random-Forest Results at the Market Level



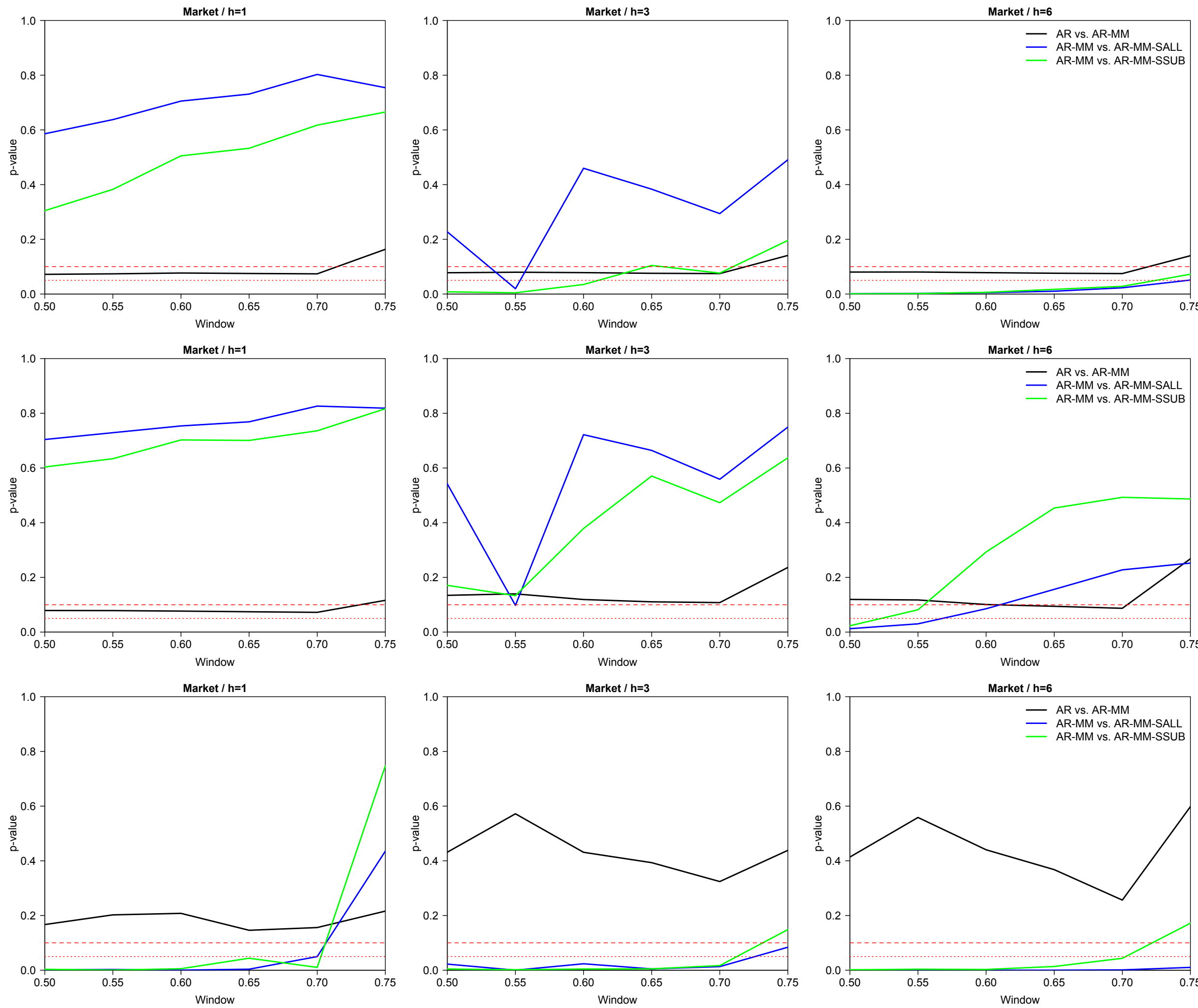
The horizontal axis denotes the length of the estimation (that is, training) window (in percent). The panels in the first (second) row depict the results for the MAFE (RMSFE) ratio. A ratio that exceeds unity indicates that the rival model performs better than the benchmark model. The results are for RV.

Figure 6: Random-Forest Results at the Sectoral Level



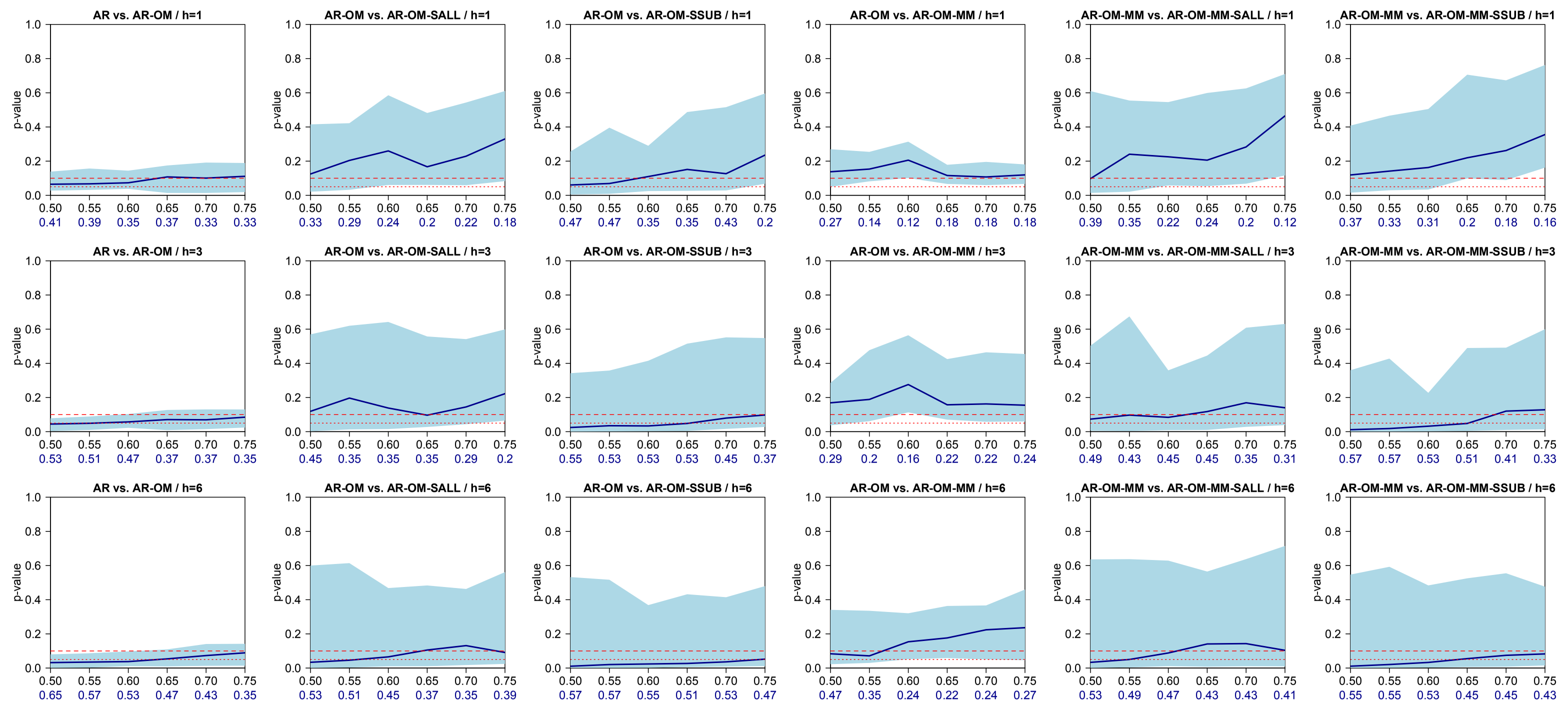
The upper numbers depicted on the horizontal axis denote the length of the estimation (that is, training) window (in percent). The lower numbers depicted on the horizontal axis denote the proportion of sectors for which the ratio exceeds unity (that is, 0.1 means 10%). A ratio that exceeds unity indicates that the rival model performs better than the benchmark model. The solid line denotes the cross-sectoral median. The shaded area denotes the cross-sectoral interquartile range. The results are for RV.

Figure 7: Test Results for Random Forests at the Market Level



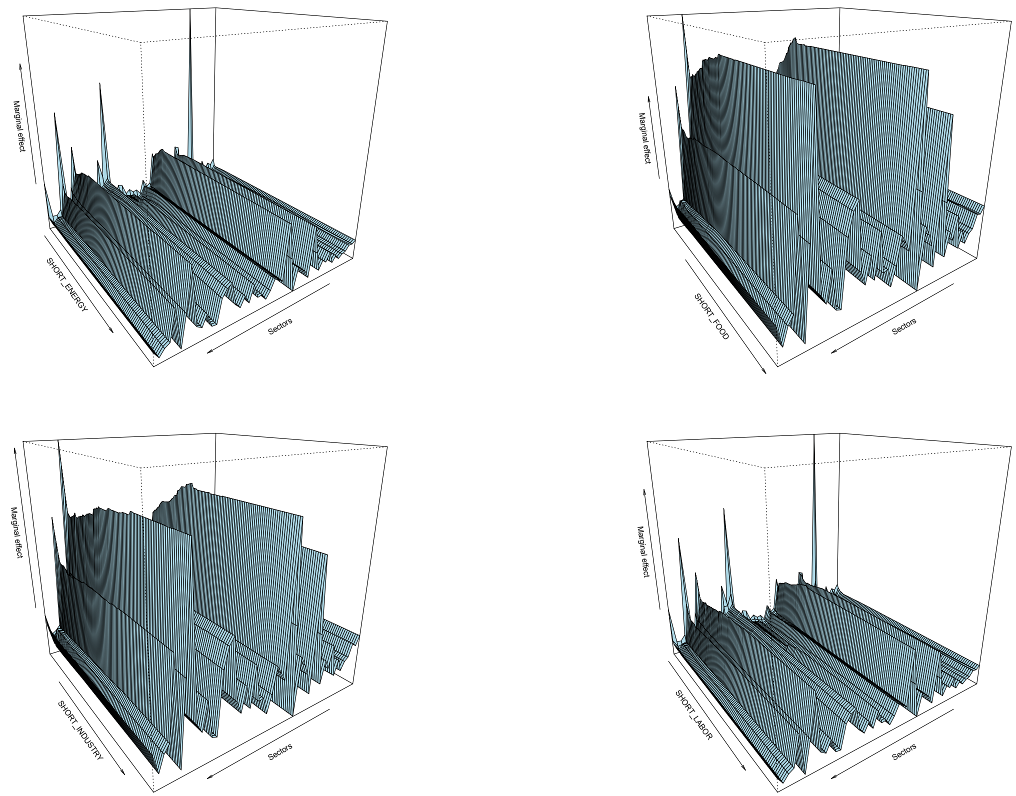
The horizontal axis denotes the length of the estimation (that is, training) window (in percent). The panels in the first row depict the results (p-values) of the CW test. The null hypothesis is that both models perform equally well. The one-sided alternative hypothesis is that the alternative model performs better than the benchmark model. The panels in the second (third) row depict the results for the modified DM test for a squared (an absolute) error-loss function. Dashed horizontal lines indicate the 5% and 10% levels of significance. The results are for RV.

Figure 8: Test Results for Random Forest at the Sectoral Level (CW test, p-values)



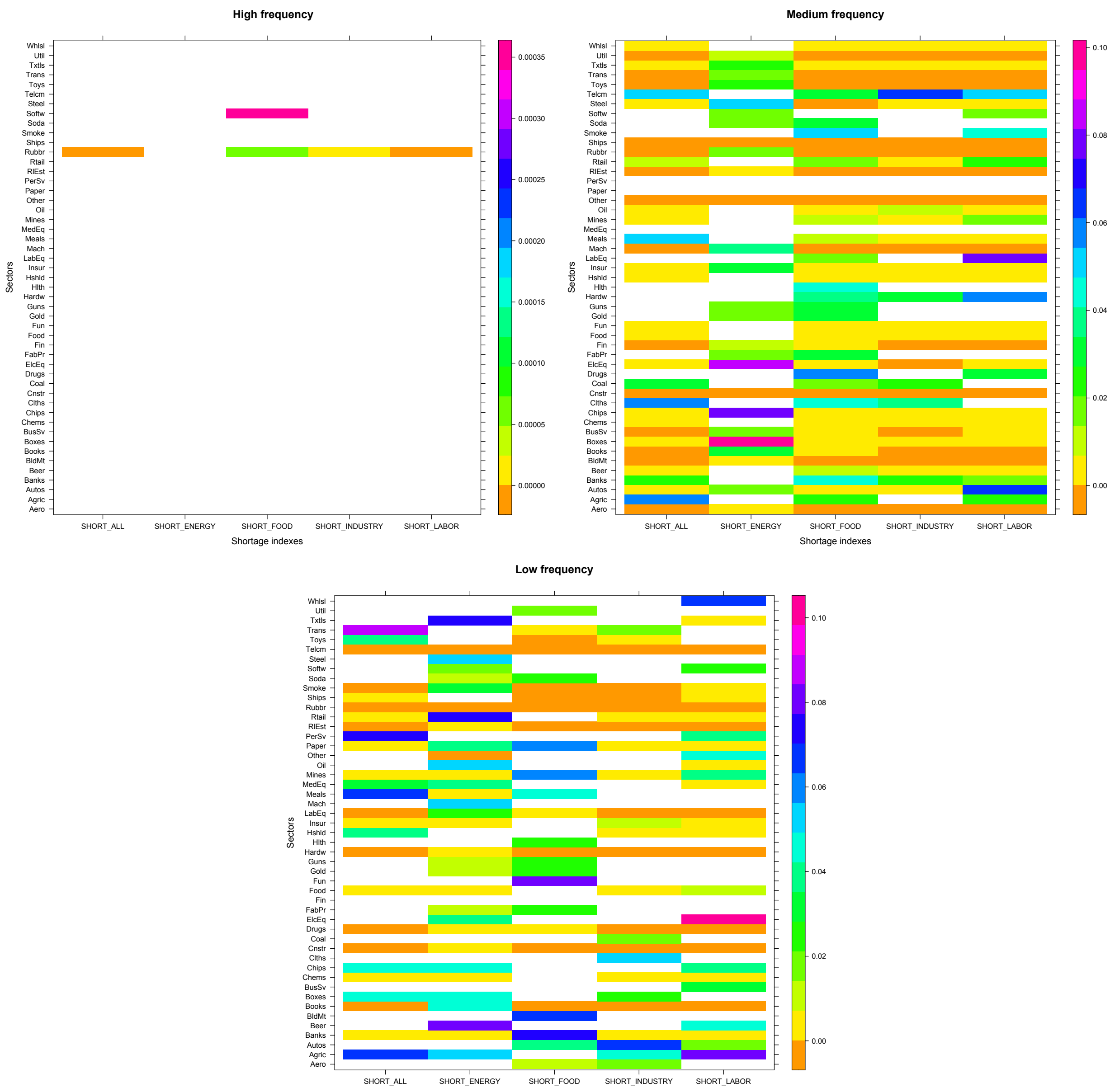
The upper numbers depicted on the horizontal axis denote the length of the estimation (that is, training) window (in percent). The lower numbers depicted on the horizontal axis denote the proportion of sectors for which the p-value is smaller than 5%. Dashed horizontal lines indicate the 5% and 10% levels of significance. The null hypothesis is that both models perform equally well. The one-sided alternative hypothesis is that the alternative model performs better than the benchmark model. The solid line denotes the cross-sectoral median. The shaded area denotes the cross-sectoral interquartile range. The results are for RV.

Figure 9: Estimated Marginal Effects at the Sectoral Level



The marginal effects show the predicted values of RV. The array of predictors includes RV, the own moments, and market moments (that is, realized market skewness, realized market kurtosis, realized market upside and downside tail risks). All other predictors except the shortage index under investigation are fixed at their respective mean values, while the shortage index being studied is varied in 100 steps from its full-sample minimum to its full-sample maximum. Estimations are done for every sector using the available full sample of data. The forecast horizon is $h = 3$.

Figure 10: Tests of the Significance of the Correlation of Shortage Indexes With the Frequency Decompositions of RV



For better readability, only p-values smaller than 0.1 are plotted.

Appendix

Figure A1: Shortages Indexes

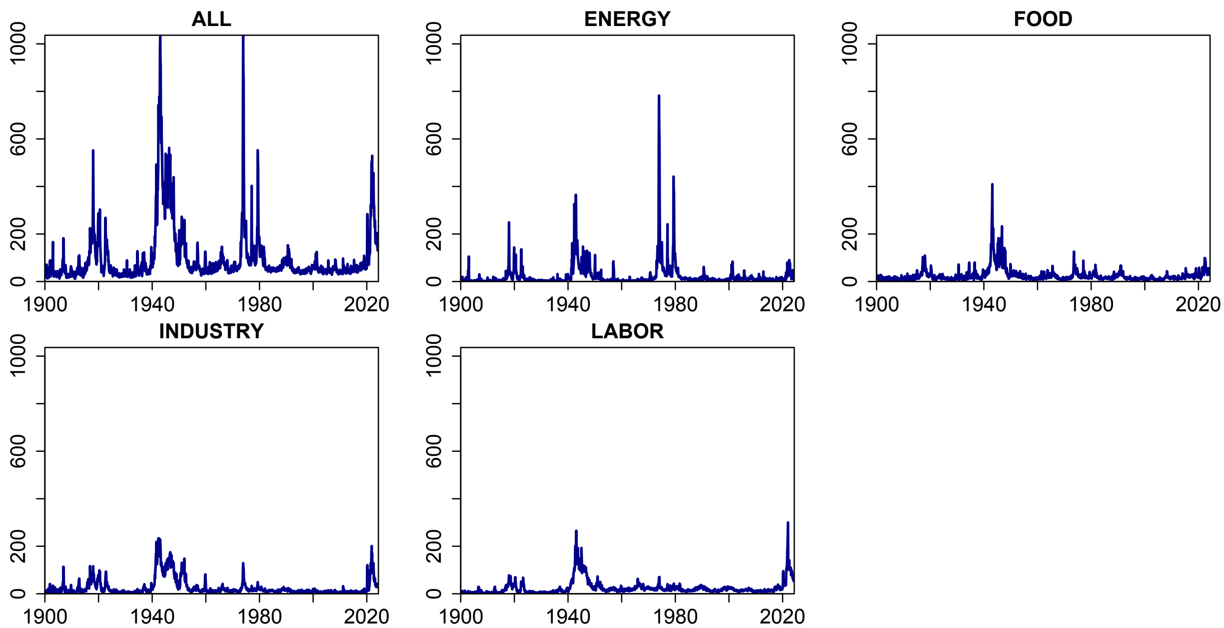
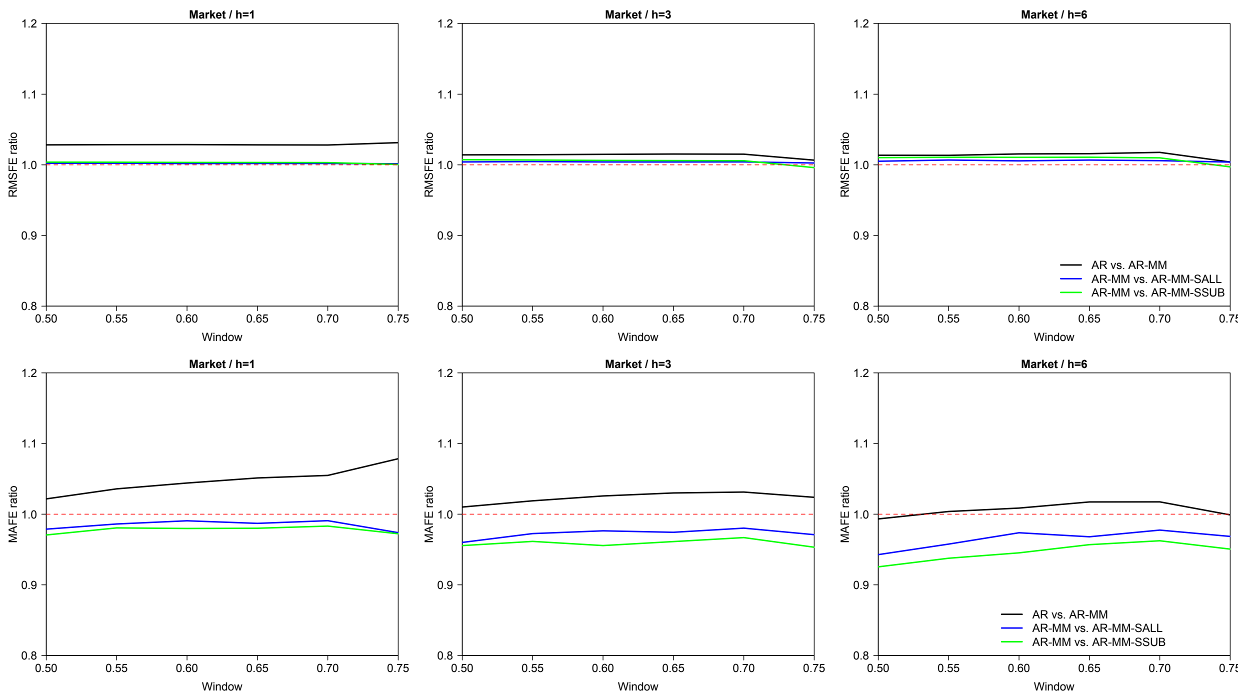


Table A1: Summary Statistics for RV

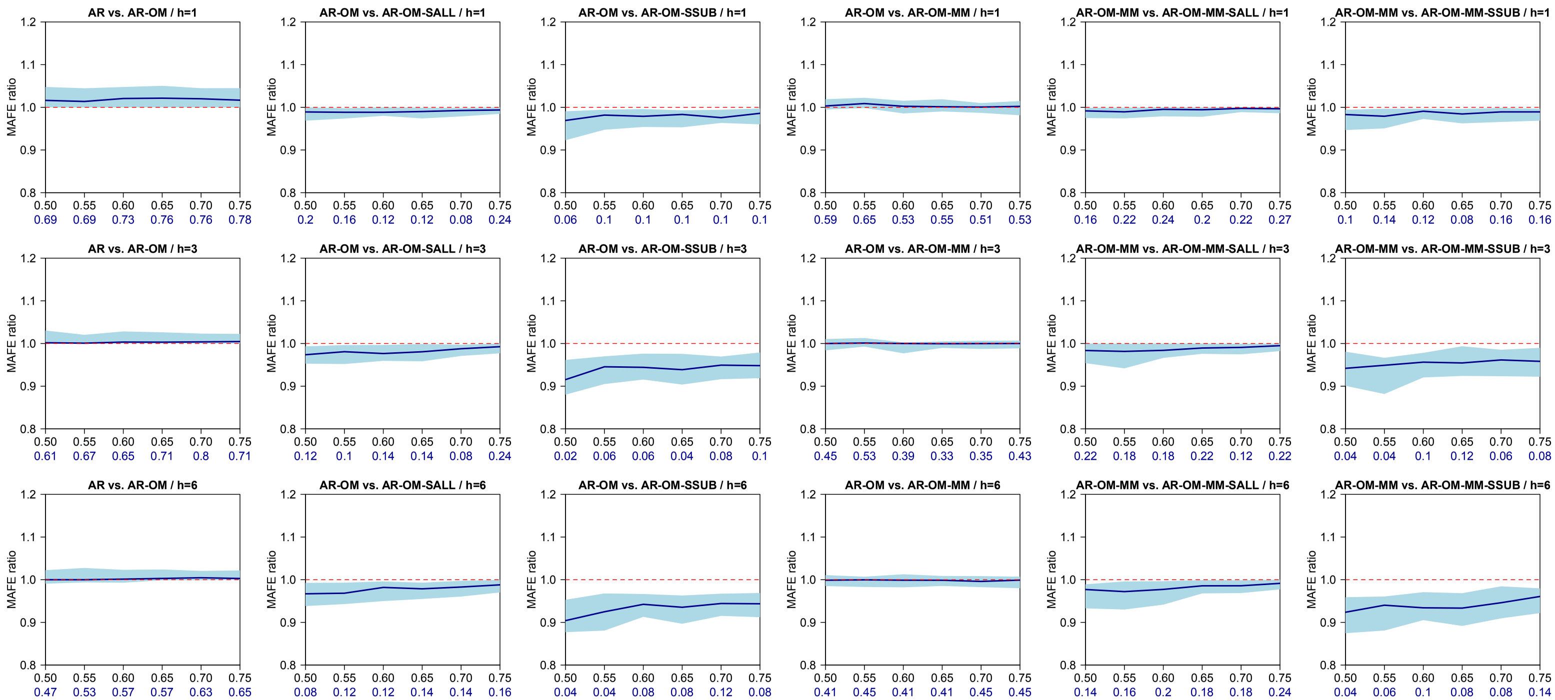
Sector	Start	End	N	Mean	Median	Max	Min
DJIA	1900-01	2024-05	1489	0.00254	0.00128	0.09725	0.00010
Aircraft	1926-07	2023-09	1167	0.00663	0.00291	0.16692	0.00035
Agriculture	1926-07	2023-09	1167	0.00482	0.00275	0.14133	0.00012
Automobiles and Trucks	1926-07	2023-09	1167	0.00582	0.00269	0.10811	0.00033
Banking	1926-07	2023-09	1167	0.00461	0.00165	0.12870	0.00017
Beer and Liquor	1926-07	2023-09	1167	0.00436	0.00188	0.17473	0.00021
Construction Materials	1926-07	2023-09	1166	0.00351	0.00156	0.11839	0.00010
Printing and Publishing	1926-07	2023-09	1167	0.00504	0.00229	0.13146	0.00024
Shipping Containers	1926-07	2023-09	1167	0.00341	0.00187	0.07705	0.00016
Business Services	1926-07	2023-09	1167	0.00748	0.00156	0.94114	0.00012
Chemicals	1926-07	2023-09	1167	0.00354	0.00167	0.09492	0.00009
Electronic Equipment	1926-07	2023-09	1167	0.00651	0.00308	0.28229	0.00035
Apparel	1926-07	2023-09	1167	0.00303	0.00154	0.09017	0.00012
Construction	1926-07	2023-09	1167	0.00821	0.00370	0.19478	0.00037
Coal	1926-07	2023-09	1166	0.01024	0.00449	0.25993	0.00027
Pharmaceutical Products	1926-07	2023-09	1167	0.00278	0.00149	0.08683	0.00017
Electrical Equipment	1926-07	2023-09	1167	0.00523	0.00248	0.10956	0.00037
Fabricated Products	1963-07	2023-09	723	0.00577	0.00321	0.17305	0.00031
Trading	1926-07	2023-09	1167	0.00526	0.00195	0.17834	0.00019
Food Products	1926-07	2023-09	1167	0.00185	0.00092	0.05733	0.00006
Entertainment	1926-07	2023-09	1167	0.00694	0.00321	0.12839	0.00037
Precious Metals	1963-07	2023-09	723	0.01079	0.00740	0.19339	0.00048
Defense	1963-07	2023-09	723	0.00407	0.00269	0.09127	0.00051
Computers	1926-07	2023-09	1167	0.00506	0.00260	0.17395	0.00017
Healthcare	1969-07	2023-09	651	0.00496	0.00278	0.09039	0.00033
Consumer Goods	1926-07	2023-09	1166	0.00286	0.00141	0.11817	0.00011
Insurance	1926-07	2023-09	1167	0.00396	0.00173	0.10911	0.00024
Measuring and Control Equipment	1926-07	2023-09	1166	0.00425	0.00242	0.07946	0.00020
Machinery	1926-07	2023-09	1167	0.00414	0.00174	0.10093	0.00018
Restaurants, Hotels, Motels	1926-07	2023-09	1167	0.00377	0.00208	0.10002	0.00021
Medical Equipment	1926-07	2023-09	1167	0.00532	0.00228	1.54142	0.00039
Non-Metallic and Industrial Metal Mining	1926-07	2023-09	1166	0.00522	0.00248	0.17601	0.00018
Petroleum and Natural Gas	1926-07	2023-09	1167	0.00392	0.00200	0.15460	0.00009
Other	1926-07	2023-09	1167	0.00460	0.00219	0.09621	0.00020
Business Supplies	1929-07	2023-09	1125	0.01874	0.00220	3.03689	0.00011
Personal Services	1927-07	2023-09	1154	0.00787	0.00287	0.32258	0.00030
Real Estate	1926-07	2023-09	1167	0.00876	0.00289	0.21910	0.00020
Retail	1926-07	2023-09	1167	0.00282	0.00138	0.07044	0.00011
Rubber and Plastic Products	1944-07	2023-09	951	0.00276	0.00168	0.06480	0.00032
Shipbuilding, Railroad Equipment	1926-07	2023-09	1167	0.00490	0.00285	0.07726	0.00019
Tobacco Products	1926-07	2023-09	1167	0.00314	0.00178	0.07212	0.00090
Candy and Soda	1963-07	2023-09	723	0.00394	0.00235	0.08919	0.00024
Computer Software	1965-07	2023-09	699	0.01118	0.00491	0.16405	0.00021
Steel Works Etc.	1926-07	2023-09	1167	0.00625	0.00259	0.19126	0.00028
Communication	1926-07	2023-09	1167	0.00230	0.00123	0.07636	0.00002
Recreation	1926-07	2023-09	1167	0.00960	0.00419	0.45992	0.00039
Transportation	1926-07	2023-09	1167	0.00391	0.00200	0.08349	0.00020
Textiles	1926-07	2023-09	1167	0.00416	0.00178	0.15340	0.00014
Utilities	1926-07	2023-09	1165	0.00254	0.00085	0.09140	0.00003
Wholesale	1926-07	2023-09	1166	0.00550	0.00180	0.66531	0.00019

Figure A2: Elastic Net Results at the Market Level



The horizontal axis denotes the length of the estimation (that is, training) window (in percent). A ratio that exceeds unity indicates that the rival model performs better than the benchmark model. The results are for the Lasso estimator and RV.

Figure A3: Elastic Net Results at the Sectoral Level



The upper numbers depicted on the horizontal axis denote the length of the estimation (that is, training) window (in percent). The lower numbers depicted on the horizontal axis denote the proportion of sectors for which the ratio exceeds unity (that is, 0.1 means 10%). A ratio that exceeds unity indicates that the rival model performs better than the benchmark model. The solid line denotes the cross-sectoral median. The shaded area denotes the cross-sectoral interquartile range. The results are for RV.