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Financial stress and realized volatility: The case of agricultural commodities☆

Matteo Bonato[a,b], Oguzhan Cepni[c,d], Rangan Gupta[e,*], Christian Pierdzioch[f]

[a] Department of Economics and Econometrics, University of Johannesburg, Auckland Park, South Africa
[b] IPAG Business School, 184 Boulevard Saint-Germain, 75006 Paris, France
[c] Ostim Technical University, Ankara, Turkiye
[d] Copenhagen Business School, Department of Economics, Porcelænshaven 16A, Frederiksberg, DK-2000, Denmark
[e] Department of Economics, University of Pretoria, Private Bag X20, Hatfield 0028, South Africa
[f] Department of Economics, Helmut Schmidt University, Holstenhofweg 85, P.O.B. 700822, 22008 Hamburg, Germany

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ABSTRACT

Given recent debates about the financialization of commodity markets, we analyze the predictive power of financial stress for the realized volatility of agricultural commodity price returns. We estimate realized volatility from high-frequency intra-day data, where the sample period ranges from 2009 to 2020. We study the in-sample and out-of-sample predictability of realized volatility using variants of the popular heterogeneous autoregressive (HAR) model for realized volatility. We analyze the predictive value of financial stress by region of origin and by financial source, and we also control for various realized moments (leverage, realized skewness, realized kurtosis, realized jumps, realized upside tail risk, and realized downside tail risk). We find for several commodities evidence of in-sample predictive value of financial stress for realized volatility, consistent with the financialization hypothesis. This in-sample evidence, however, does not necessarily extend to an out-of-sample forecasting environment.

1. Introduction

In general, financial stress is considered to be capturing disruptions to the normal functioning of financial markets. One key aspect of financial stress involves heightened uncertainty about the fundamental value of assets as well as uncertainty about the behavior of investors (Hakkio and Keeton, 2009). In this regard, volatility may rise when increased uncertainty causes investors to react more strongly to new information (Balcilar et al., 2022; Shiba et al., 2022). With recent studies arguing that agricultural commodities have become increasingly financialized (Aıt-Youcef, 2019; Bonato, 2019), the objective of our paper is to analyze, for the first time, the predictive ability of financial stress for the second moment movement of agricultural commodities. In this regard, it is interesting to note that results reported by Flori et al. (2021) indicate that weather-related events, which have been shown to contain significant predictive information for the volatility of agricultural commodities price returns (Bonato et al., 2023; Gupta and Pierdzioch, 2023), is reflected in the stress of the entire financial system, as climate risks have been shown to adversely affect a large number of asset classes, including currencies, equities, fixed-income securities, and real estate, as well as financial institutions (Battiston et al., 2021; Giglio et al., 2021). Hence, it can be hypothesized that indicators of financial stress drive agricultural commodity price volatility

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* Corresponding author.
E-mail addresses: matteobonato@gmail.com (M. Bonato), oce.eco@cbs.dk (O. Cepni), rangan.gupta@up.ac.za (R. Gupta), macroeconomics@hsu-hh.de (C. Pierdzioch).

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by reflecting risks of rare disaster events associated with extreme weather variations, with a similar line of reasoning originating from the predictive role of oil returns volatility spillover on food price variance (Chatziantoniou et al., 2021), and simultaneously oil uncertainty being a driver of financial stress (Sheng et al., 2023).

Because the process of financialization has caused institutional investors to increase their holdings in agricultural commodities relative to traditional assets, accurate predictability of the volatility of agricultural commodities price movements is of paramount importance to investors. This is because volatility is a key input in investment and portfolio allocation decisions, risk management, derivatives pricing, and assessments of hedging performance (Poon and Granger, 2003). Moreover, agricultural commodities are an important proportion of household consumption, thereby price volatility in agricultural commodities markets is likely to have substantial consequences for food security, especially as far as the economically vulnerable groups of a population are concerned (Ordu et al., 2018). Naturally, from the perspective of policy authorities, it is important value to develop models and derive accurate predictions of agricultural commodity price volatility, so that policies can be developed to shelter vulnerable groups of a population from large and adverse food price fluctuations (Greb and Prakash, 2017).

In the evolving landscape of global financial markets, the interplay between financial stress and market volatility has garnered significant attention. While the relationship between financial stress and market dynamics in traditional asset classes has been extensively studied, the specific impact on agricultural commodities, particularly through the lens of realized volatility, remains underexplored. This gap is notable given the increasing financialization of agricultural commodities, a trend that intertwines their price movements more closely with broader financial market dynamics than ever before. Given that rich information contained in intraday data can produce more accurate estimates and forecasts of daily (realized) volatility (McAleer and Medeiros, 2008), we augment the Heterogeneous Autoregressive (HAR) model developed by Corsi (2009) to include measures of global financial stress to predict, both in- and out-of-sample, the daily realized volatility (RV), as computed from 5-minute-interval data, of 16 important agricultural commodities price returns over the period of September, 2009 to May, 2020. While our primary focus is on investigating the role of financial stress in predicting the RV of price returns of multiple agricultural commodities, it is also essential to compare the performance of the metrics of financial stress with those of realized moments (such as leverage, realized skewness and kurtosis, realized upside and downside volatility, realized jumps, and realized upside and downside tail risks). This is in light of a large number of studies examining the contribution of these realized moments to the accuracy of predictions of RV of food price returns (see for example, Tian et al. (2017a), Yang et al. (2017), Degiannakis et al. (2022), Luo et al. (2019), Bonato et al. (2024)). In our findings, we uncover significant relationships between financial stress indicators and the realized volatility of agricultural commodity prices, which underline the substantial impact of financial market dynamics on agricultural markets. Notably, our analysis reveals that different sources and regional origins of financial stress have varied effects on the volatility of these commodities, suggesting that the financialization process impacts commodities in complex and multifaceted ways. These results challenge and extend previous assumptions within the literature, highlighting the necessity for investors and policymakers to consider a broader array of factors when assessing the agricultural commodity markets. Ultimately, our study not only sheds light on the intricate mechanisms at play between financial stress and commodity price volatility but also offers practical implications for risk management and strategic planning in the face of financial uncertainties.

Our paper fills a critical gap by examining the in-sample and out-of-sample predictability of financial stress on the realized volatility of agricultural commodities. This is particularly significant as the interplay between financial markets and agricultural commodities deepens due to financialization, affecting not just investors but also policy-making and global food security. By delving into the detailed effects of financial stress emanating from various regions and financial sectors, we extend a more nuanced and comprehensive perspective than has been previously offered. This broader view helps to clarify complex relationships that have not been entirely unraveled in existing studies within the agricultural commodities context. Furthermore, our paper goes beyond the earlier literature on predicting intraday data-based daily RV of agricultural commodity returns using realized moments by investigating the role of financial stress in the context of financialization, which, in turn, has led some researchers (see, Ji et al., 2020; Akyildirim et al., 2022 for detailed discussions) to point out the prominence of factors such as financial and macroeconomic uncertainties, investor sentiment, and speculation in causing agricultural commodity price returns (but not volatility). Our findings aim to guide investors, policymakers, and academics in better understanding and reacting to the intricate dynamics between financial markets and agricultural commodity prices.

At this juncture, we must point out that the main advantage of using RV is in it being an observable and unconditional metric of "volatility", unlike the latent processes underlying Generalized AutoRegressive Conditional Heteroskedasticity (GARCH) and Stochastic Volatility (SV) models that often have been utilized in earlier research for predicting agricultural commodity price volatility (see, Degiannakis et al., 2022; Luo et al., 2019, for a review of this literature). At the same time, the underlying HAR-RV econometric framework, in spite of its simplistic structure, has the ability to capture long-memory and multi-scaling properties of agricultural commodities price returns volatility, as detected by Gil-Alana et al. (2012), Živkov et al. (2019), and Tian et al. (2017b). Moreover, because the HAR-RV model employs RV at different time resolutions to model and predict RV, it can be interpreted as an empirical representation of the theory of the heterogeneous market hypothesis (HMH; Müller et al., 1997). The HMH posits that financial markets (in our case, the markets for agricultural commodities) are populated by various groups of market participants (such as, investors, speculators and traders), who, in turn, differ in their sensitivity to information flows at different time horizons.

We structure the remaining sections of this research as follows: In Section 2, we provide a description of the data we used in our study, while we outline in Section 3 our forecasting models. We present our empirical results in Section 4, Finally, we conclude in Section 5.

Table 1
Commodity summary statistics.

Commodity	Ticker	Sample starts	Sample ends
Soybean oil	BO	9/28/2009	5/18/2020
Corn	C	9/28/2009	5/18/2020
Cocoa	CC	9/28/2009	5/15/2020
Cotton	CT	5/16/2007	5/18/2020
Feeder cattle	GF	9/28/2009	5/15/2020
Lean hogs	HE	9/28/2009	5/15/2020
Coffee	KC	9/28/2009	5/15/2020
Lumber	LB	9/28/2009	5/15/2020
Live cattle	LE	9/28/2009	5/15/2020
Oats	O	9/28/2009	5/15/2020
Orange juice	OJ	9/28/2009	5/15/2020
Rough rice	RR	9/28/2009	5/15/2020
Soybeans	S	9/28/2009	5/18/2020
Sugar	SB	9/28/2009	5/15/2020
Soybean meal	SM	9/28/2009	5/18/2020
Chicago wheat	W	9/28/2009	5/18/2020

2. Data

We sourced intraday commodity futures prices from the following online resource: https://www.kibot.com/. The data, assembled in 5-minute increments throughout a trading day, have the advantage that they have a continuous format where, nearing the expiration of a contract, a position is rolled over to the next available contract provided that activity has increased. The data are available for 16 agricultural commodities belonging to three categories: grains, softs, and livestock.[1] Table 1 depicts the agricultural commodities in our sample, along with the corresponding ticker symbol, and information on when the data start and end.

As far as metrics of financial stress are concerned, we use the Office of Financial Research (OFR) Financial Stress Indexes (FSIs), which provide daily market-based snapshots of stress in global financial markets. The global FSI is constructed from 33 financial market variables, such as yield spreads, valuation measures, and interest rates. The reader is referred to Monin (2019) for a detailed description involving the construction of the FSIs. The FSI incorporates five categories of indicators: credit, equity valuation, funding, safe assets, and volatility. Further, the FSI shows stress contributions by three regions: the United States (US), other advanced economies, and emerging markets, with the weighted average capturing global financial stress.[2] Finally, the indexes are positive when stress levels are above average, and negative when stress levels are below the same.

3. Methods

In order to set the stage for our empirical analysis, we start with the classical estimator of realized variance, i.e., the sum of squared intraday returns (Andersen and Bollerslev, 1998). We compute:

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

where $r_{t,i}$ denotes the intraday $N \times 1$ return vector, and $i = 1, \ldots, N$ denotes the number of intraday returns.

We emphasize that we report results for the realized volatility (the square root of realized variance) to mitigate the influence of the usual large peaks in RV on our empirical results.[3] Furthermore, we study the natural logarithm of the realized volatility to bring the data closer to normality. When using our empirical models for prediction, however, we convert the data back to anti-logs, where we account for the usual Jensen–Ito term.

We use the heterogeneous autoregressive realized volatility (HAR-RV) model developed by Corsi (2009) as the platform for our empirical models. The HAR-RV model can be estimated by the ordinary-least-squares technique, and can be represented by the following equation:

$$RV_{t+h} = \beta_0 + \beta_1 RV_t + \beta_2 RV_{w,t} + \beta_3 RV_{m,t} + u_{t+h}, \tag{2}$$

where $\beta_j, j = 0, \ldots, 3$ denote the coefficients of the model, u_{t+h} denotes the usual disturbance term, and RV_{t+h} denotes the average realized volatility over the forecast horizon, h, where we set $h = 1, 5, 22$. As predictors, we use the daily realized volatility, RV_t, the weekly realized volatility, $RV_{t,w}$, defined as the average realized volatility from period $t-5$ to period $t-1$, and the monthly realized volatility, $RV_{t,m}$, which we define as the monthly realized volatility defined as the average realized volatility from period $t-22$ to period $t-1$.

[1] According to the Food and Agriculture Organization (FAO) of the United Nations (UN), these commodities typically are highly traded within the agricultural sector. For further details, see, https://www.fao.org/faostat/en/#home.

[2] The FSIs are freely available for download from: https://www.financialresearch.gov/financial-stress-index/.

[3] Results for the realized variance are qualitatively similar to the results for realized volatility. See Fig. 6.

Starting with the model given in Eq. (2), we add to the HAR-RV model a measure of financial stress, FSI_t. The resulting extended HAR-RV model is given by:

$$RV_{t+h} = \beta_0 + \beta_1 RV_t + \beta_2 RV_{w,t} + \beta_3 RV_{m,t} + \beta_4 \mathrm{FSI}_t + u_{t+h}. \tag{3}$$

Finally, we take into account a vector of realized moments, M_t. This gives the following empirical models:

$$RV_{t+h} = \beta_0 + \beta_1 RV_t + \beta_2 RV_{w,t} + \beta_3 RV_{m,t} + \beta_5 M_t + u_{t+h}, \tag{4}$$

$$RV_{t+h} = \beta_0 + \beta_1 RV_t + \beta_2 RV_{w,t} + \beta_3 RV_{m,t} + \beta_4 \mathrm{FSI}_t + \beta_5 M_t + u_{t+h}. \tag{5}$$

where β_5 denotes an appropriately dimensioned coefficient vector. As realized moments, we use, in addition to a leverage effect, realized skewness, realized kurtosis, realized jumps, realized upside tail risk, and realized downside tail risk. The definitions of the realized moments follow standard practice (see Bonato et al., 2023). We briefly summarize the computation of the realized moments at the end of the paper (Appendix; A.1).

In our empirical analysis, we proceed in two steps. In a first step, we focus on in-sample predictability and estimate the empirical models on the full-sample of data so as to recover a potential structural link between financial stress and RV. In a second step, we estimate the empirical models on a recursive-estimation window to shed light on the out-of-sample predictive value of FSI for RV. We use the first 250 observations to initialize the recursive estimation of the empirical models, and then progressively expand the estimation window in a stepwise manner until we reach the end of the sample period.[4]

Finally, given that we study empirical models, we use the test proposed by Clark and West (2007) for equal predictive performance of nested forecasting models to assess the statistical significance of any out-of-sample prediction gains.

4. Empirical results

We summarize our full-sample results in Figs. 1 and 2. While we plot in Fig. 1 the results we obtain when we consider financial stress according to its region of origin, we plot in Figs. 2 the results we obtain when we study financial stress according to the segment of financial markets where it originates. The upper panels of the figures show results for the FSI coefficient β_4, and the lower panels show results for the p-values (based on robust standard errors) of this coefficient. In both figures, we use boxplots to summarize the results, where the solid horizontal line denotes the median coefficient (p-value) and the boxes represent the interquartile range of the results. In line with the discussions presented in the introduction relating to the channels through which FSI can impact RV of the returns on the prices of agricultural commodities, we would expect a positive relationship between the two variables of concern.

Starting with an analysis of the results that Fig. 1 depicts, we observe that the estimated coefficients are largely positive, indicating that financial stress, sorted according to its region of origin, has a positive impact in the cross section on the realized volatilities of the agricultural commodities in our sample. The variability of the coefficients that we estimate when we use financial stress originating in emerging markets is much larger than the variability of the estimates that we observe for the other regions. The mirror-image of this variability is that the estimated coefficient in case of emerging markets is largely statistically insignificant, with this finding being not necessarily surprising given the dominance of the US and the other advanced countries in driving the movement of the overall global financial stress.[5] For the other regions (and OFR), we observe that the median of the p-values indicates several significant results, where the significance of the results weakens as we move from the short to the long prediction horizon.

Turning next to Fig. 2, we again observe that the estimated full-sample coefficients are positive in the majority of cases. Hence, financial stress, when disentangled according to the segments of financial market where it originates, has a positive effect on realized volatility in the cross-section of agricultural commodities. The distribution of the p-values, however, is large. We observe the strongest results, in terms of statistical significance, when funding and volatility are the sources of financial stress, again due to the relative dominance of these two categories in shaping the overall FSI.[6] As in Fig. 1, the statistical significance of the results tends to weaken when the length of the prediction horizon increases.

In-sample predictability does not necessarily carry over to an out-of-sample context (Rapach and Zhou, 2022; in the context of the realized volatility of agricultural commodities, see Degiannakis et al., 2022), with the latter being a relatively more stringent test of predictability due to it using only a part of the sample period to fit the underlying predictive model. We, therefore, summarize out-of-sample results in Fig. 3, which plots the p-values of the (Clark and West, 2007) test. We find that a comparison of the baseline HAR-RV model with the HAR-RV model including realized moments tends to yield statistically significant test results at all prediction horizons (note that the results of the comparison HAR-RV vs. HAR-RV-M do not depend on whether we sort financial stress according to its regional source or according to market segments). However, adding financial stress to the baseline HAR-RV model or the HAR-RV-M model (i.e., the model that also features the realized moments as predictors), leads, for several commodities to statistically insignificant test results. This finding is possibly indicative of the fact, that unlike over the entire sample period, i.e., for in-sample tests, the dynamics of realized moments internalizes the information content of the process of financialization, at each point in time over the out-of-sample period, whereby the estimates of the parameters of the predictive model is repeatedly updated (see, Bonato et al. (forthcoming) for a detailed discussion in this regard).

[4] Using longer initialization period or a rolling-estimation window gives qualitatively similar results. We report these results at the end of the paper (Appendix). For our empirical research, we utilize the R language and environment for statistical computing (R. Core Team, 2023).

[5] The reader is referred to the "Regions" tab at: https://www.financialresearch.gov/financial-stress-index/ for further details.

[6] The reader is referred to the "Indicator Categories" tab at: https://www.financialresearch.gov/financial-stress-index/ for further details.

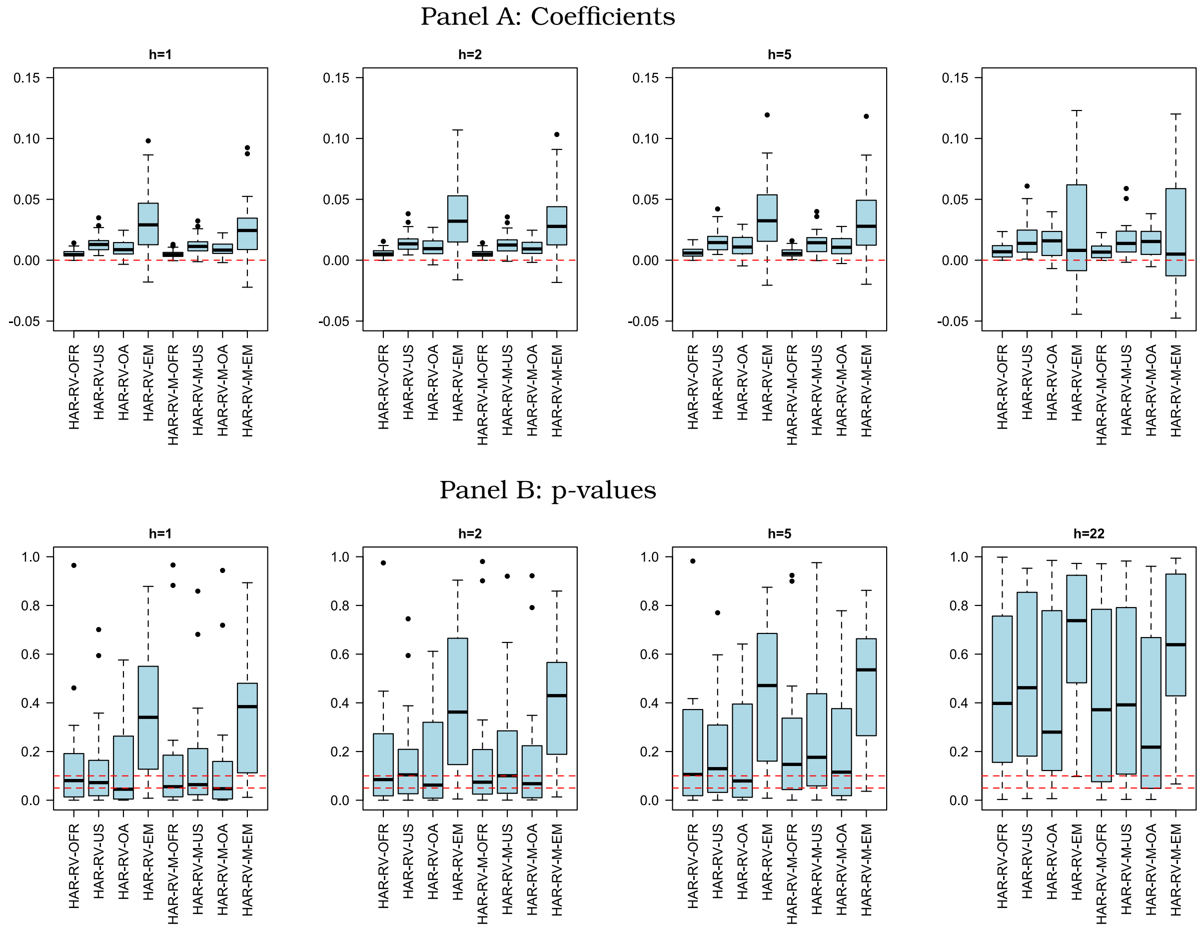

Fig. 1. In-sample results based on the regional origin of financial stress.
The models (horizontal axis) are estimated by the OLS technique on the full sample of the data. The boxplots plotted in Panel A depict the distribution (across the agricultural commodities in the sample) of the estimated coefficient of the FSI component included in the models. The boxplot plotted in Panel B depicts the distribution (across the agricultural commodities in the sample) of the *p*-value (calculated using robust standard errors) of the null hypothesis that this coefficient is zero. The solid lines denote the median, the boxes denote the interquartile range, the upper whisker extends the third quantile to 1.5 times the interquartile range (or the maximum of the data, provided this is smaller), and the lower whisker extends the first quantile to 1.5 the interquartile range (or the minimum of the data, provided this is larger). Black dots denote outliers outside of this range. The parameter h denotes the forecast horizon. OFR: total financial stress index. US: United States. OA: other advanced economies. EM: emerging markets. HAR-RV-M: model features realized moments as predictors.

Figs. 4 (regional origin of financial stress) and 5 (financial origin of financial stress) show in detail the results of the in-sample tests (Panel A) and the out-of-sample tests (Panel B) for every combination of commodities and forecasting model, where the white cells indicate an insignificant test result (the *p*-value is larger than a significance level of 0.10). When we study the regional origin of financial stress (Fig. 4), we find strong evidence of in-sample predictability for cocoa (CC), cotton (CT), orange juice (OJ), and rough rice (RR), but there are also several statistically significant test results for other commodities, especially at the short forecast horizons. Test results are hardly statistically significant when we study financial stress originating in emerging markets. As for out-of-sample predictability, the test results, with only a few exceptions, are statistically significant at all four forecast horizons when we compare the HAR-RV model with the HAR-RV-M model. Hence, realized moments matter for predictive performance. As in the case of in-sample predictability, we often obtain statistically significant test results when we study cacoa, cotton, orange juice, and rough rice.[7] Occasionally, the test results for the other commodities are statistically significant as well, mainly when we study the short forecast horizons. Taken together, however, the evidence of out-of-sample-predictability due to financial stress is weaker for the cross-section of commodities than the evidence of in-sample predictability.

Turning next to the results for the financial origin of financial stress plotted in Fig. 5, we again observe several statistically significant tests of in-sample predictability for cotton, orange juice, and rough rice, and several statistically significant test results

[7] Hence, though evidence of in-sample predictability, across all sixteen commodities, is stronger than evidence of out-of-sample predictability, for individual commodities there is not necessarily a conflict between the two types of evidence.

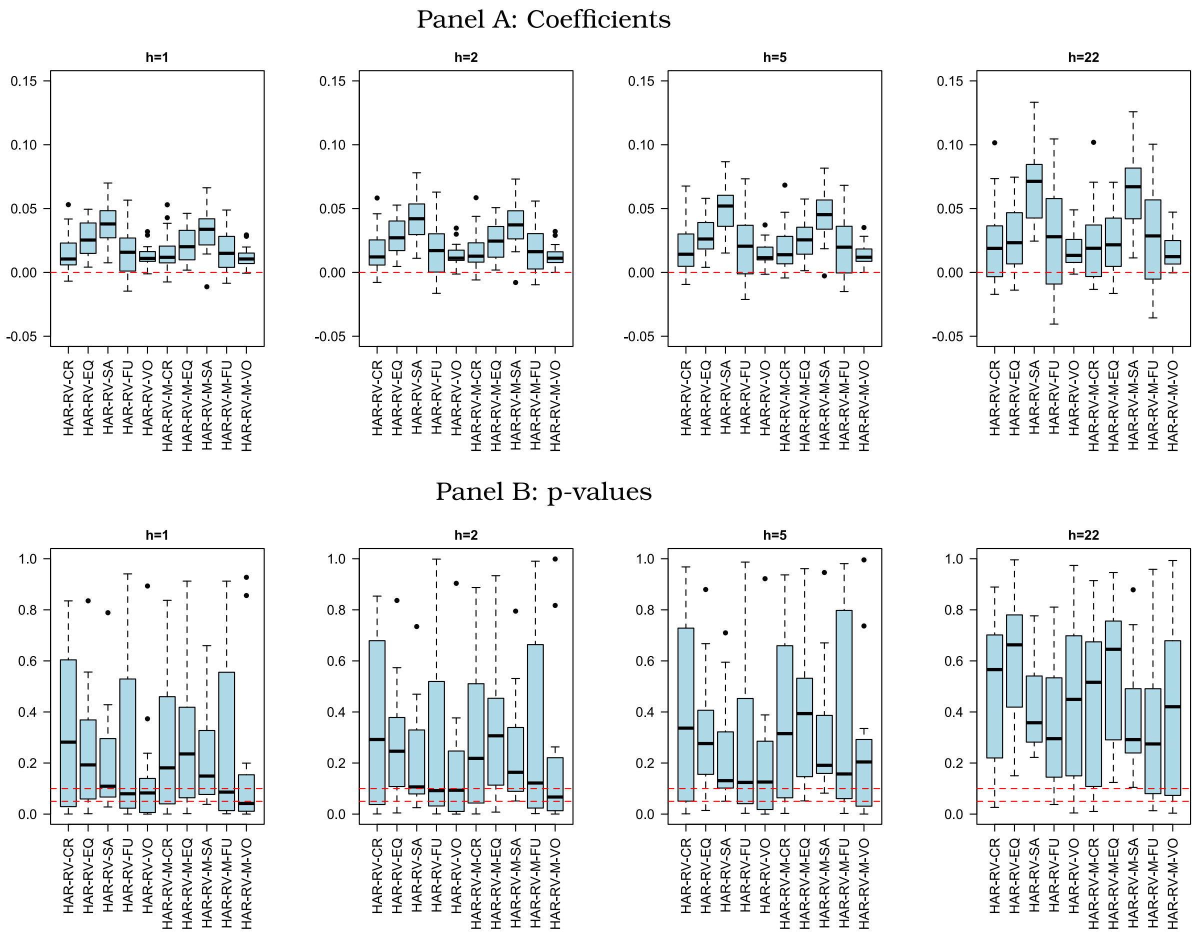

Fig. 2. In-sample results based on the financial origin of financial stress.
The models (horizontal axis) are estimated by the OLS technique. The boxplots plotted in Panel A depict the distribution (across the agricultural commodities in the sample) of the estimated coefficient of the FSI component included in the models. The boxplot plotted in Panel B depicts the distribution (across the agricultural commodities in the sample) of the *p*-value (calculated using robust standard errors) of the null hypothesis that this coefficient is zero. The solid lines denote the median, the boxes denote the interquartile range, the upper whisker extends the third quantile to 1.5 times the interquartile range (or the maximum of the data, provided this is smaller), and the lower whisker extends the first quantile to 1.5 the interquartile range (or the minimum of the data, provided this is larger). Black dots denote outliers outside of this range. The parameter h denotes the forecast horizon. CR: credit. SA: safe assets. FU: funding. VO: volatility. HAR-RV-M: model features realized moments as predictors.

for other commodities when we study the short forecast horizons. As for the evidence of out-of-sample predictability, the test results for the comparison of the HAR-RV model with the HAR-RV-M model are statistically significant in the majority of cases, and there are also several statistically significant results for cotton, orange juice, and rough rice. Evidence of out-of-sample predictability for the other commodities, however, is unsystematic.

As an extension, we summarize in Fig. 6 out-of-sample results for the (natural logarithm of) realized variance. Again, we observe strong evidence that realized moments rather than financial stress matter in the cross-section of commodities for the accuracy of the out-of-sample forecasts. Moreover, as three additional extensions, we present in Fig. A1 results that we obtain when we use a longer training period comprising 2000 observations to initialize the recursive estimations, in Fig. A2 results for a somewhat shorter sample period that ends in 12/31/2019, and in Fig. A3 results for a rolling-estimation window. The longer training period implies that the period of the COVID-19 pandemic at the end of the sample period receives a larger weight for the out-of-sample results, the shorter sample period ensures that the period of the COVID-19 pandemic is excluded from the analysis, and the rolling-estimation window comprises 250 observations to make sure that the results are comparable to the baseline results for the recursive estimation window that we present in Fig. 3. For the longer training period and the shorter sample period, we again observe that realized moments are the key drivers of out-of-sample performance. For the rolling-estimation window and the short forecast horizon, we observe that evidence of out-of-sample predictability due to regional financial stress largely disappears once we control for realized moments.

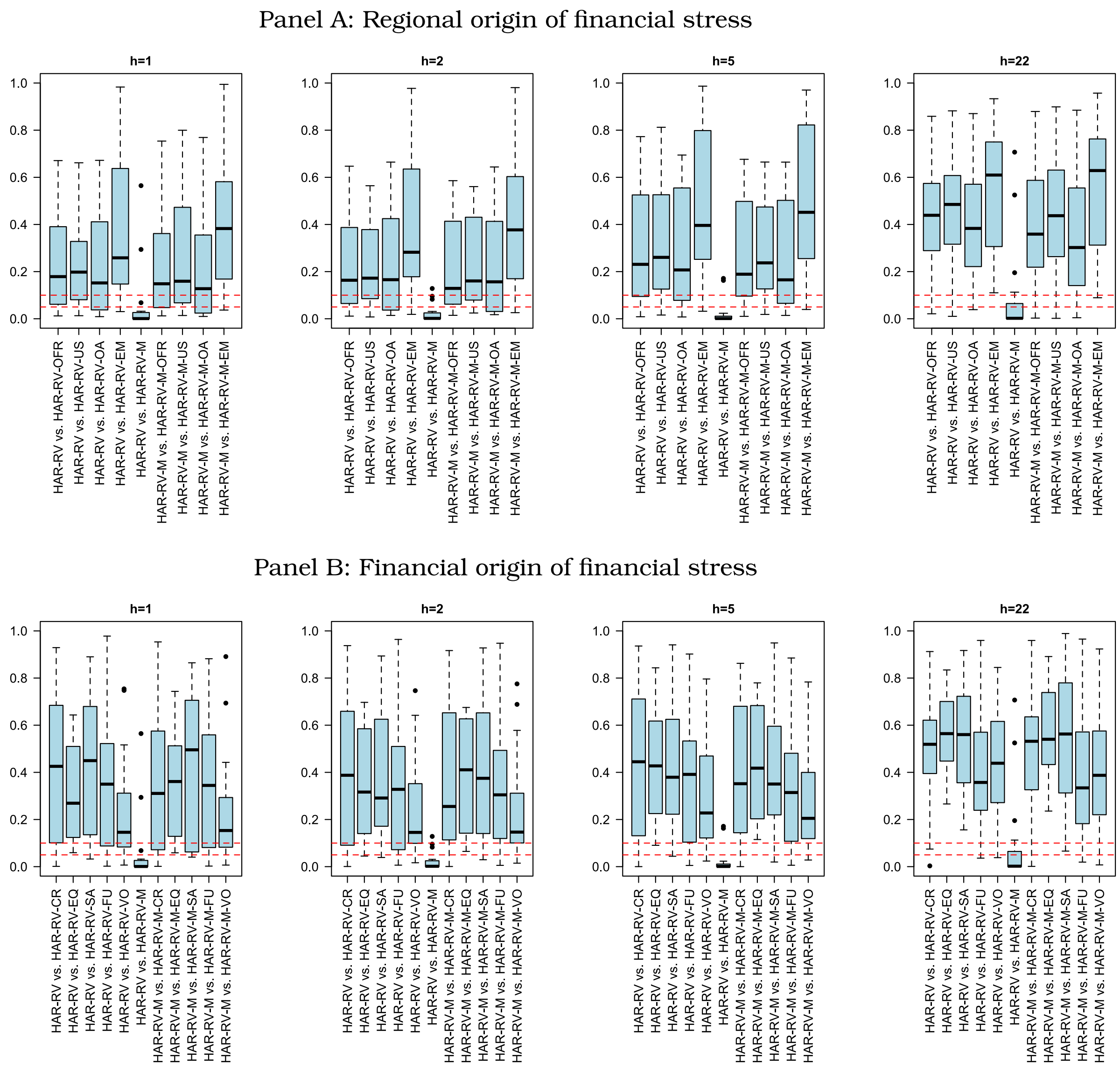

Fig. 3. Out-of-sample results.
The forecasting models are estimated by the OLS technique using a recursive-estimation window (initialization period = 250 observations) and out-of-sample forecasts for the forecast horizon, *h*, are computed. The boxplots depict the distribution (across the agricultural commodities in the sample) of the *p*-value (calculated using robust standard errors) of the Clark–West test. The Clark–West test is an approximately normal one-sided test for equal predictive accuracy in nested models, where the alternative hypothesis is that the rival model yields more accurate forecasts than the benchmark (= nested) model. The combination of the benchmark model vs. rival model that is being studied is depicted on the horizontal axis. Panel A depicts the results for the regional origin of financial stress. Panel B depicts the results for the financial origin of financial stress. The solid lines denote the median, the boxes denote the interquartile range, the upper whisker extends the third quantile to 1.5 times the interquartile range (or the maximum of the data, provided this is smaller), and the lower whisker extends the first quantile to 1.5 the interquartile range (or the minimum of the data, provided this is larger). Black dots denote outliers outside of this range. OFR: total financial stress index. US: United States. OA: other advanced economies. EM: emerging markets. CR: credit. SA: safe assets. FU: funding. VO: volatility. HAR-RV-M: model features realized moments as predictors.

In sum, our findings suggest that, unlike for the in-sample predictive analysis, real-time forecasting of RV of several commodities can be conducted efficiently without the FSI, purely based on the time-series properties of the data and the associated realized moments.

5. Concluding remarks

Using high-frequency data for the period from 2009 to 2020 for sixteen important agricultural commodities, we have found that the realized volatilities, in the cross-section of agricultural commodities, tend to be positively associated in-sample to financial

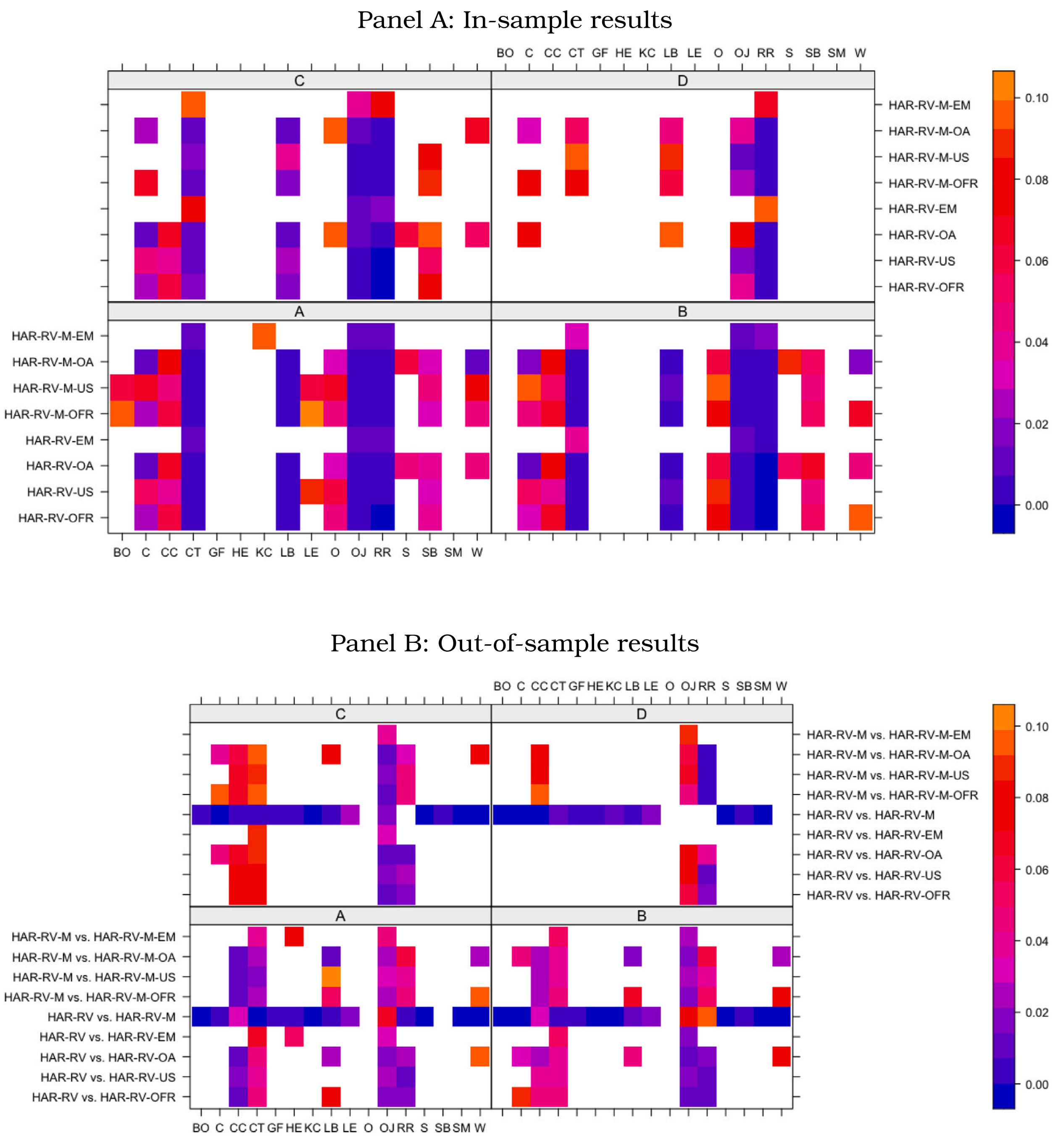

Fig. 4. In-sample vs. out-of-sample results (regional origin of financial stress).
Panel A: The models (horizontal axis) are estimated by the OLS technique. The plots depict the *p*-value (calculated using robust standard errors) of the null hypothesis that the FSO coefficient is zero. Panel B: The forecasting models are estimated by the OLS technique using a recursive-estimation window (initialization period = 250 observations) and out-of-sample forecasts for the forecast horizon, h, are computed. The plots depict the *p*-value (calculated using robust standard errors) of the Clark–West test. The Clark–West test is an approximately normal one-sided test for equal predictive accuracy in nested models, where the alternative hypothesis is that the rival model yields more accurate forecasts than the benchmark (= nested) model. HAR-RV-M: model features realized moments as predictors. The white cells indicate an insignificant test results (the *p*-value is larger than a significance level of 0.10). The panels headed A, B, C, D show the results for $h = 1, 2, 5, 22$.

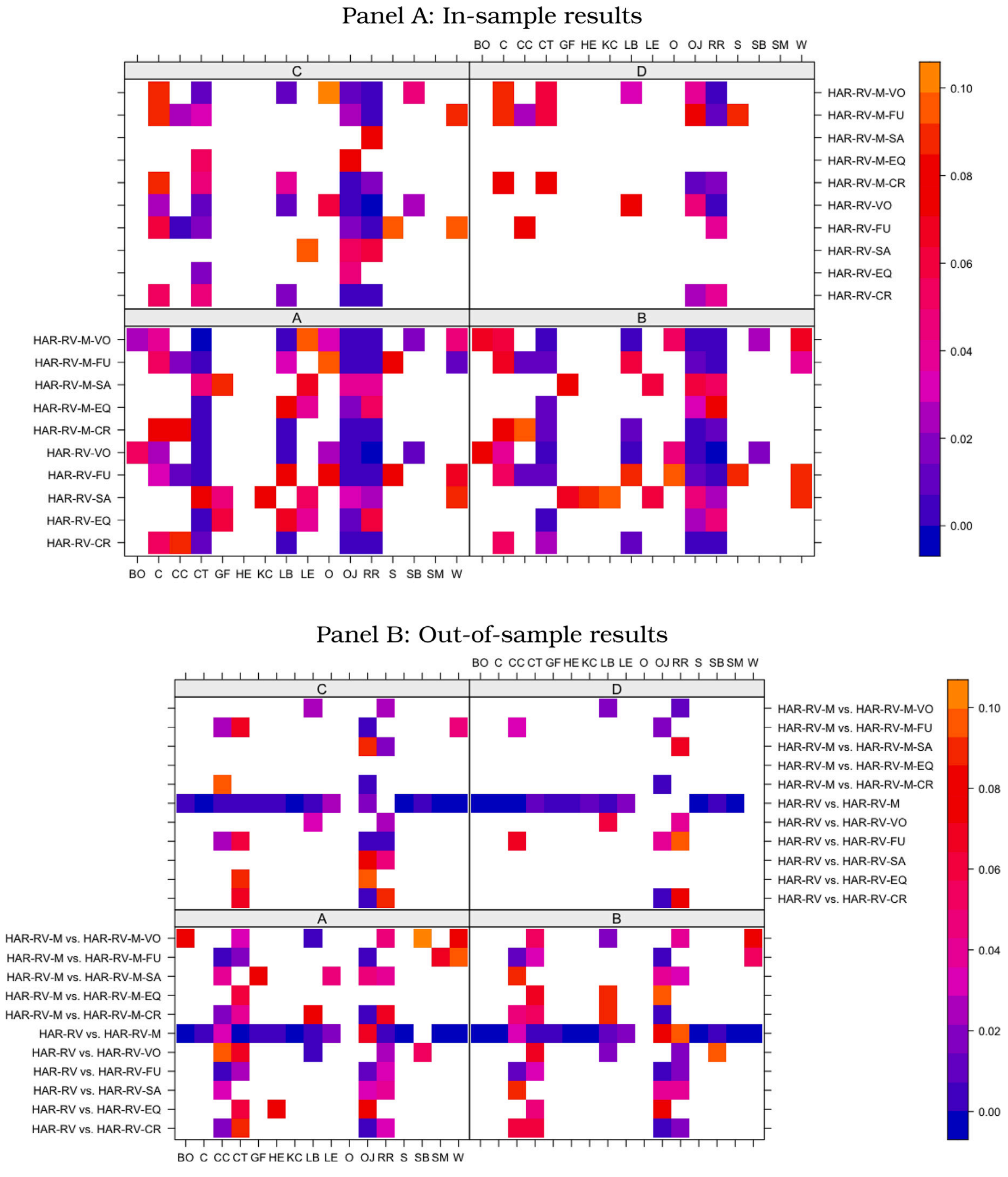

Fig. 5. In-sample vs. out-of-sample results (financial origin of financial stress).
Panel A: The models (horizontal axis) are estimated by the OLS technique. The plots depict the p-value (calculated using robust standard errors) of the null hypothesis that the FSO coefficient is zero. Panel B: The forecasting models are estimated by the OLS technique using a recursive-estimation window (initialization period = 250 observations) and out-of-sample forecasts for the forecast horizon, h, are computed. The plots depict the p-value (calculated using robust standard errors) of the Clark–West test. The Clark–West test is an approximately normal one-sided test for equal predictive accuracy in nested models, where the alternative hypothesis is that the rival model yields more accurate forecasts than the benchmark (= nested) model. CR: credit. SA: safe assets. FU: funding. VO: volatility. HAR-RV-M: model features realized moments as predictors. The white cells indicate an insignificant test results (the p-value is larger than a significance level of 0.10). The panels headed A, B, C, D show the results for $h = 1, 2, 5, 22$.

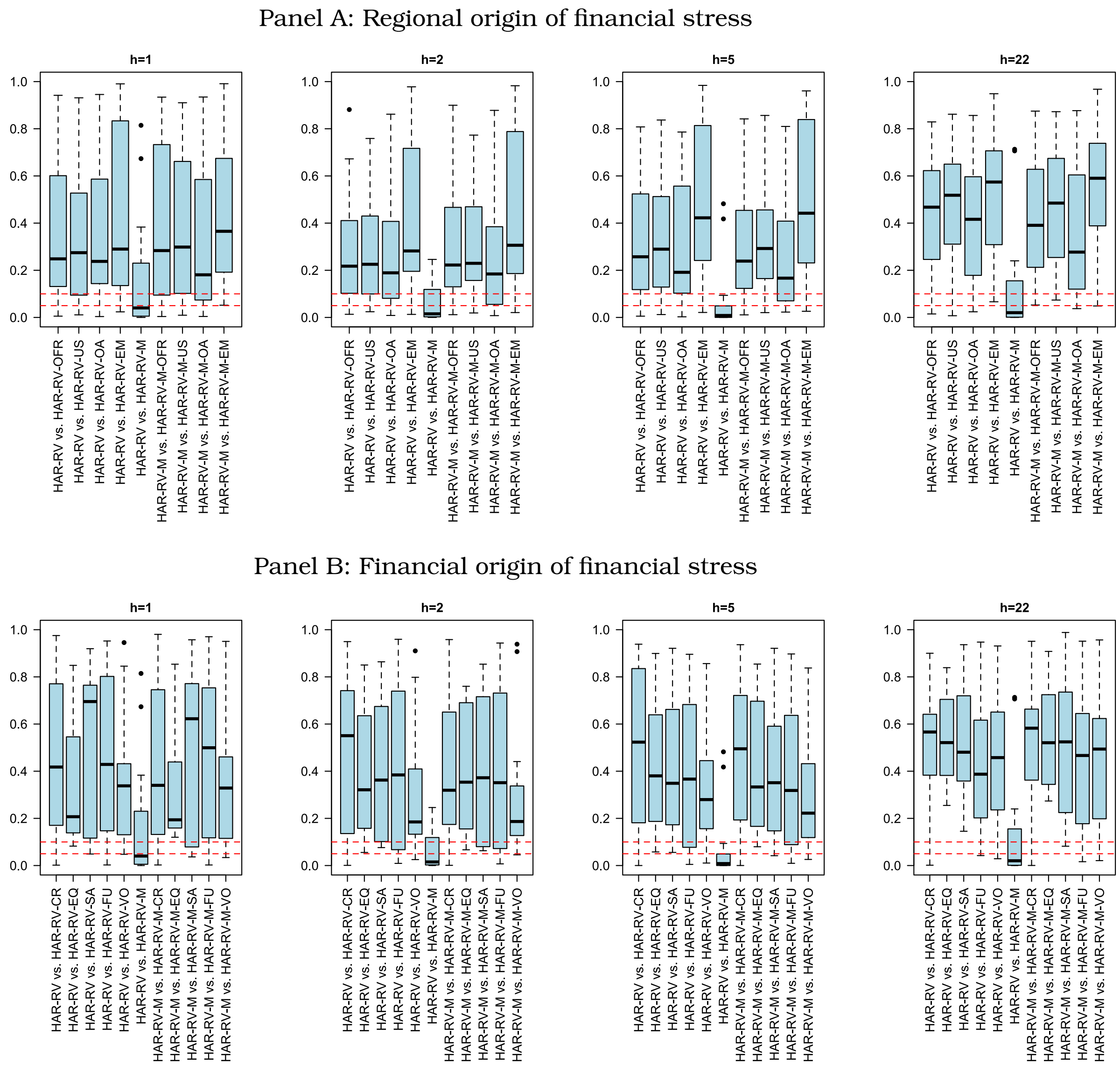

Fig. 6. Out-of-sample results: realized variance.

The forecasting models are estimated by the OLS technique using a recursive-estimation window (initialization period = 250 observations) and out-of-sample forecasts for the forecast horizon, *h*, are computed. The boxplots depict the distribution (across the agricultural commodities in the sample) of the *p*-value (calculated using robust standard errors) of the Clark–West test. The Clark–West test is an approximately normal one-sided test for equal predictive accuracy in nested models, where the alternative hypothesis is that the rival model yields more accurate forecasts than the benchmark (= nested) model. The combination of the benchmark model vs. rival model that is being studied is depicted on the horizontal axis. Panel A depicts the results for the regional origin of financial stress. Panel B depicts the results for the financial origin of financial stress. The solid lines denote the median, the boxes denote the interquartile range, the upper whisker extends the third quantile to 1.5 times the interquartile range (or the maximum of the data, provided this is smaller), and the lower whisker extends the first quantile to 1.5 the interquartile range (or the minimum of the data, provided this is larger). Black dots denote outliers outside of this range. OFR: total financial stress index. US: United States. OA: other advanced economies. EM: emerging markets. CR: credit. SA: safe assets. FU: funding. VO: volatility. HAR-RV-M: model features realized moments as predictors.

stress. We have observed this link when financial stress originates in the US or other advanced economies, and when financial stress reflects funding and volatility developments in financial markets. We have also found that this evidence of in-sample predictability, for several commodities, has no counterpart in an out-of-sample analysis. Improvements in out-of-sample prediction accuracy relative to the HAR-RV model mainly can be traced back to realized moments rather than financial stress. Hence, our empirical findings are twofold. First, we show that agricultural commodities are not insulated from developments in financial markets, and from financial stress in particular. The fact that increases in financial stress are associated with subsequent increases in volatility can be considered to be an implication of the widely-discussed issue of financialization of the food market. In this context, given evidence of co-movement of RV of returns of agricultural commodities (Marfatia et al., 2022), an interesting question for future research is to analyze the role of FSI in explaining the comovement in the second moments across markets. Keeping this in mind, from an academic perspective, multivariate HAR-RV models could also be employed to conduct our forecasting analysis, but it must be realized that simultaneously looking at all the sixteen commodities in a fully specified system will be computationally difficult, and might require a grouping of the commodities into specific overall categories like, for example, grains, softs, and livestock. Furthermore, econometrically speaking, we confirm that in-sample results depicting predictability of financial stress on agricultural price volatility might not necessarily translate into forecasting gains, thus confirming the stringency of out-of-sample tests. Second, our empirical findings show that investors most likely will find it difficult to improve in a systematic and robust way the accuracy of predictions of the realized volatility of the returns of agricultural commodity prices by using financial stress as a predictor in addition to realized moments. Similarly, just like portfolio managers, policy authorities too should rather rely on moments of agricultural commodities than financial stress when aiming at designing policies to counteract the volatility of food prices.

Our empirical findings do not rule out the possibility that financial stress has a noticeable impact on out-of-sample prediction performance for individual agricultural commodities and/or during specific short-lived periods of time (like, for example, the Global Financial Crisis of 2009 or during the COVID-19 pandemic). In this regard, it is important to keep in mind that we have focused in our empirical research on linear prediction models. It may be possible to gain additional insights in future research using nonlinear models. As a preliminary step in this direction, we report in Fig. A4 at the end of the paper (Appendix, A.3) partial-dependence (PD) functions computed by means of random forests as estimated on the full sample of data.[8] The PD functions visualize the response of (the anti-log of) realized volatility to financial stress originating in the United States. For several agricultural commodities, the PD functions exhibit a characteristic J-shaped pattern. Such a J-shaped pattern, while based on full sample estimates, may indicate that financial stress has to increase beyond some threshold level to exert a noticeable effect on the out-of-sample accuracy of predictions of realized volatility. Studying such potential nonlinear links in the data in a systematic way is an exciting avenue for future research.

CRediT authorship contribution statement

Matteo Bonato: Data curation, Formal analysis, Methodology, Resources, Software. **Oguzhan Cepni:** Conceptualization, Data curation, Formal analysis, Investigation, Supervision, Writing – review & editing. **Rangan Gupta:** Conceptualization, Methodology, Project administration, Supervision, Writing – original draft, Writing – review & editing. **Christian Pierdzioch:** Investigation, Methodology, Software, Supervision, Writing – original draft, Writing – review & editing.

Declaration of competing interest

The authors declare no conflict of interest.

Data availability

Data will be made available on request.

Funding statement

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Appendix

A.1. Realized moments

We describe the calculation of the realized moments only briefly. Our description closely follows the description outlined in the recent research by Bonato et al. (2023), where an interested reader can find a more detailed formal description of how the realized moments are computed, and links to the relevant literature. The calculations for realized skewness, RSK, and realized kurtosis,

[8] We computed the partial dependence functions by means of the R add-on package randomForestSRC (Ishwaran and Kogalur, 2021). Sampling is with replacement, the minimum node size is five, and one third of the predictors are used for splitting.

RKU, are as follows:

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

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

where the sum is computed over the intraday returns, $r_{i,t}, i = 1, \dots, M$, as observed on day t. Taking into account the fact that realized variance comprises both a discontinuous (jump) component and a permanent component, we calculate realized jumps as follows:

$$\lim_{M\to\infty} RV_t = \int_{t-1}^{t} \sigma^2(s)ds + \sum_{j=1}^{N_t} k_{t,j}^2, \tag{A.3}$$

where N_t = number of jumps within day t, and $k_{t,j}$ = jump size. Hence, RV_t is a consistent estimator of the jump contribution plus the integrated variance $\int_{t-1}^{t}\sigma^2(s)ds$.

Next, we introduce BV_t, the daily realized bipolar variation:

$$BV_t = \mu_1^{-2}\left(\frac{M}{M-1}\right)\sum_{i=2}^{M} |r_{t,i-1}||r_{i,t}| = \frac{\pi}{2}\sum_{i=2}^{M} |r_{t,i-1}||r_{i,t}|, \tag{A.4}$$

where $\lim_{M\to\infty} BV_t = \int_{t-1}^{t}\sigma^2(s)ds$, and $\mu_a = E(|Z|^a), Z \sim N(0,1), a > 0$. A consistent estimator of the pure daily jump contribution is defined as:

$$J_t = RV_t - BV_t. \tag{A.5}$$

where we test for the statistical significance of the jump component as follows:

$$JT_t = \frac{RV_t - BV_t}{(v_{bb} - v_{qq})\frac{1}{N}QP_t}, \tag{A.6}$$

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

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

which converges to $TP_t \to \int_{t-1}^{t}\sigma^4(s)ds$, even in the presence of jumps. For each t, $JT_t \sim N(0,1)$ as $M \to \infty$.

In order to ensure that the jump contribution is non-negative, we redefine the jump measure as follows:

$$RJ_t = \max(RV_t - BV_t; 0). \tag{A.8}$$

Last, we compute two measures of tail risk. To this end, we construct $X_{t,i}$, the set of reordered intraday returns $r_{t,i}$, such that $X_{t,i} \geq X_{t,j}$ for $i < j$ with $i, j = 1, \dots, M$ where M is the number of observations per day. The positive tail risk estimator is computed as

$$H_t^{up} = \frac{1}{k}\sum_{j=1}^{k} \ln(X_{t,j}) - \ln(X_{t,k}) \tag{A.9}$$

and the negative tail risk estimator as

$$H_t^{down} = \frac{1}{k}\sum_{j=n-k}^{M} \ln(X_{t,j}) - \ln(X_{t,M-k}) \tag{A.10}$$

where k = observation denoting the chosen α tail interval.

A.2. Additional results

See Figs. A1–A4.

A.3. Partial dependence functions

See Fig. A4.

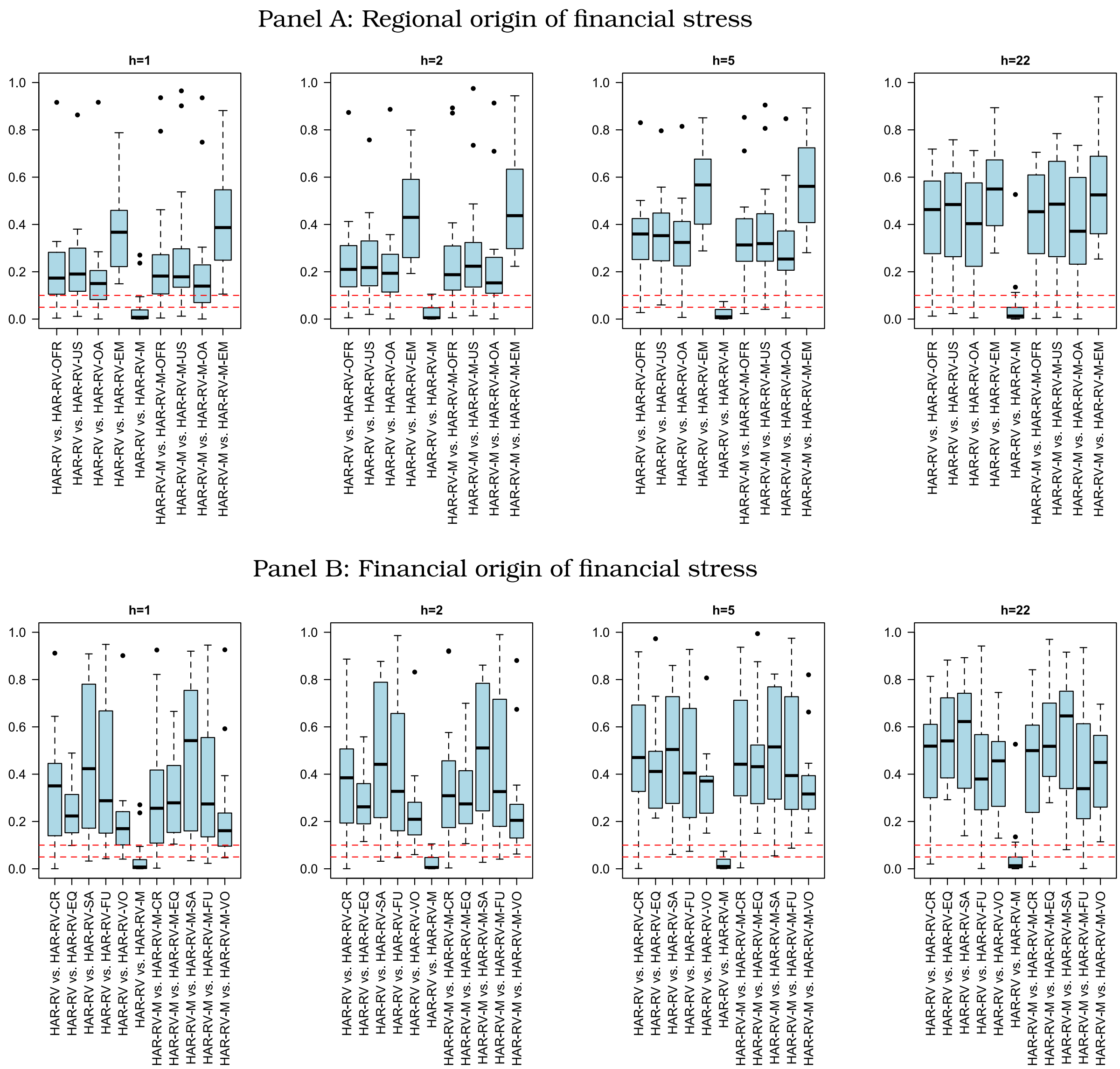


Fig. A1. Out-of-sample results: longer training period.
The forecasting models are estimated by the OLS technique using a recursive-estimation window (initialization period = 2,000 observations) and out-of-sample forecasts for the forecast horizon, *h*, are computed. The boxplots depict the distribution (across the agricultural commodities in the sample) of the *p*-value (calculated using robust standard errors) of the Clark–West test. The combination of the benchmark model vs. rival model that is being studied is depicted on the horizontal axis. Panel A depicts the results for the regional origin of financial stress. Panel B depicts the results for the financial origin of financial stress. OFR: total financial stress index. US: United States. OA: other advanced economies. EM: emerging markets. CR: credit. SA: safe assets. FU: funding. VO: volatility. HAR-RV-M: model features realized moments as predictors.

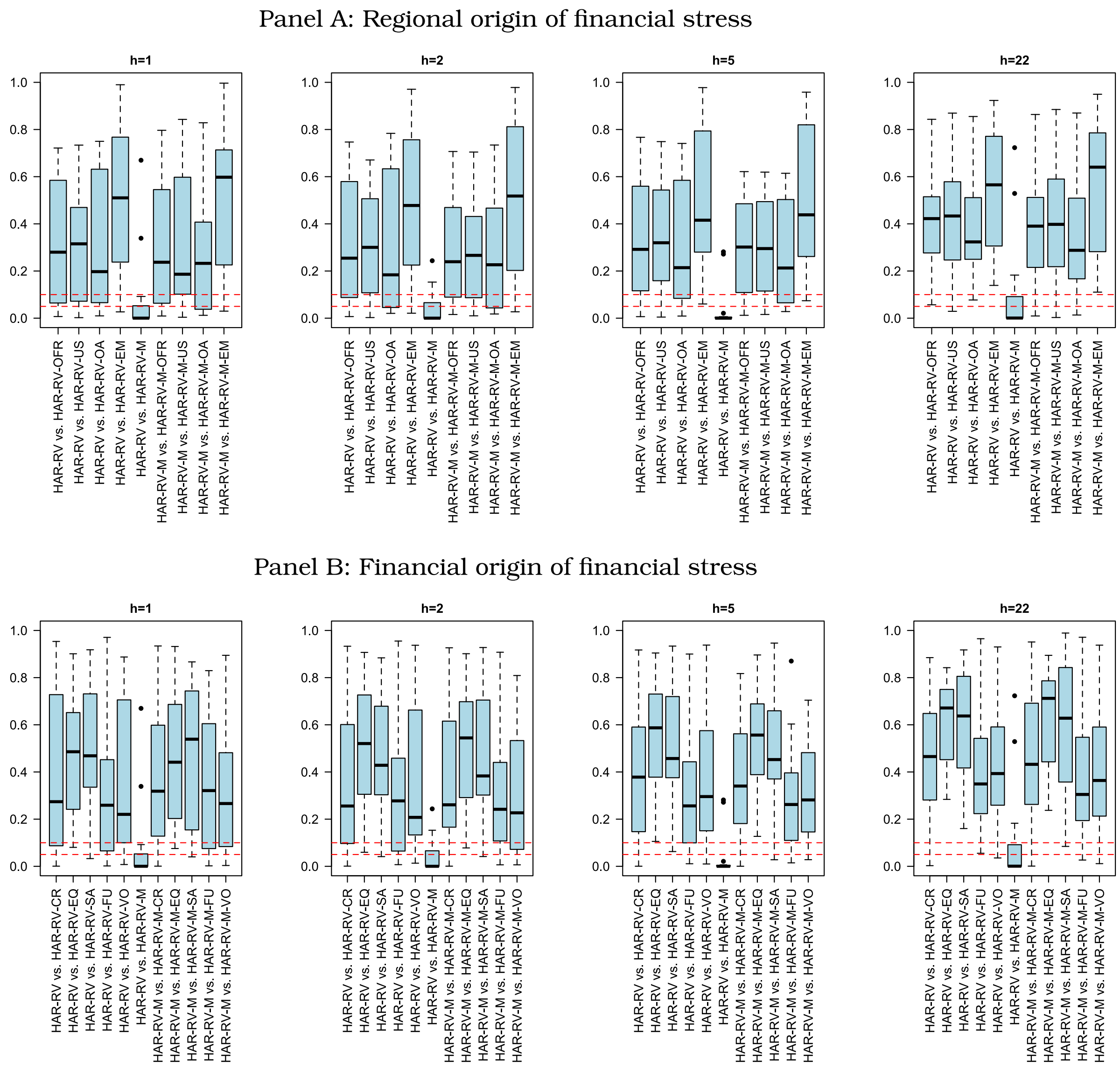
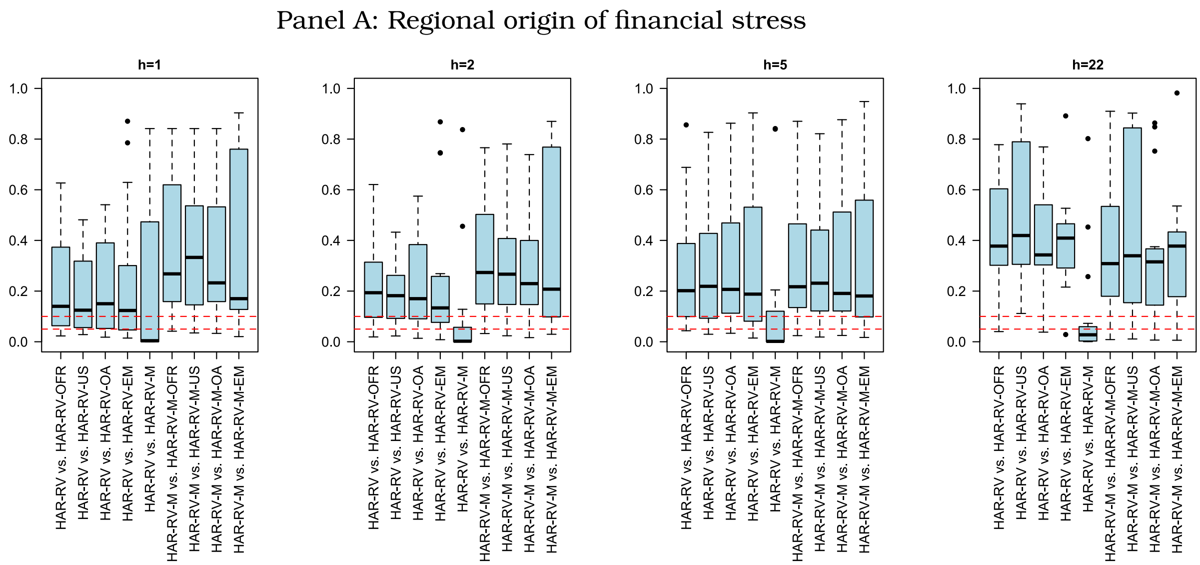


Fig. A2. Out-of-sample results: shorter sample period.
The forecasting models are estimated by the OLS technique using a recursive-estimation window (initialization period = 250 observations) and out-of-sample forecasts for the forecast horizon, *h*, are computed. The sample period ends 12/31/2019. The boxplots depict the distribution (across the agricultural commodities in the sample) of the *p*-value (calculated using robust standard errors) of the Clark–West test. The combination of the benchmark model vs. rival model that is being studied is depicted on the horizontal axis. Panel A depicts the results for the regional origin of financial stress. Panel B depicts the results for the financial origin of financial stress. OFR: total financial stress index. US: United States. OA: other advanced economies. EM: emerging markets. CR: credit. SA: safe assets. FU: funding. VO: volatility. HAR-RV-M: model features realized moments as predictors.



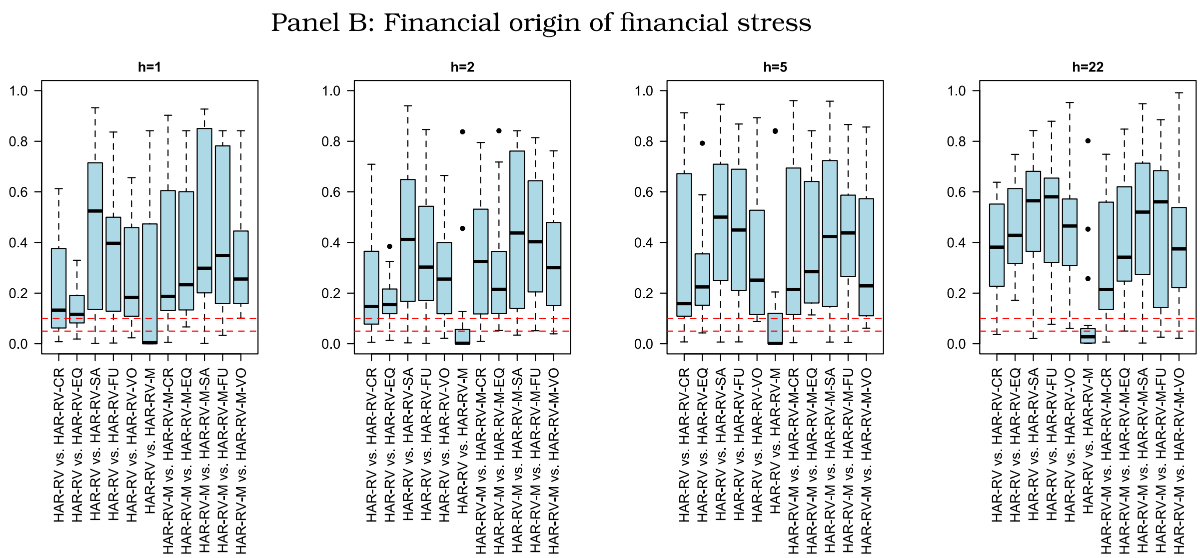


Fig. A3. Out-of-sample results: rolling-estimation window.
The forecasting models are estimated by the OLS technique using a rolling-estimation window of length 250 observations and out-of-sample forecasts for the forecast horizon, h, are computed. The boxplots depict the distribution (across the agricultural commodities in the sample) of the p-value (calculated using robust standard errors) of the Clark–West test. The combination of the benchmark model vs. rival model that is being studied is depicted on the horizontal axis. Panel A depicts the results for the regional origin of financial stress. Panel B depicts the results for the financial origin of financial stress. OFR: total financial stress index. US: United States. OA: other advanced economies. EM: emerging markets. CR: credit. SA: safe assets. FU: funding. VO: volatility. HAR-RV-M: model features realized moments as predictors.

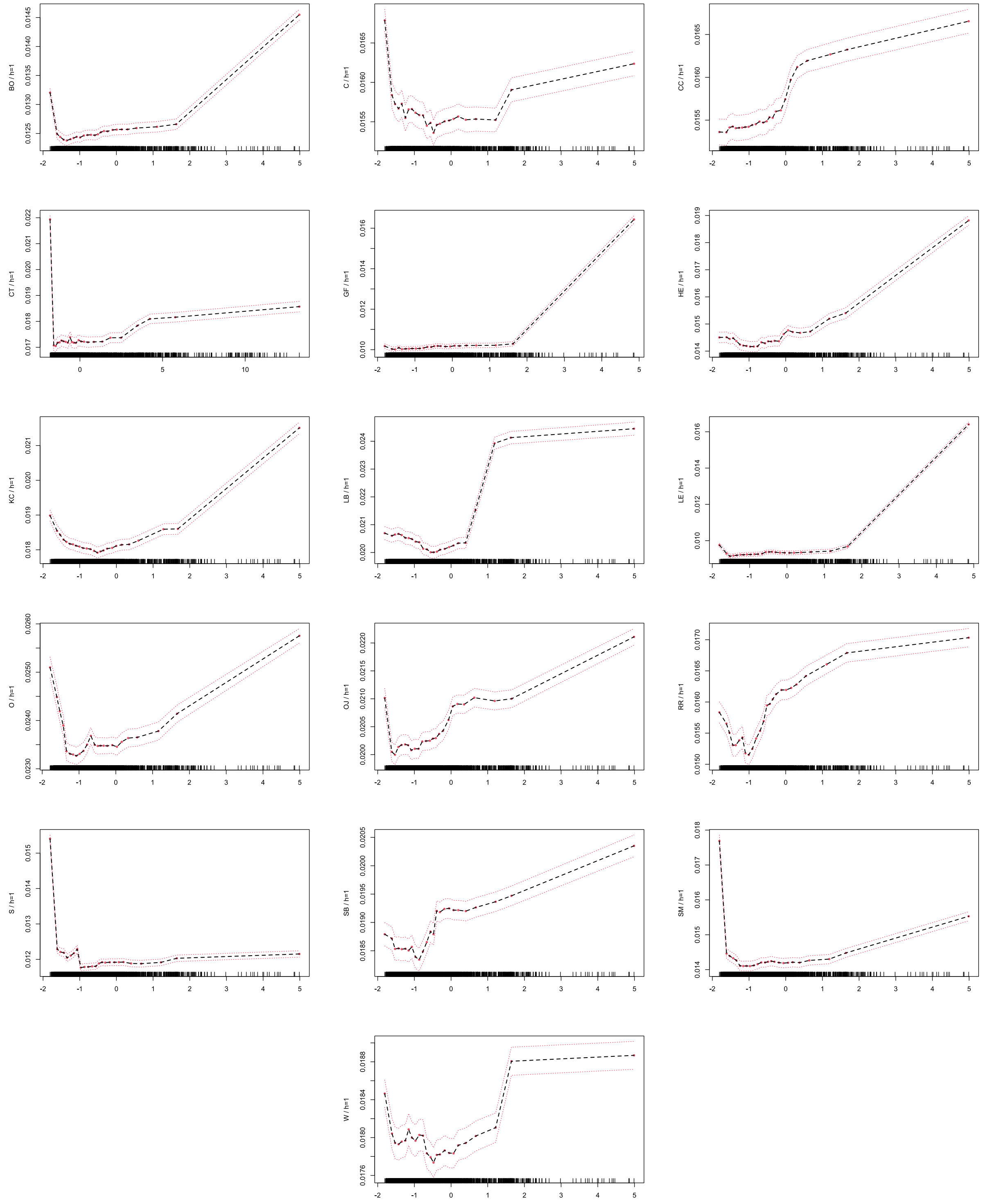


Fig. A4. Partial dependence functions.
The models are estimated (using the anti-log of *RV* as the dependent variable) by the random forest technique on the full sample of the data (a random forest consisting of 1,000 regression trees) and then the partial dependence functions are computed. The models use as predictors (i) the predictors of the HAR-RV baseline model, (ii) the realized moments, and, (iii) the financial stress originating in the United States, other advanced economics, and emerging market economies. The prediction horizon is $h = 1$. The partial dependence functions are based on out-of-bag data. Red points/black dashed lines: partial values. Dashed red lines: error band (plus/minus two standard errors). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

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