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Multi-Task Forecasting of the Realized Volatilities of Agricultural Commodity Prices

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Abstract: Motivated by the comovement of realized volatilities (RVs) of agricultural commodity prices, we study whether multi-task forecasting algorithms improve the accuracy of out-of-sample forecasts of 15 agricultural commodities during the sample period from July 2015 to April 2023. We consider alternative multi-task stacking algorithms and variants of the multivariate Lasso estimator. We find evidence of in-sample predictability but scarce evidence that multi-task forecasting improves out-of-sample forecasts relative to a classic univariate heterogeneous autoregressive (HAR)-RV model. This lack of systematic evidence of out-of-sample forecasting gains is corroborated by extensive robustness checks, including an in-depth study of the quantiles of the distributions of the RVs and subsample periods that account for increases in the total spillovers among the RVs. We also study an extended model that features the RVs of energy commodities and precious metals, but our conclusions remain unaffected. Besides offering important lessons for future research, our results are interesting for financial market participants, who rely on accurate forecasts of RVs when solving portfolio optimization and derivatives pricing problems, and policymakers, who need accurate forecasts of RVs when designing policies to mitigate the potential adverse effects of a rise in the RVs of agricultural commodity prices and the concomitant economic and political uncertainty.

Keywords: agricultural commodities; realized volatility; multi-task forecasting

MSC: 62-08; 62-11; 62H12; 62P20

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1. Introduction

Quite a number of empirical studies have been undertaken to shed light on the connectedness of volatility across agricultural commodities (see, for example, refs. [1–7], with [8] highlighting that accounting for co-volatility of Chinese futures of five agricultural commodities (corn, cotton, palm, wheat, and soybeans) improved the accuracy of volatility forecasts—in particular for corn, cotton, and wheat. It must be noted that the underlying spillovers of risk across agricultural commodities is not surprising, given that behavioral, macroeconomic, and financial shocks, which define the underlying state of these markets, tend to be common and that the commonality has grown stronger in recent years (see the detailed discussions in [9–11] in this regard). We contribute to this area of research by exploring whether stacking algorithms that have been developed in the recent bioinformatics literature can help to improve the accuracy of out-of-sample forecasts of the intraday data-based realized volatility (RV) of 15 important agricultural commodities during the daily sample period of July 2015 to April 2023.

An important advantage of using RV for our empirical analyses derives from the rich information contained in intraday data, besides being a consistent and asymptotically unbiased estimator of volatility [12–14]. In addition, RV is an observable and unconditional metric of "volatility". This, in turn, is unlike the latent processes underlying the class of Generalized Autoregressive Conditional Heteroskedasticity (GARCH) and Stochastic Volatility (SV) models that have been widely used in predicting agricultural commodity price volatility (see [15,16] for reviews of this extensive literature). Moreover, the dynamics of RV can be easily modeled by means of the heterogeneous autoregressive (HAR)-RV model [17]. The HAR-RV model has been extensively studied in research on realized volatility, including that of agricultural commodities (as reviewed in [18–20]) because it is able to capture long-memory and multi-scaling properties of realized volatility, as reported by [21–23]. Because the HAR-RV model employs RVs at different time resolutions to model and predict RV, it can be interpreted as a simple empirical representation of the heterogeneous market hypothesis (HMH; Ref. [24], which stipulates that asset markets (in our case, markets for agricultural commodities) are populated by various types of market participants, such as investors, speculators and traders, who, in turn, in turn, vary in their sensitivity to information flows at high and low frequencies.

Another advantage of the HAR-RV model is that it can easily be adapted to a multi-task forecasting setting, i.e., a setting where a forecaster seeks to forecast not only the RV of a single agricultural commodity but the RVs of several agricultural commodities simultaneously. One possibility to address such a multi-task forecasting problem is to consider as a modeling framework one of the multivariate HAR-RV models with heteroskedastic error structures, as has been studied by, for instance, refs. [5,8,25–28]. The focus of many studies in this area, however, has been on modeling and forecasting co-volatilities (see, for example, refs. [5,27,29–32]). Moreover, applications of HAR-RV cum heteroskedastic error models are often restricted to settings where the number of RVs to be analyzed is relatively small, as was the case in [5,8], involving seven and five agricultural commodities, respectively. This is due to the fact that, in a multivariate setting, the number of parameters to be estimated rapidly increases in the dimension of the model unless a researcher is willing to impose restrictions on parameters and/or functional forms so as to obtain a parsimonious representation of the heteroskedastic error structures.

In our case, the dataset comprises the RVs of 15 agricultural commodities (and, in an extended model, the RVs of three additional important energy commodities and the RVs of five precious metals), so we use various computationally efficient multi-task stacking algorithms that have been proposed in the recent bioinformatics literature (along with a multivariate shrinkage estimator) to re-examine the out-of-sample predictability of the RVs of the commodities in our sample (for a recent application of stacking in a univariate forecasting exercise of stock returns, see [33]). We also focus on direct spillovers among the RVs as captured by a multi-task HAR-RV model and do not consider the issue of forecasting co-volatility, which requires the imposition of further structure on the residuals. The multi-task stacking algorithms are easy to implement, even when the dimension of the model is large. Moreover, they make it possible to employ and combine alternative popular machine learning algorithms that make it possible to estimate a multi-task HAR-RV model in a data-driven way, that is, without imposing any specific structure that restricts the spillover dynamics across the RVs a priori. Finally, the multi-task stacking algorithms can be set up in a way such that the resulting statistical model captures potential nonlinear structures in the data, an issue that certainly deserves special attention in the wake of the type of sudden outbreaks and clustering of volatility typical of financial markets and of markets for agricultural commodities as well. In the process, our paper adds to the growing literature on modeling and predicting the RVs of agricultural commodities by investigating the role of volatility spillovers; thus far, researchers in this literature have otherwise relied on realized moments (such as realized kurtosis and realized jumps) and various other predictors that relate, for example, to the state of financial and other (non-agricultural) commodity markets, investor sentiment, climate change-related risks, and infectious disease-related uncertainty (see, for example, [8,15,16,18–20,34–39]).

Agricultural commodities have become increasingly financialized [40–42]. This process has caused institutional investors to increase their holdings in agricultural commodities relative to traditional assets. Naturally, besides the academic value of our work, accurate forecasts of the volatility of agricultural commodity prices are of key importance for investors because volatility is a core input in investment and portfolio allocation decisions, risk management, derivatives pricing, and assessments of hedging performance [43,44]. In addition, agricultural commodities comprise a large proportion of household consumption spending, implying that price volatility in agricultural commodities markets is likely to have substantial consequences for food security, especially as far as the economically vulnerable groups of the population are concerned [45–47]. Hence, from a policy perspective, it is important to produce accurate high-frequency forecasts of agricultural commodity price volatility so that policies can be discussed and implemented in a timely manner to protect vulnerable groups, in particular, from large and adverse food price fluctuations [48,49].

In order to present 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 in Section 3, we outline our methods. In Section 4, we present our empirical results. In Section 5, we conclude the paper.

2. Data

In our empirical analysis, we use data on the RVs of 15 agricultural commodities. The data are available publicly for download from the Internet page of Professor Dacheng Xiu. (Internet address: https://dachxiu.chicagobooth.edu/#risklab. Data downloaded on 4 May 2024). The data are based on (Globex) data for the following 15 agricultural commodity futures: soybean oil futures (BO), cocoa futures (CC), corn futures (C), cotton no. 2 futures (CT), feeder cattle futures (FC), coffee C futures (KC), lumber futures (LB), live cattle futures (LC), lean hog futures (LH), orange juice futures (OJ), oat futures (O), sugar #11 futures (SB), soybean meal futures (SM), soybean futures (S), and CBOT wheat futures (W). After matching the data by date, the matched dataset starts on 27 July 2015 and ends on 28 April 2023. We plot the RV data of the agricultural commodities in Figure 1. The RVs display a discernible heterogeneity across the agricultural commodities, and they also exhibit the type of clusters and sudden outbursts characteristic of many financial market volatilities.

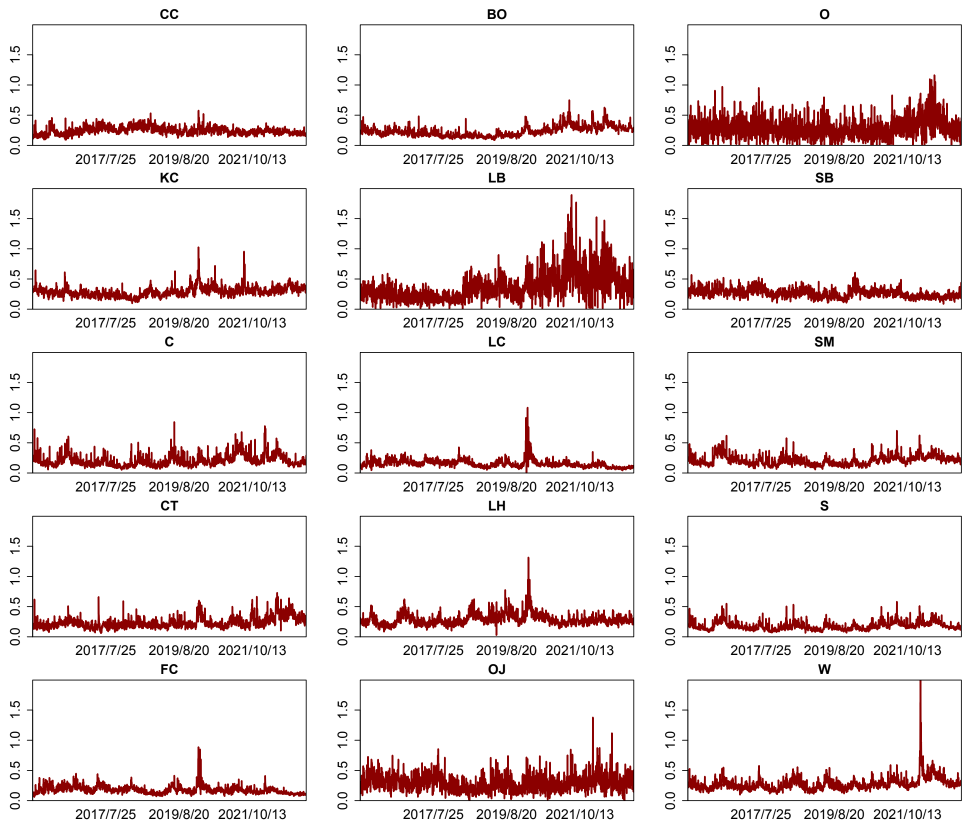

Figure 1. RVs of agricultural commodities.

In order to obtain a first glimpse of the comovement of the RVs, we plot their full-sample contemporaneous correlation matrix in Figure 2. The contemporaneous correlations vary from weakly negative to strongly positive, with the positive correlations mainly collected in the lower part of the matrix. For example, we observe strong positive contemporaneous correlations between C and S, S and SM, and LC and FC, among others. While the full-sample contemporaneous correlations shed light on an important feature of the data, one should bear in mind that the correlations do not inform about the question as to whether the comovement of the RVs can be exploited in a multi-task out-of-sample forecasting exercise to improve predictive accuracy at various forecast horizons.

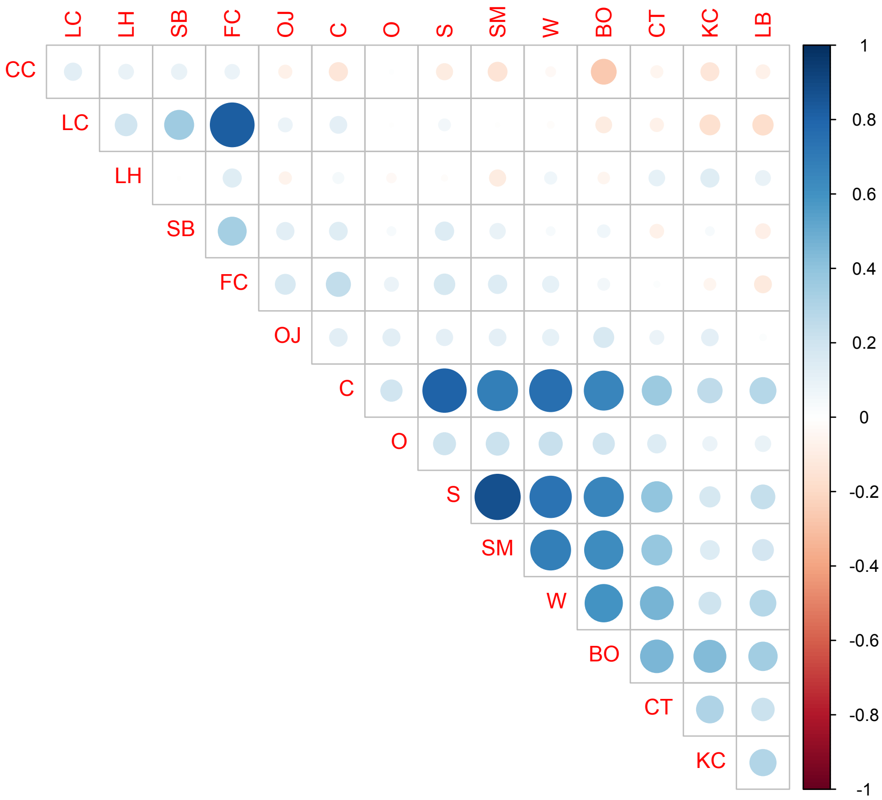

Figure 2. Full−sample correlation matrix.

3. Methods

3.1. Forecasting Models

We frame our empirical analysis in terms of the popular HAR-RV model developed by [17]. This model can be specified by the following equation:

$$RV_{t+h} = \beta_0 + \beta_1 RV_t + \beta_2 RV_{IF,t} + \beta_3 RV_{LF,t} + u_{t+h}, \quad (1)$$

which we estimate using the ordinary least squares (OLS) technique, where $\beta_j, j = 0, \ldots, 3$ are the coefficients to be estimated, u_{t+h} denotes a disturbance term, and RV_{t+h} denotes the average realized volatility over the forecast horizon (h). In our empirical research, we study one short, two intermediate, and one long forecast horizon. To this end, we specify $h = 1, 5, 10, 22$. The predictors are the daily realized volatility (RV_t), the intermediate-frequency (IF) realized volatility, ($RV_{t,IF}$), and the low-frequency (LF) realized volatility, ($RV_{t,LF}$). We define IF realized volatility as the average realized volatility from period $t-5$ to period $t-1$ and LF realized volatility as the average realized volatility from period $t-22$ to period $t-1$, as computed using the matched data.

We emphasize that in order to avoid non-negativity constraints and to bring the data closer to normality, we use the natural logarithm of the RV to estimate the HAR-RV model (and its extension to the HAR-RV-S model), which accounts for potential spillover effects. However, we evaluate the resulting forecasts in terms of the anti-log of the RV.

The variant of the HAR-RV model that accounts for spillover effects, the HAR-RV-S model, is expressed by the following equation:

$$\begin{aligned} RV_{t+h,i} = {} & \beta_0 + \beta_1 RV_{t,i} + \beta_2 RV_{IF,t,i} + \beta_3 RV_{LF,t,i} \\ & + \sum_{j \neq i} \left(\beta_{4,j} RV_{t,j} + \beta_{5,j} RV_{IF,t,j} + \beta_{6,j} RV_{LF,t,j} \right) + u_{t+h}, \end{aligned} \tag{2}$$

where i is the agricultural commodity being studied and the index j denotes the other agricultural commodities. Hence, we obtain the HAR-RV-S model by adding the daily, intermediate-frequency, and low-frequency realized volatilities of the other agricultural commodities and, thereby, account for potential spillover effects at different time resolutions. We emphasize that the HAR-RV-S model captures direct spillover effects among the RVs, not the dynamics of co-volatilities.

We use the R language and environment for statistical computing ([50]; R version 4.3.1) to estimate our forecasting models and to compute all other results that we lay out in this research. We estimate the forecasting models either by means of a recursively expanding estimation window or by means of a rolling estimation window. We use 50% of the data to initialize the recursive estimations. Similarly, we use 50% of the data to define the length of a rolling estimation window. Finally, we use the root mean squared forecasting error (RMSFE) and the mean absolute forecasting error (MAFE) to evaluate the out-of-sample performance of the forecasting models, where we compute the ratio of the RMSFE (MAFE) of the HAR-RV-S model and the HAR-RV model to alleviate the interpretation of our empirical results. Hence, an RMSFE (MAFE) ratio smaller than unity implies that the HAR-RV-S model outperforms the HAR-RV model, while a ratio larger than unity signals that the HAR-RV model is the better forecasting model.

3.2. Stacking Algorithms

Given that our sample comprises 15 agricultural commodities and we have to consider (leaving the intercept term apart) a total of $15 \times 3 = 45$ predictors, we use computationally efficient stacking algorithms to estimate the forecasting model given in Equation (2).

The first stacking algorithm that we use (we call this algorithm the baseline stacking algorithm) was studied recently by [51]. This baseline stacking algorithm requires that we treat the forecasting model given in Equation (2) as a base learner. Accordingly, we estimate 15 base learners—one for every agricultural commodity. Given the large number of parameters to be estimated, we estimate the base learners either by means of the Lasso estimator, as an elastic net, or by means of the Ridge regression estimator (see [52,53]), where we choose the corresponding shrinkage parameter using 10-fold cross validation (CV). We use the CV-based out-of-fold predictions from the base learners to construct a matrix ($\hat{H}^{CV}$) with 15 columns—one for every agricultural commodity. Finally, we construct a meta learner by estimating a regression model—one for every agricultural commodity—of RV_{t+h} on all predictors in $\hat{H}^{CV}$. Hence, the baseline stacking algorithm implies that the second-stage meta learners extract the information embedded in the predictors of the base learners in a way such that the forecast of RV_{t+h} combines the first-stage estimated effects on all RVs in a linear way. We use the shrinkage estimator that we apply to the base learners to estimate the meta learners. We use R add-on package "joinet" [51] to implement the baseline stacking algorithm.

In addition, we use a modified stacking algorithm that was proposed recently by [54]. Specifically, we use their residual stacking algorithm and corresponding R add-on package"MTPS". The modified stacking algorithm requires that we fit base learners in the first stage and compute the resulting fitted values of the RVs. One then models the residuals one obtains for agricultural commodity k using the fitted first-stage RVs (excluding the one for k) and obtains a meta learner using the first-stage base learner plus the fitted residual function. As a result, one can combine, for example, a first-stage Lasso estimator with a another Lasso estimator or, in case one suspects that the data feature nonlinear patterns that are worthwhile studying, regression trees [55] to obtain a meta learner. We call the latter a Lasso-RF model because a regression tree represents a general (rather than a linear) residual function.

4. Empirical Results

4.1. Full-Sample Results

We start the discussion of our empirical results by eyeballing the heat maps we plot in Figure 3, which show the full-sample coefficients of the HAR-RV-S model for the four different forecasting horizons. The results are based on the Lasso version of the baseline stacking algorithm. The upper-left heat map shows that at the short forecasting horizon ($h = 1$), the coefficients of the classic HAR-RV model (that is, the diagonal cells of the map) dominate the scenery. The colors of most of the off-diagonal cells indicate that the spillover coefficients are close to zero and, in some cases, negative. The coefficients of the HAR-RV-S model somewhat gain in prominence as we move on to one of the intermediate forecast horizons ($h = 5, 10$) plotted in the upper-right and lower-left heat maps. While there are several positive off-diagonal coefficients, we also observe various negative estimated coefficients, especially when we consider the off-diagonal (RV_{LF}) coefficients in the upper part of the heat maps. Finally, at the long forecast horizon ($h = 20$), it appears that, while there are still some noticeable spillover effects, the own RV_{LF} coefficients gain somewhat in relative importance again (lower-right panel). Taken together, the estimated coefficients indicate that it may be possible to improve in-sample model fit by accounting for spillover effects.

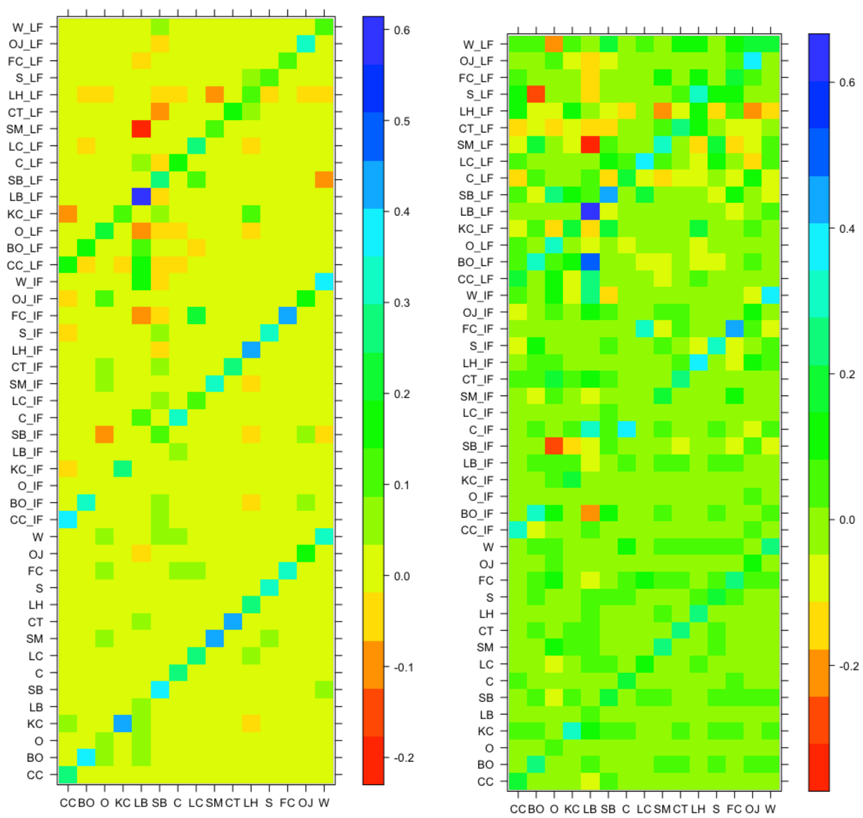

Figure 3. *Cont.*

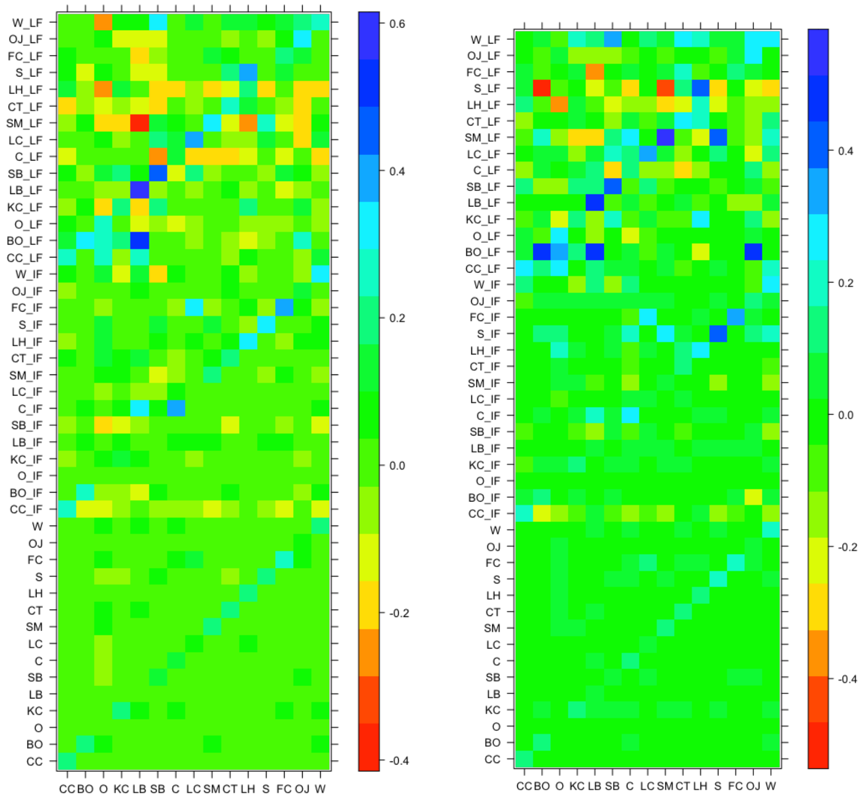

Figure 3. Full−sample estimated coefficients (baseline stacking algorithm). The forecast horizons are $h = 1, 5, 10, 20$ (starting in the upper-left panel).

The results we summarize in Figure 4 illustrate that this is, indeed, the case. Figure 4 plots in-sample ratios of the RMSFE for a comparison of the HAR-RV-S model with the HAR-RV model. An RMSFE ratio smaller than unity indicates that the HAR-RV-S model produces a smaller in-sample RMSFE than the HAR-RV model. The results, irrespective of whether we study a Lasso estimator, an elastic net, or a Ridge regression estimator, indicate that the in-sample fit of the HAR-RV-S model relative to the classic HAR-RV model tends to improve as we increase the length of the forecast horizon.

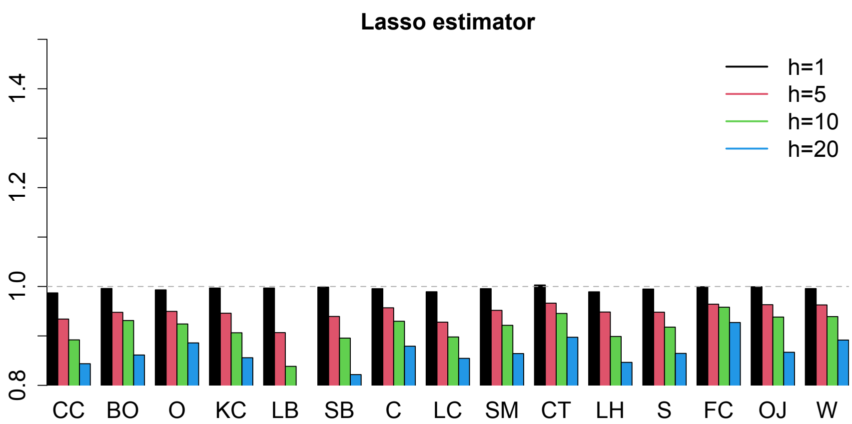

Figure 4. *Cont.*

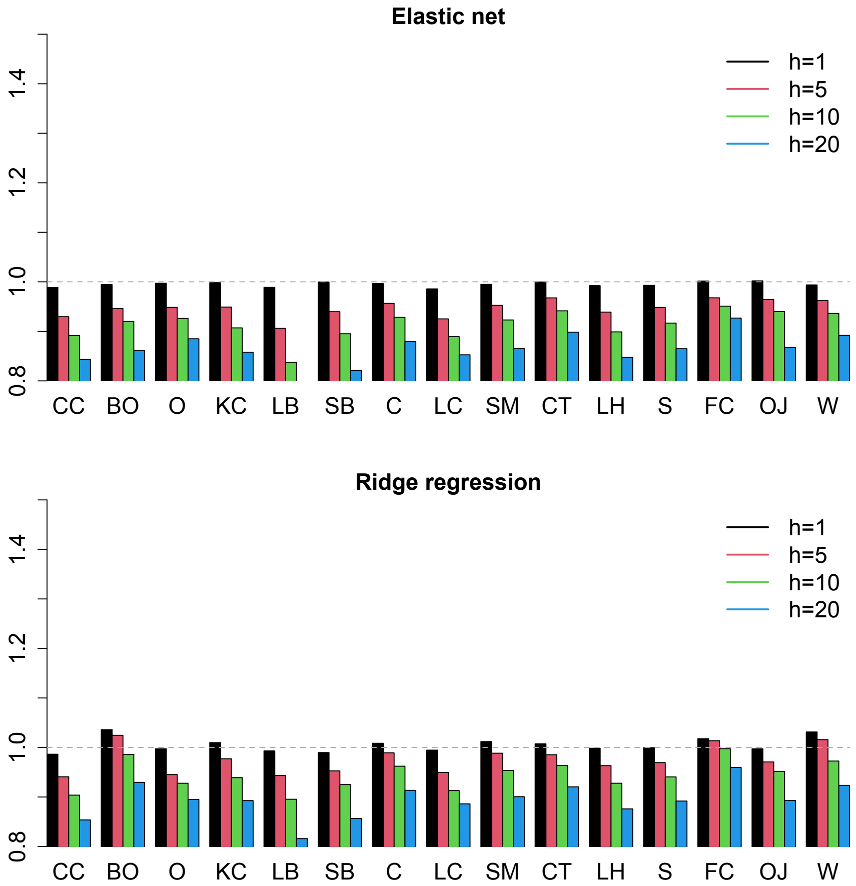

Figure 4. RMSFE ratios for the full sample (baseline stacking algorithm). RMSFE ratios for a comparison of the HAR-RV-S model (meta learner) with the HAR-RV model. An RMSFE ratio smaller than unity indicates that the meta learner produces a smaller in-sample RMSFE than the HAR-RV model. The forecast horizons are $h = 1, 5, 10, 20$.

4.2. Forecasting Results

In-sample fit does not necessarily carry over to an out-of-sample analysis. We start our comparison of the out-of-sample performance of the HAR-RV-S model, as estimated by the baseline stacking estimator, with that of the HAR-RV model, as estimated by the OLS technique. Figure 5 depicts the resulting RMSFE ratios that we obtain when we consider a recursive estimation window, while Figure 6 depicts the corresponding RMSFE ratios for a rolling estimation window. The key result for both types of estimation windows is that the classic HAR-RV model outperforms the HAR-RV-S model for the vast majority of commodities, especially when we increase the length of the forecasting horizon. This key result is not sensitive to the specific choice of the shrinkage estimator (Lasso estimator, elastic net, or ridge regression).

Figure 7 shows, for the example of a recursive estimation window, that we observe the superior performance of the HAR-RV model relative to the HAR-RV-S model when we also consider the MAFE as our metric of forecasting accuracy. The MAFE ratios should be less sensitive to large forecasting error in the wake of a sudden outburst of RV (see Figure 1) than the RMSFE ratio, but the results clearly demonstrate that our key result is robust to changes in the metric of forecast accuracy.

Figure 8 (for a recursive estimation window) and Figure 9 (for a rolling estimation window) summarize the results we obtain when we study the modified stacking algorithm. For the modified stacking algorithm, we consider the following four alternative combinations of estimators: a Lasso–Lasso estimator, a Lasso-RF (that is, a general regression tree-based residual function) estimator, a ridge–ridge estimator, and a ridge-RF estimator. Four all four combinations of estimators, we use the RMSFE ratio to quantify relative forecasting performance. Across the four combinations of estimators, we observe that the HAR-RV-S model does not outperform the classic HAR-RV model. Quite to the contrary, the HAR-RV model exhibits a robustly superior performance, especially as the length of the forecasting horizon increases.

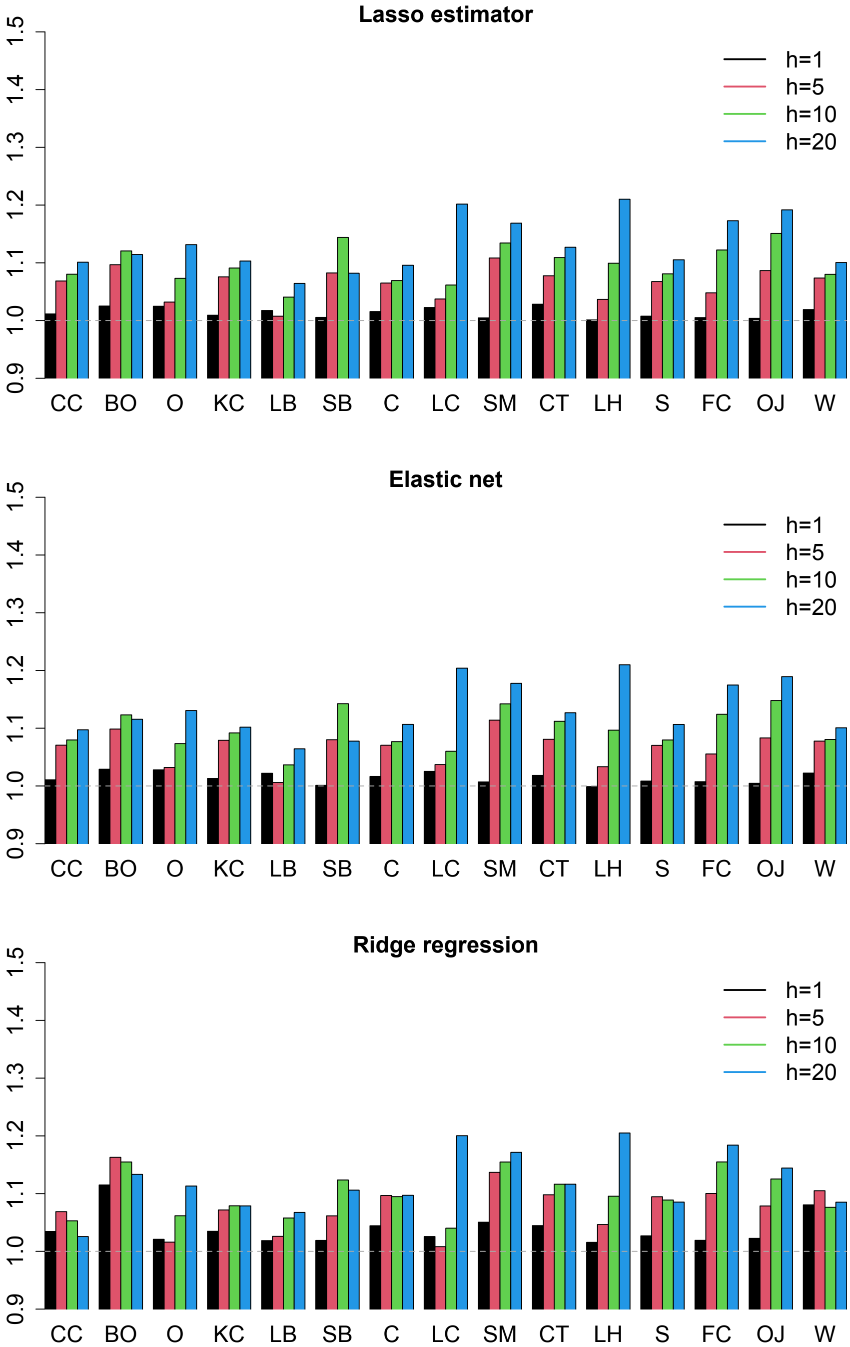

Figure 5. RMSFE ratios for a recursive window (baseline stacking algorithm). RMSFE ratios for a comparison of the HAR-RV-S model (meta learner) with the HAR-RV model. An RMSFE ratio smaller than unity indicates that the meta learner produces a smaller in-sample RMSFE than the HAR-RV model. The forecast horizons are $h = 1, 5, 10, 20$.

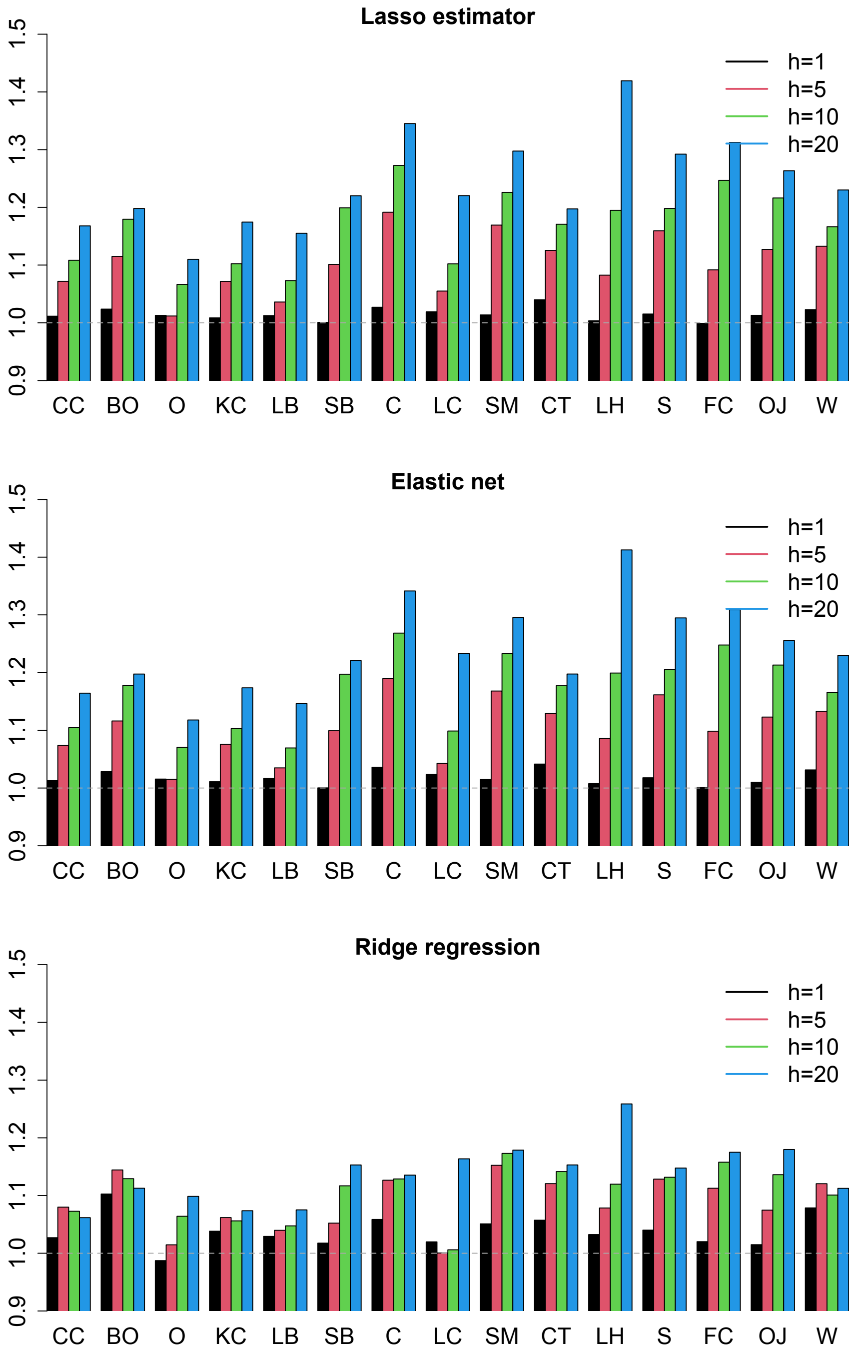

Figure 6. RMSFE ratios for a rolling window (baseline stacking algorithm). RMSFE ratios for a comparison of the HAR-RV-S model (meta learner) with the HAR-RV model. An RMSFE ratio smaller than unity indicates that the meta learner produces a smaller in-sample RMSFE than the HAR-RV model. The forecast horizons are $h = 1, 5, 10, 20$.

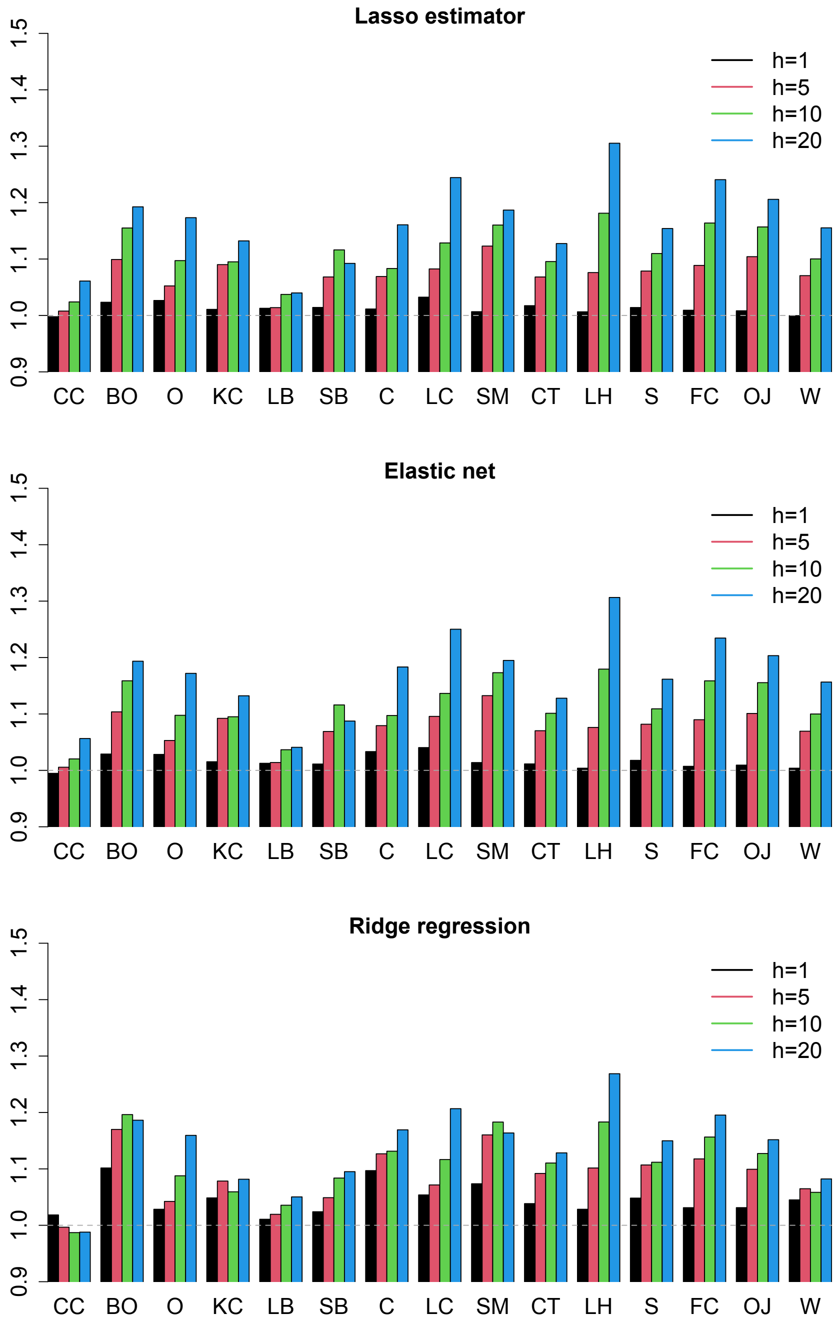

Figure 7. MAFE ratios for a recursive window (baseline stacking algorithm). MAFE ratios for a comparison of the HAR-RV-S model (meta learner) with the HAR-RV model. A MAFE ratio smaller than unity indicates that the meta learner produces a smaller in-sample MAFE than the HAR-RV model. The forecast horizons are $h = 1, 5, 10, 20$.

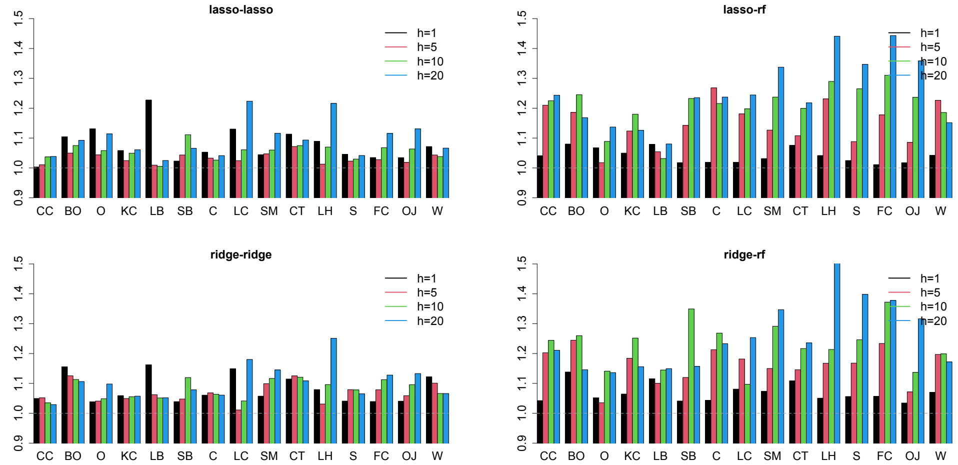

Figure 8. RMSFE ratios for a recursive window (modified stacking algorithm). RMSFE ratios for a comparison of the HAR-RV-S model (meta learner) with the HAR-RV model. An RMSFE ratio smaller than unity indicates that the meta learner produces a smaller in-sample RMSFE than the HAR-RV model. The forecast horizons are $h = 1, 5, 10, 20$.

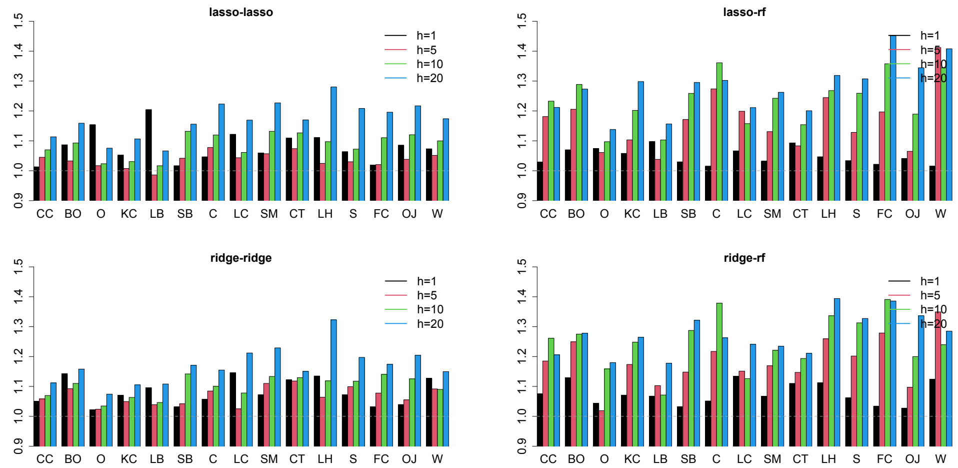

Figure 9. RMSFE ratios for a rolling window (modified stacking algorithm). RMSFE ratios for a comparison of the HAR-RV-S model (meta learner) with the HAR-RV model. An RMSFE ratio smaller than unity indicates that the meta learner produces a smaller in-sample RMSFE than the HAR-RV model. The forecast horizons are $h = 1, 5, 10, 20$.

4.3. Robustness Checks

As our first robustness check, in Figure 10 (recursive estimation window) and Figure 11 (rolling estimation window) we summarize the results for multivariate Lasso, multivariate elastic net, and multivariate ridge regression estimators. For estimation of the multivariate shrinkage estimators, we use R add-on package "glmnet" [56]. For the short forecast horizon, we observe a few cases for which the HAR-RV-S model performs better than the classic HAR-RV model, but the general message conveyed by the results is in line with the results for the stacking algorithms. The classic HAR-RV model performs well for the majority of agricultural commodities at the short forecast horizon, and it performs better than the HAR-RV-S model at the intermediate and long forecast horizons.

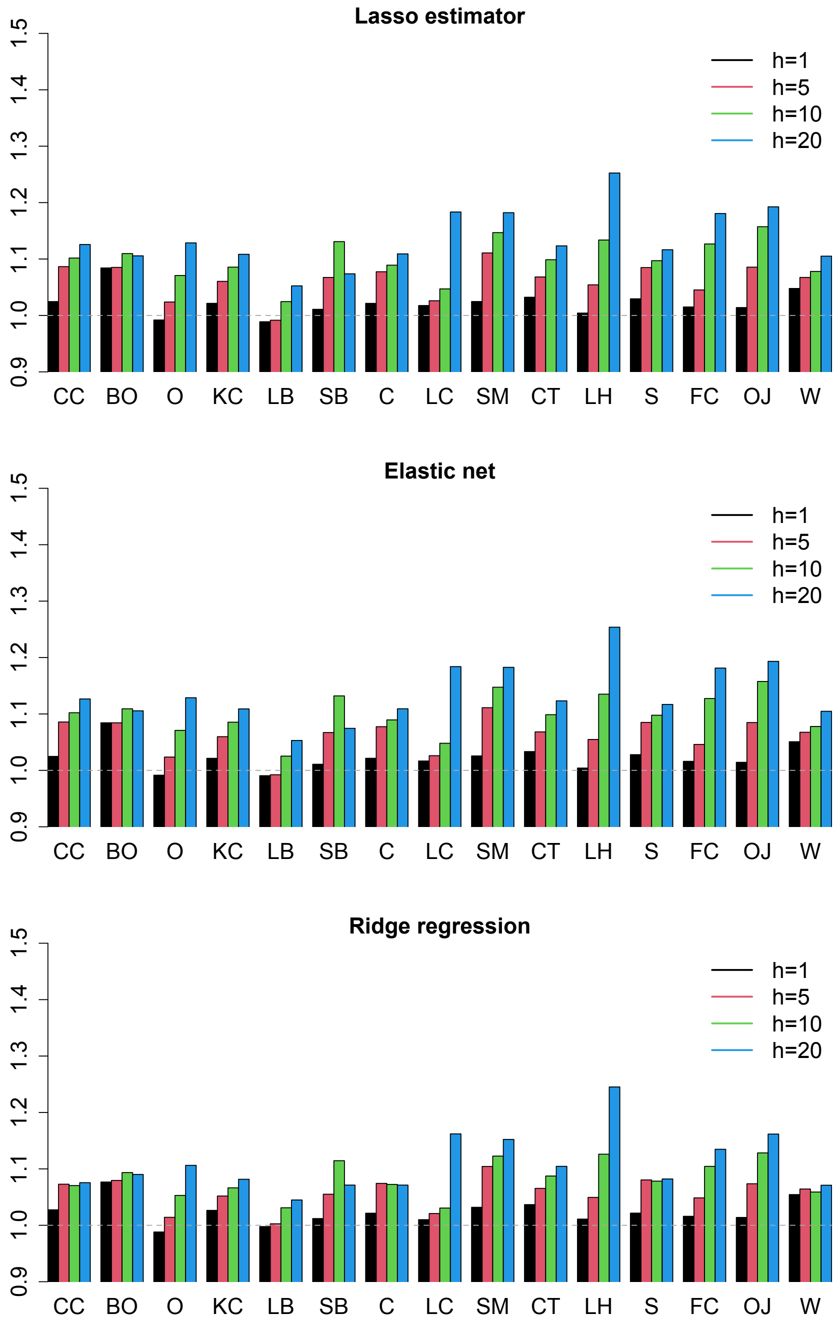

Figure 10. RMSFE ratios for a recursive window (multivariate shrinkage estimator). RMSFE ratios for a comparison of the HAR-RV-S model (meta learner) with the HAR-RV model. An RMSFE ratio smaller than unity indicates that the meta learner produces a smaller in-sample RMSFE than the HAR-RV model. The forecast horizons are $h = 1, 5, 10, 20$.

As another robustness check, we study the relative performance of the HAR-RV-S model along the quantiles of the distribution of the actual realizations of RV during the out-of-sample period. We plot the results in Figure 12 (recursivce estimation window) and Figure 13 (rolling estimation window), where we focus on the baseline stacking algorithm for the sake of space. We observe that the HAR-RV-S model slightly outperforms the HAR-RV model at the short forecast horizon for intermediate quantiles close to the median, mainly when we consider a Lasso estimator. For the intermediate and long forecast horizons, in contrast, the HAR-RV model clearly outperforms the HAR-RV-S model. The relative performance of the HAR-RV-S model only starts improving at some of the very upper quantiles, but this improvement is not strong enough to beat the forecasting performance of the HAR-RV model in a robust way.

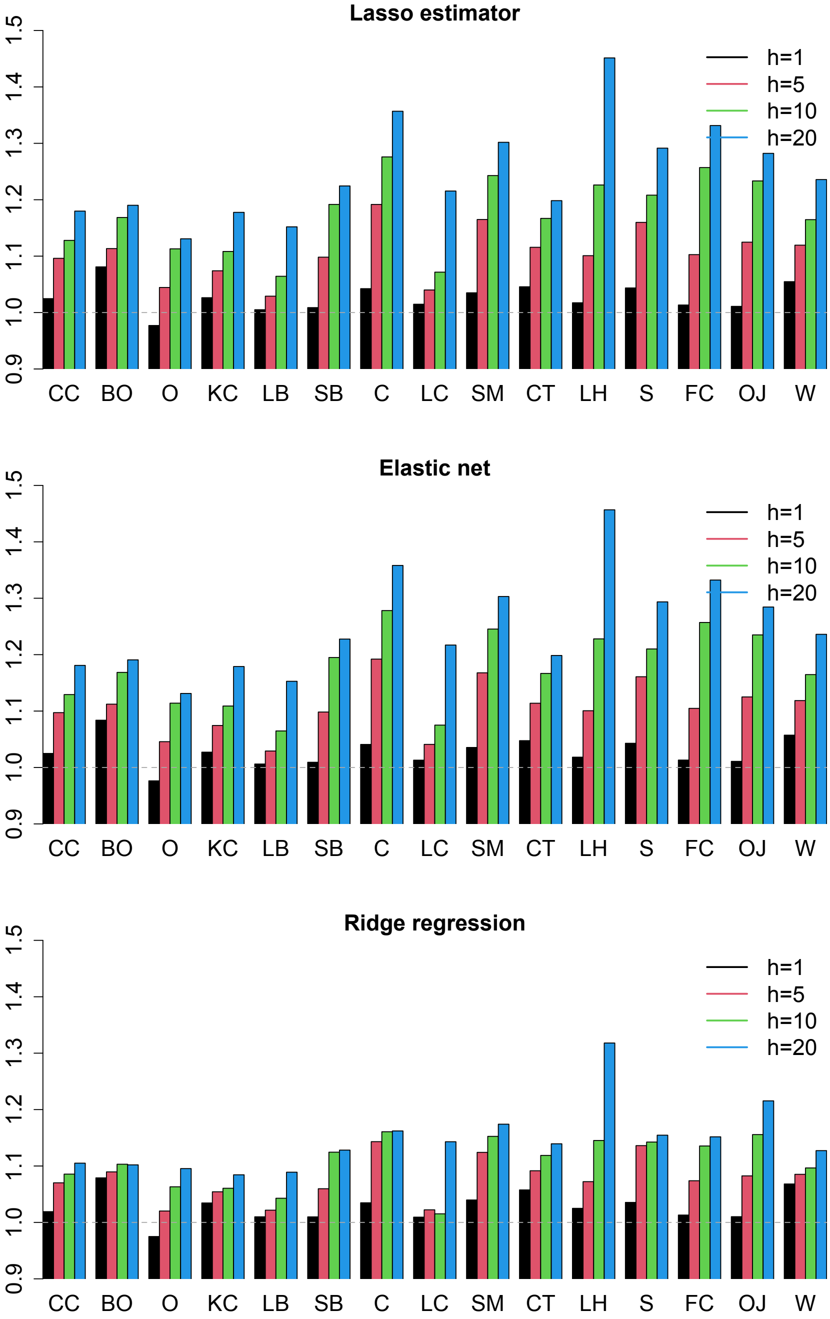

Figure 11. RMSFE ratios for a rolling window (multivariate shrinkage estimator). RMSFE ratios for a comparison of the HAR-RV-S model (meta learner) with the HAR-RV model. An RMSFE ratio smaller than unity indicates that the meta learner produces a smaller in-sample RMSFE than the HAR-RV model. The forecast horizons are $h = 1, 5, 10, 20$.

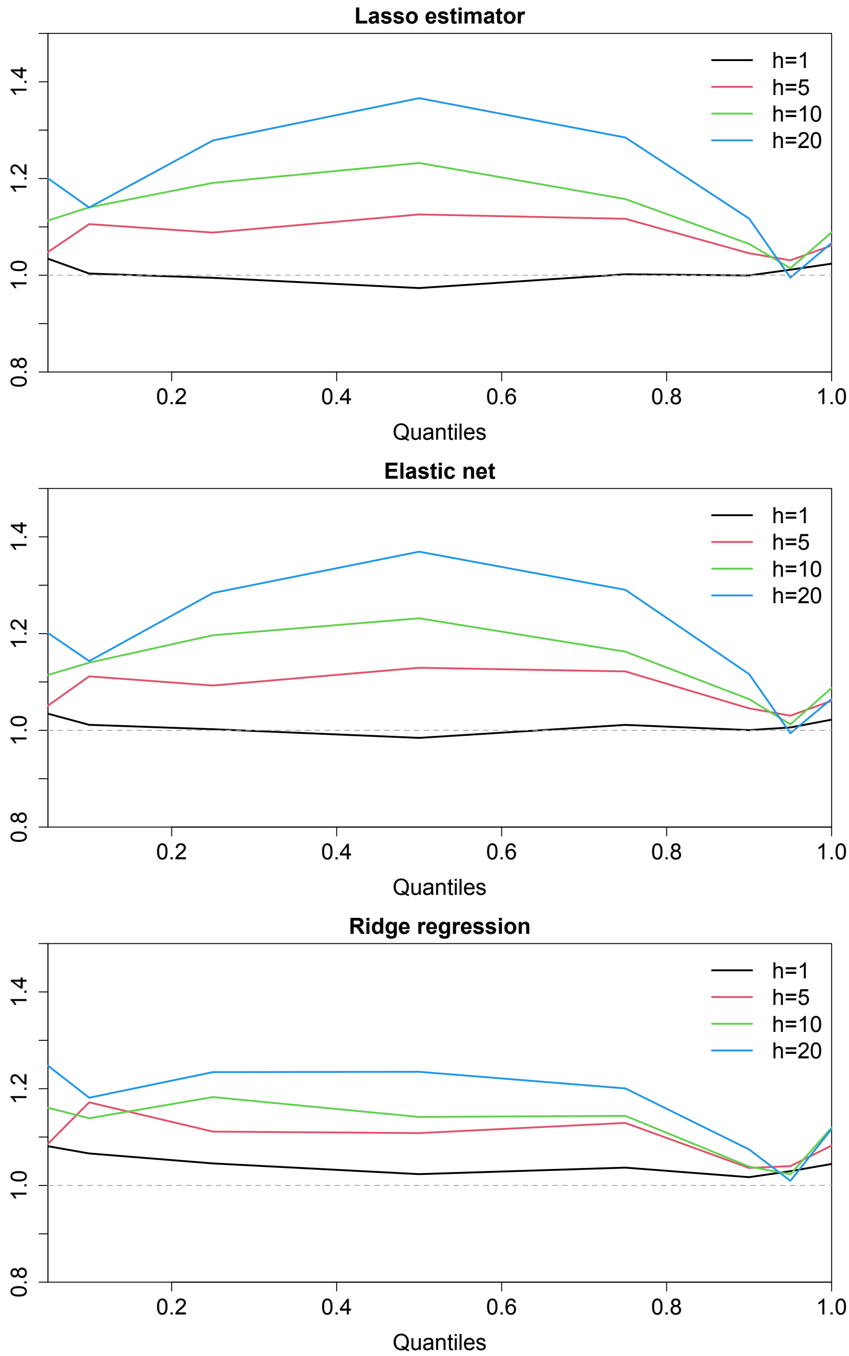

Figure 12. Quantile-based RMSFE ratios for a recursive window (baseline stacking algorithm). RMSFE ratios for different quantiles of the realizations of RV. RMSFE ratios for a comparison of the HAR-RV-S model (meta learner) with the HAR-RV model. An RMSFE ratio smaller than unity indicates that the meta learner produces a smaller in-sample RMSFE than the HAR-RV model. The forecast horizons are $h = 1, 5, 10, 20$.

As yet another robustness check, we consider the possibility that the strength of spillover effects between the RVs varies over time. If so, the performance of the HAR-RV-S model relative to that of the classic HAR-RV model may have undergone corresponding changes over time. In order to study this question in some more detail, in Figure 14, we plot rolling-window estimates of the Diebold–Yilmaz [57,58] total dynamic spillover index (implemented using the add-on package "Spillover"; see [25,59] for a discussion of the link between the multivariate HAR-RV model and the Diebold–Yilmaz index). The estimation results clearly reveal that the strength of the total spillover effects among the RVs of the agricultural commodities in our sample has increased over time. This increase in the strength of the total spillover effects warrants a closer inspection of the relative forecasting performance of the HAR-RV-S and HAR-RV models during subsample periods.

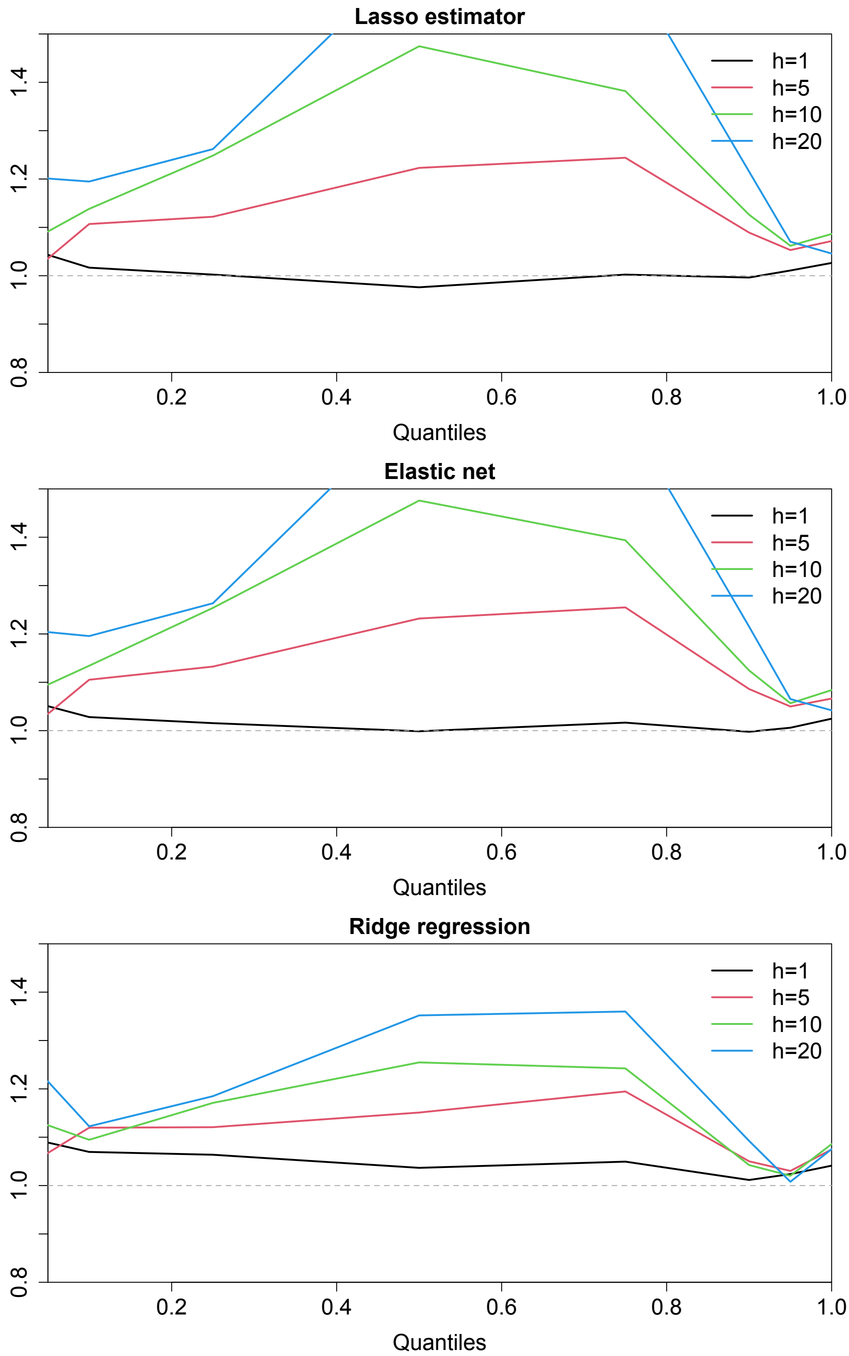

Figure 13. Quantile-based RMSFE ratios for a rolling window (baseline stacking algorithm). RMSFE ratios for different quantiles of the realizations of RV. RMSFE ratios for a comparison of the HAR-RV-S model (meta learner) with the HAR-RV model. An RMSFE ratio smaller than unity indicates that the meta learner produces a smaller in-sample RMSFE than the HAR-RV model. The forecast horizons are $h = 1, 5, 10, 20$.

While providing a detailed examination of the sources of the increase in the strength of the total spillover effects is beyond the scope of this research, a plausible economic conjecture is that factors like increased geopolitical tensions and war attention, as well as climate policy uncertainty, are factors that have contributed to the increase in the strength of the total spillover effects. These global factors are likely to have had an impact on the agricultural commodities in our sample, although perhaps different in magnitude and timing. Furthermore, the trends towards a deeper financialization of commodity markets may have strengthened the importance of behavioral aspects like investor sentiment and investor panic for the total spillover effects. With respecto the roles played by war attention, climate risks, and investor panic for financial markets, as well as financial and economic stability, see the recent research by [59–61]. Also see the remarks on the relevant literature in the introductory section.

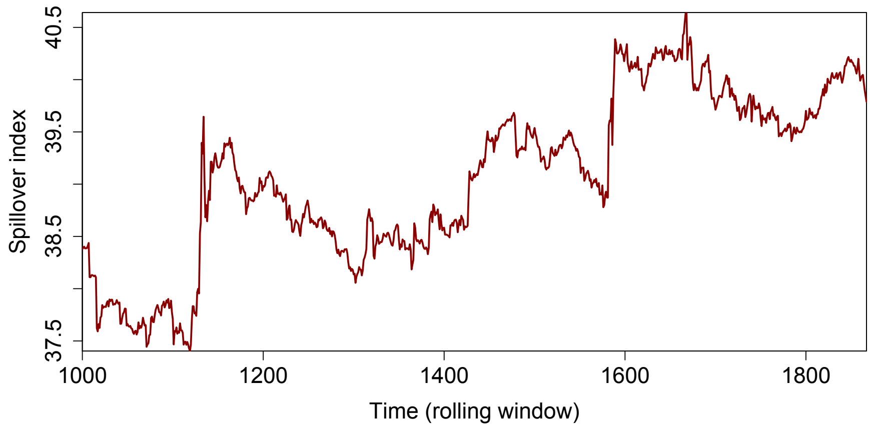

Figure 14. Rolling-window estimates of a spillover index. The total dynamic spillover index is derived from a VAR(5) model estimated using a rolling estimation window with a length of 1000 observations and a 10-step-ahead generalized forecast error variance decomposition.

We summarize the results of such a subsample analysis in Figure 15 (recursive estimation window) and Figure 16 (rolling estimation window), where we use the first 450 out-of-sample forecasts to define the first subsample period and the remaining forecasts to define the second subsample period (the exact number of out-of-sample forecasts depends on the forecast horizon). While we find the superior performance of the HAR-RV-S model in terms of the RMSFE ratio for some combinations of agricultural commodities and forecast horizons, the general picture that emerges from the analysis of the subsamples is that the relative forecasting performance of the HAR-RV-S model is not systematically better in the second than in the first subsample. There are a few exceptions to this general picture. For example, in some model configurations, the HAR-RV-S model outperform the HAR-RV model in the second but not in the first subsample when we consider the RVs of CC and KC, but not at all forecast horizons and not for all four combinations of estimators. Moreover, as in the case of the full-sample analysis, the relative performance of the HAR-RV model, in general, strengthens with the length of the forecast horizon. It is also interesting to observe that in the first subsample, the HAR-RV-S-model outperforms the HAR-RV model for C and S (in the case of the latter, only for the rolling estimation window) when we use the Lasso–Lasso and the ridge–ridge estimators, where the performance of the HAR-RV-S model tends to strengthen with the length of the forecast horizon. Thus, our results for the first subsample partially overlap (that is, for C and S) with the results reported by [8], who reported results for the sample period of 2013–2018 (using Chinese data, so it is clear that the results are not directly comparable).

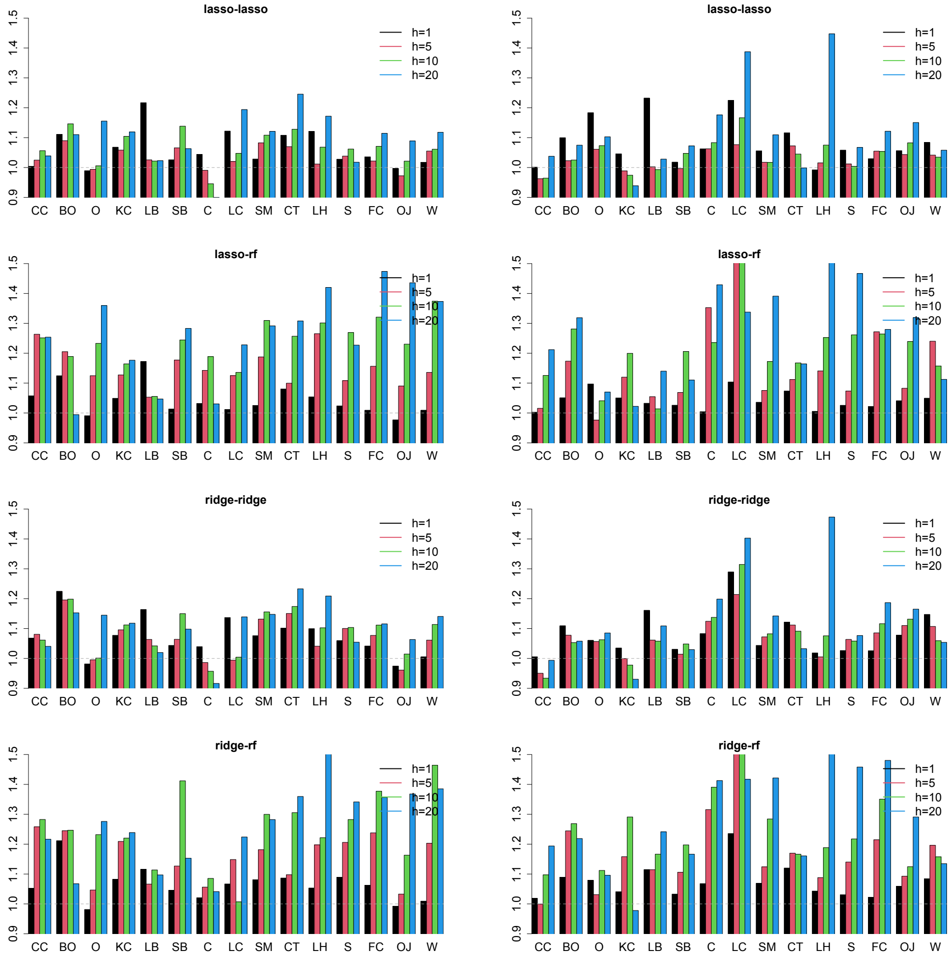

Figure 15. Subsample analysis for a recursive window (modified stacking algorithm). The panels on the left-hand side summarize the results for the first subsample. The panels on the right-hand side summarize the results for the first subsample. The first subsample comprises the first 450 out-of-sample forecasts. The second subsample is obtained upon deleting the first 450 out-of-sample forecasts. RMSFE ratios for a comparison of the HAR-RV-S model (meta learner) with the HAR-RV model. An RMSFE ratio smaller than unity indicates that the meta learner produces a smaller in-sample RMSFE than the HAR-RV model. The forecast horizons are $h = 1, 5, 10, 20$.

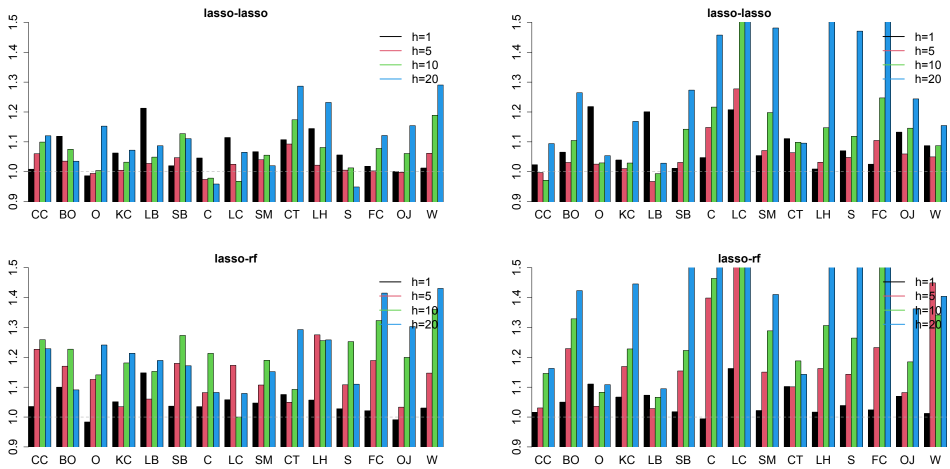

Figure 16. *Cont.*

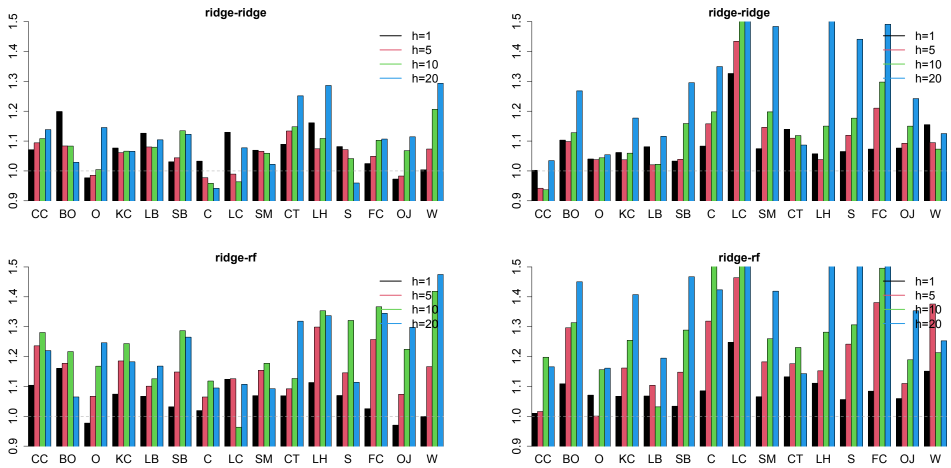

Figure 16. Subsample analysis for a rolling window (modified stacking algorithm). The panels on the left-hand side summarize the results for the first subsample. The panels on the right-hand side summarize the results for the first subsample. The first subsample comprises the first 450 out-of-sample forecasts. The second subsample is obtained upon deleting the first 450 out-of-sample forecasts. RMSFE ratios for a comparison of the HAR-RV-S model (meta learner) with the HAR-RV model. An RMSFE ratio smaller than unity indicates that the meta learner produces a smaller in-sample RMSFE than the HAR-RV model. The forecast horizons are $h = 1, 5, 10, 20$.

4.4. Extension to Energy Commodities and Precious Metals

It is interesting to study whether the out-of-sample results obtained when we extend our HAR-RV-S model for agricultural commodities to include other important commodities. In extending the model in this way, we can account for the potential impact of spillover effects across different classes of commodities, as noted in a number of studies involving the agriculture, energy, and precious metals markets, (see, for example, refs. [62–71]) on out-of-sample forecasting performance. In order to extend the HAR-RV-S model in this way, we consider the RVs of several energy commodities (natural gas (NG), heating oil (HO), and coal (CL)) and precious metals (gold (GC), copper (HG), palladium (PA), platinum (PL), and silver (SI)). The data source is the same as that described in detail in Section 2, so we can directly match the RVs of the agricultural commodities with those of the energy commodities and the precious metals by date. We plot the RVs of the energy commodities and the precious metals at the end of the paper (Appendix A; Figures A1 and A2), where we also report the full-sample correlation matrix for the members of the three commodity groups (Figure A3). We also plot the corresponding total dynamic spillover index (Figure A4), which shows that the spillover effects among the three members of the three commodity groups increased towards the end of the sample period. As in the agricultural-commodities-only model, the spillover effects are also visible in the full-sample RMSFE ratios (based on the modified stacking algorithm; Figure A5). The RMSFE ratios clearly decrease with the length of the forecast horizon, especially when we combine the shrinkage estimators with regression trees. Finally, the results that we report in Figure A6 (for a recursive estimation window) and in Figure A7 (for a rolling estimation window) corroborate the main finding of our empirical research that the HAR-RV-S model—with only a few exceptions—does not outperform out-of-sample the forecasting performance of the classic HAR-RV model, especially as the length of the forecasting horizon increases.

5. Concluding Remarks

Modeling and forecasting realized volatilities of financial asset prices, in general, and of commodity price fluctuations, in particular, is of key importance for financial market participants and policymakers. Financial market participants rely on accurate forecasts of realized volatilities when solving portfolio optimization problems and pricing derivative securities. Policymakers, in turn, need accurate forecasts of realized volatilities when designing policies to mitigate the potential adverse effects of a rise in economic and—in case of agricultural commodities—perhaps even political uncertainty associated with sudden increases in the volatility of price fluctuations. A natural and important research question, therefore, is whether forecasts of the realized volatilities of commodity price fluctuations can benefit when a forecaster takes into account spillover effects across the realized volatilities of agricultural commodities. The results we report in this research clearly demonstrate that such spillover effects exist, that they can be strong, that they may vary over time, and that accounting for spillover effects by means of a simple HAR-RV-S model has beneficial effects in an in-sample analysis. However, we do not observe systematic out-of-sample forecasting gains relative to a classic HAR-RV model.

In order to obtain out-of-sample forecasts of the RVs of 15 agricultural commodities (and, in an extended model, three energy commodities and five precious metals), we use various multi-task stacking algorithms, as well as a multivariate shrinkage estimator. The multi-task stacking algorithms, in particular, have the advantage of being straightforward to implement in high-dimensional multi-task forecasting problems. Modeling and forecasting the realized volatilities of the various agricultural commodities that we studied in this research can be interpreted as belonging to this class of problems. While the multivariate shrinkage estimator retains a simple linear structure of the forecasting model, the multi-task stacking algorithm opens up the possibility of combining different base and meta learners, where for the latter, we also have use regression trees so as to explore potential nonlinear structures in the data. Irrespective of the algorithm or combination of base and meta learners that we studied, we obtained the same main finding that spillover effects do not leverage out-of-sample forecast accuracy relative to the classic HAR-RV model. Our main finding implies that the research strategy used by some researchers in recent papers (see, for example, refs. [18–20]) to forecast the RVs of agricultural commodities in an univariate modeling approach is likely to be a good starting point for further analysis and can be also considered beneficial from the perspective of investors looking for optimal portfolio allocations and policymakers aiming to stabilize food prices.

This does not mean that a multivariate modeling approach cannot yield important additional and novel insights. In fact, in future research, it would be interesting to study whether other algorithms developed in the large and rapidly growing machine learning literature corroborate our main finding or whether the application of other algorithms brings to the forefront features of the data that the algorithms and estimators we applied in our research fail to detect. In technical terms, it is also interesting to explore how the stacking algorithms we studied in this research can be combined with the type of multivariate HAR-RV cum GARCH models discussed in related earlier literature. Such an extension would also render it possible to more directly compare the results we report in this paper with the results that [8] reported in their recent empirical study of a small set of agricultural commodities (with a shorter sample period and using Chinese data). Furthermore, against the background of the much discussed financialization of commodity markets, it is worthwhile to investigate whether accounting for spillover effects across the realized volatilities of different asset classes (for example, agricultural commodities and stock markets) yields insights that can help to improve the accuracy of out-of-sample forecasts of realized volatilities (as in, for example, ref. [26]).

Author Contributions: Conceptualization, R.G.; Methodology, R.G. and C.P.; Software, C.P.; Formal analysis, C.P.; Data curation, R.G.; Writing—original draft, R.G. and C.P.; Writing—review and editing, R.G. and C.P. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement: The data used to derive the results documented in this research are available from the authors upon reasonable request.

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

Appendix A

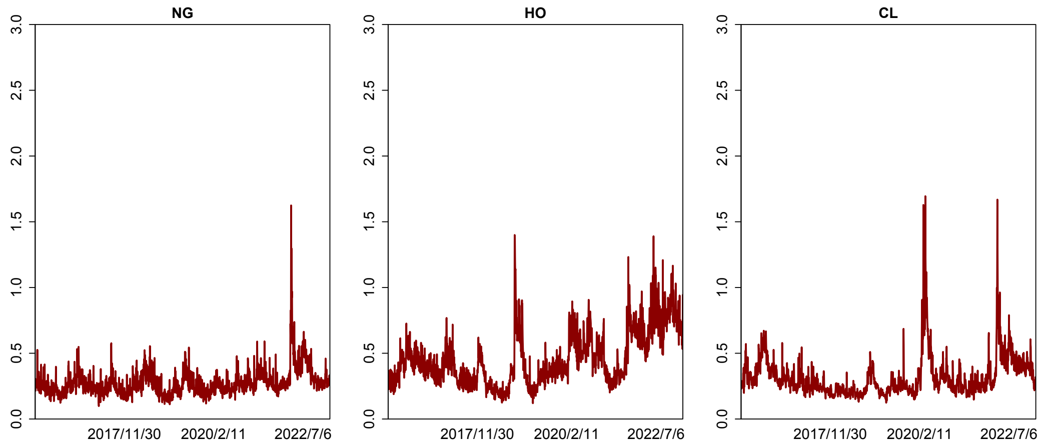

Figure A1. RVs of energy commodities.

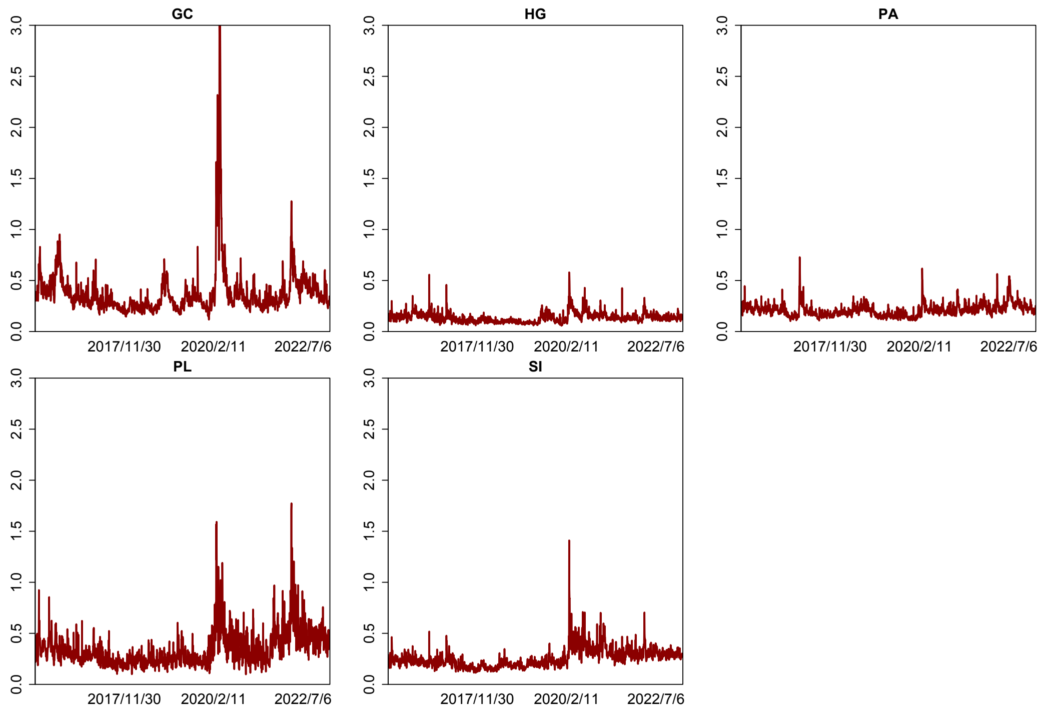

Figure A2. RVs of precious metals.

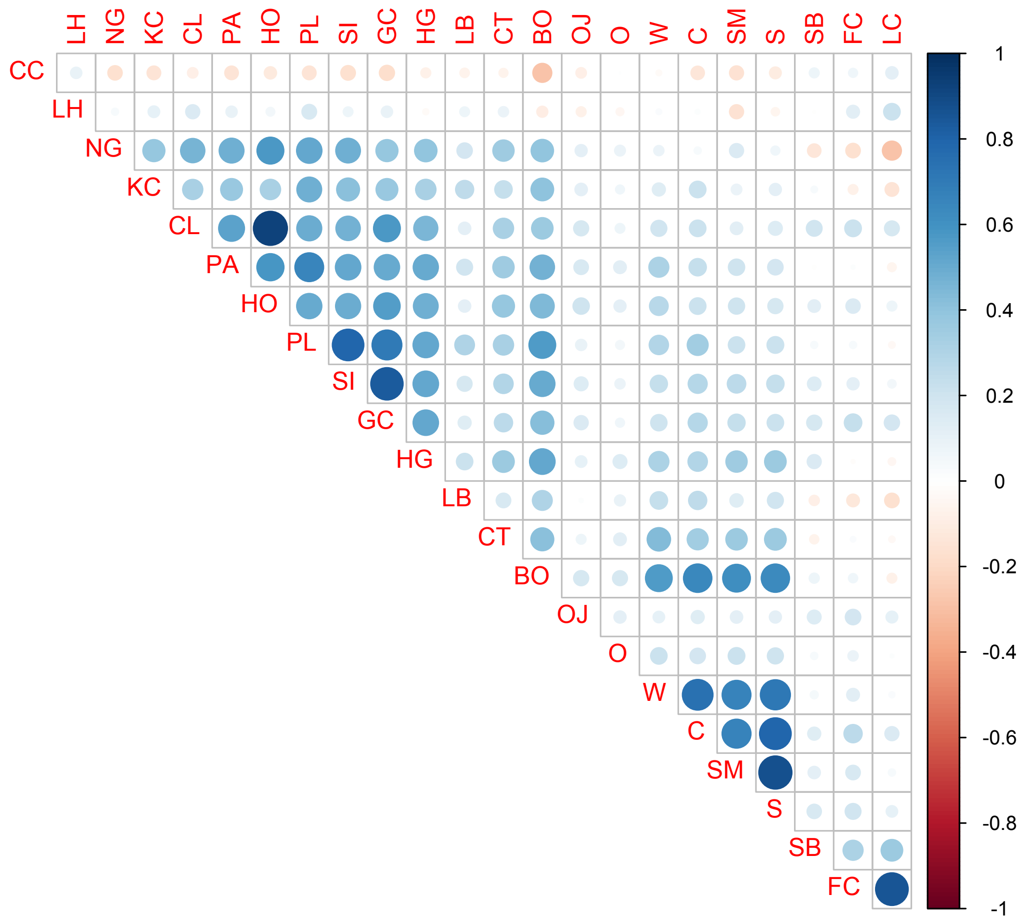

Figure A3. Full−sample correlation matrix (extended sample of commodities).

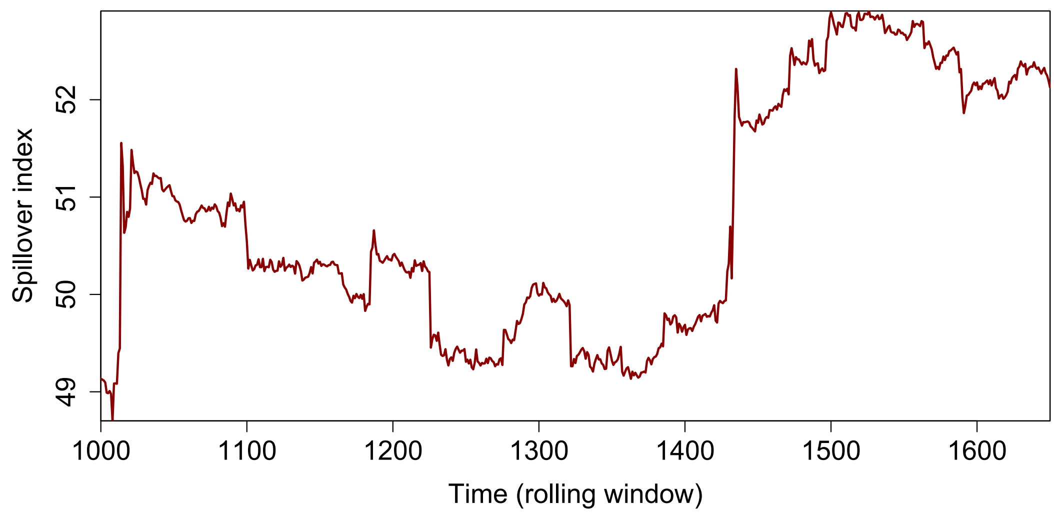

Figure A4. Rolling-window estimates of a spillover index (extended sample of commodities). The total dynamic spillover index is derived from a VAR(5) model estimated using a rolling estimation window with a length of 1000 observations and a 10-step-ahead generalized forecast error variance decomposition.

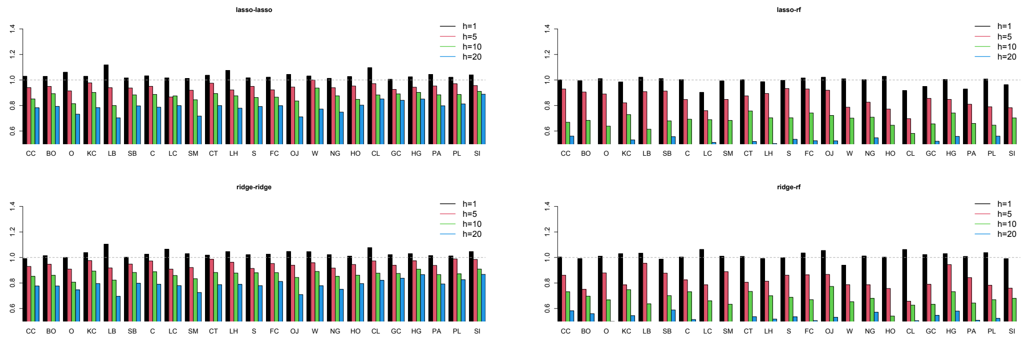

Figure A5. Full-sample RMSFE ratios (modified stacking estimator). RMSFE ratios for a comparison of the HAR-RV-S model (meta learner) with the HAR-RV model. An RMSFE ratio smaller than unity indicates that the meta learner produces a smaller in-sample RMSFE than the HAR-RV model. The forecast horizons are $h = 1, 5, 10, 20$.

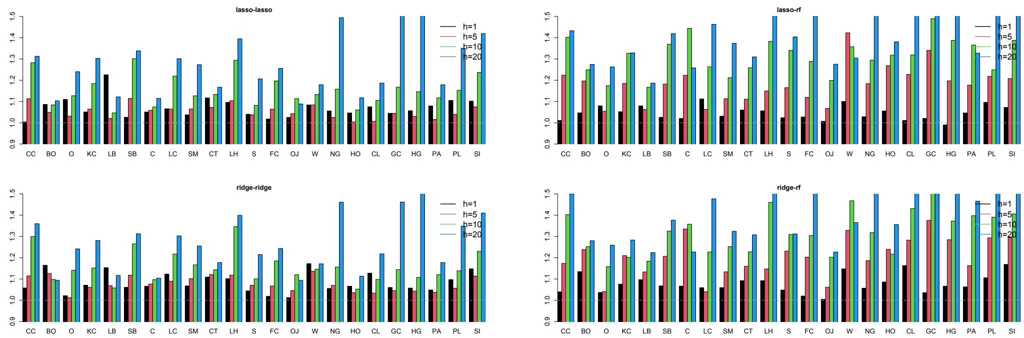

Figure A6. RMSFE ratios for a recursive window (modified stacking estimator). RMSFE ratios for a comparison of the HAR-RV-S model (meta learner) with the HAR-RV model. An RMSFE ratio smaller than unity indicates that the meta learner produces a smaller in-sample RMSFE than the HAR-RV model. The forecast horizons are $h = 1, 5, 10, 20$.

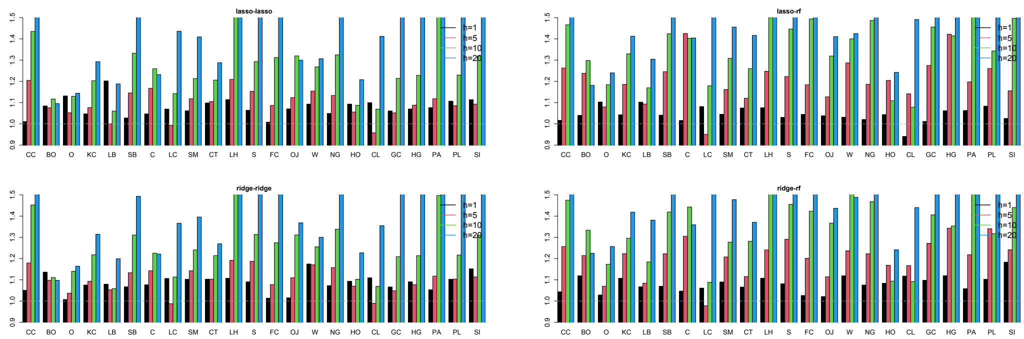

Figure A7. RMSFE ratios for a rolling window (modified stacking estimator). RMSFE ratios for a comparison of the HAR-RV-S model (meta learner) with the HAR-RV model. An RMSFE ratio smaller than unity indicates that the meta learner produces a smaller in-sample RMSFE than the HAR-RV model. The forecast horizons are $h = 1, 5, 10, 20$.

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