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Book

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Financial Stress and Realized Volatility: The Case of Agricultural Commodities

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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 evidence of in-sample predictive value of financial stress for realized volatility, consistent with the financialialization hypothesis. This in-sample evidence, however, in general does not extend to an out-of-sample forecasting environment.

JEL Classifications: C22, C53, G41, Q10.

Keywords: Realized volatility; Agricultural commodities; Financialization; Realized moments; Predictability

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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 (Aït-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 food prices. 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 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).

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 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., (2022), Bonato et al. (2022)). In the process, 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) and 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).

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 process underlying Generalized AutoRegressive Conditional Heteroskedasticity (GARCH) and Stochastic Volatility (SV) models that have been traditionally utilized for predicting agricultural commodity price volatility (see, Degiannakis et al. (2022), and Luo et al. (2022), for a review of this literature). At the same time, the underlying HAR-RV econometric framework 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) and Živkov et al. (2019), inspite of its simplistic structure. Moreover, because the HAR-RV model employs RV at different time resolutions to model and predict RV, it is an empirical representation of the theory of the heterogeneous market hypothesis (HMH; Müller et al., 1997). The HMH posits that the 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.

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.

– Tabl 1 about here. –

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

[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.

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 $i = 1, ..., N$ 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 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 $\beta_j, j = 0, .., 3$ 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 $t - 1$.

[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 and, therefore, are not reported (but available upon request from the authors).

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

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

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

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

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

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; Section A1).

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 Figures 1 and 2. While we plot in Figure 1 the results we obtain when we consider financial stress according to its region of origin, we plot

[4]Using longer initialization period or a rolling-estimation window gives qualitatively similar results (not reported for reasons of space).

in Figures 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.

– Figures 1 and 2 about here. –

Starting with an analysis of the results that Figure 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 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. 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 Figure 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 the strongest results, in terms of statistical significance, when funding and volatility are the sources of financial stress. As in Figure 1, the statistical significance of the results tends to weaken when the length of the prediction horizon increases.

– Figure 3 about here. –

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). We, therefore, summarize out-of-sample results in Figure 3, which plots the p-values of the Clark and West (2007) test. We find that augmenting the the baseline HAR-RV model with realized moments tends to significantly improve prediction accuracy at all three prediction horizons (note that the results of the comparison HAR-RV vs- HAR-RV-M do not depend on whether 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 in the cross section largely to statistically insignificant test results

– Figure 4 about here. –

As two extensions, we summarize in Figure 4 out-of-sample results for the (natural logarithm of) realized variance (Panel A) and a rolling-estimation window (Panel B), where we focus on financial stress according to its regional source. Again, we observe that mainly realized moments rather than financial stress matter for the accuracy of the out-of-sample forecasts. Similarly, for the rolling-estimation window and the short forecast horizon, we observe that any evidence of out-of-sample predictability due to financial stress disappears once we control for realized moments.

In sum, our findings suggest that, unlike for the full-sample predictive analysis, real-time forecasting of RV 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 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 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. Second, our empirical findings also show that investors most likely will find it difficult to improve in a systematic 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.

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 Figure A1 at the end of the paper (Appendix, Section A2) partial-dependence (PD) functions computed by means of random forests as estimated on the full sample of data.[5] 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.

[5]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.

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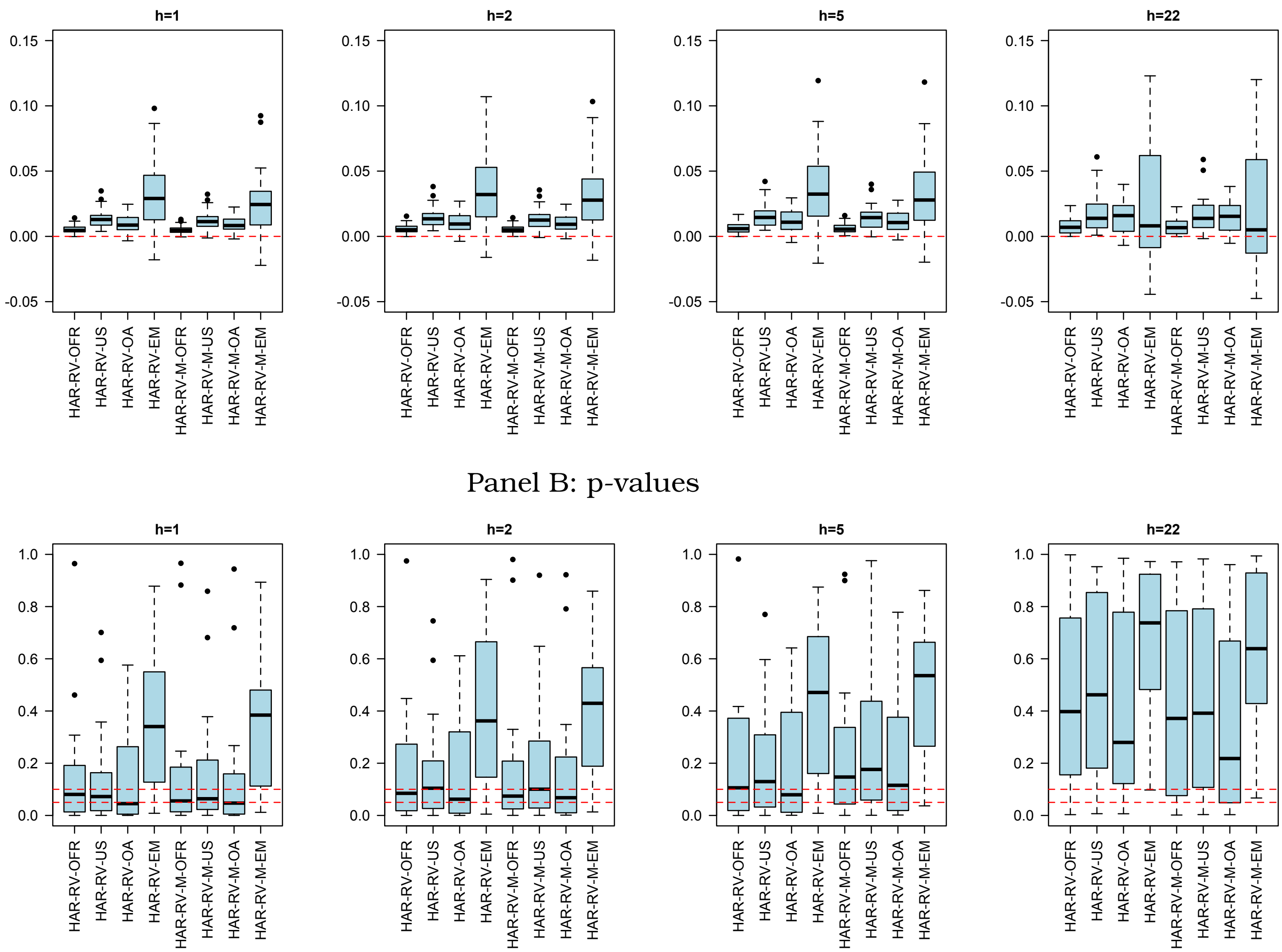
Table 1: Commodity summary statistics

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
Live cattle	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

Figure 1: In-sample results based on the regional origin of financial stress

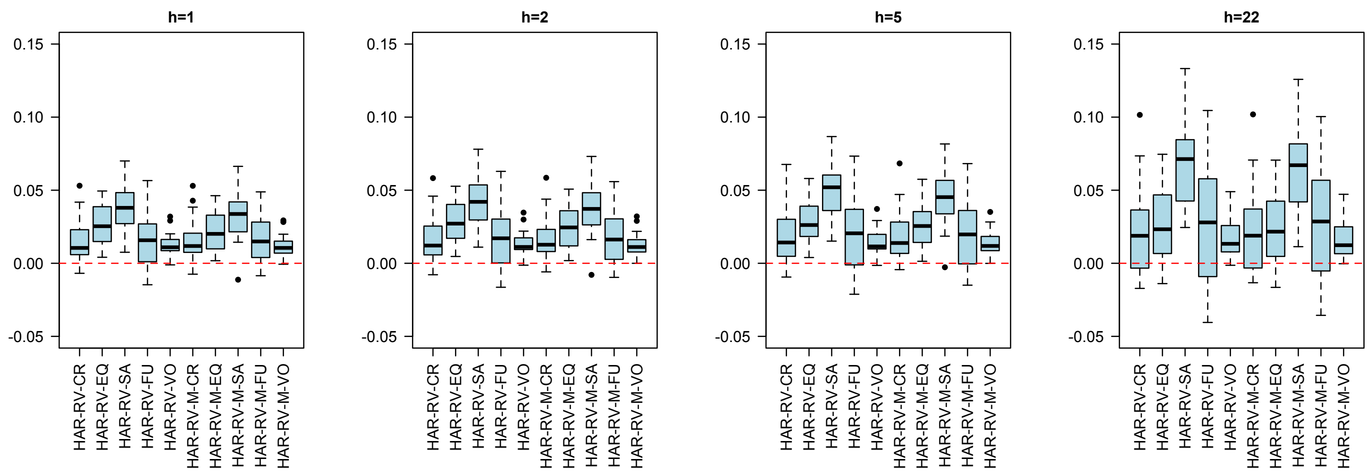
Panel A: Coefficients



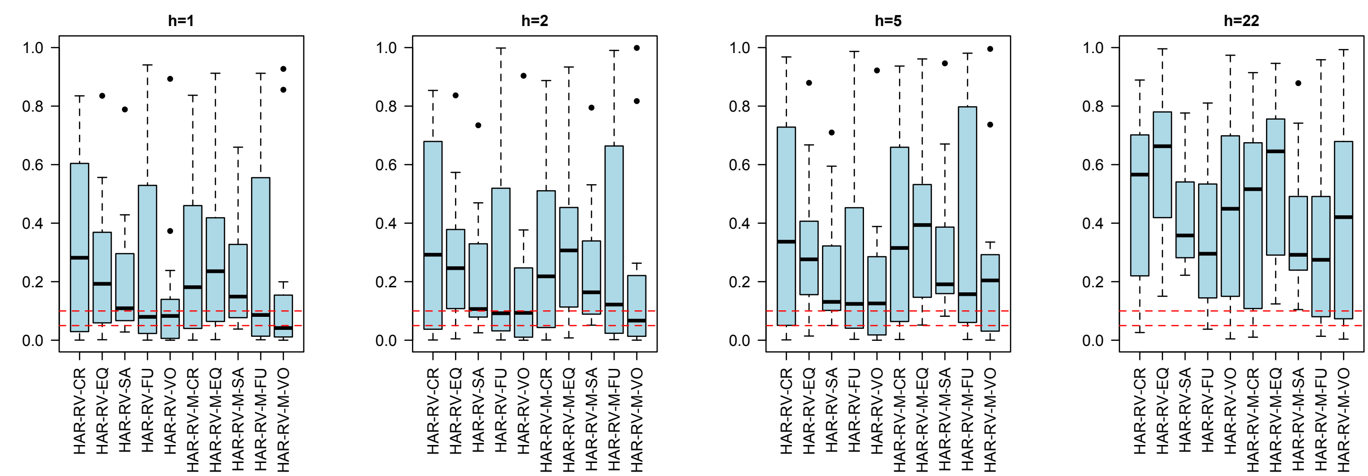
The models (horizontal axis) are estimated by the OLS technique on the full sample of the data. The boxplots plotted in Panel A depict the distribution (across the agricultural commodities in the sample) of the estimated coefficient of the FSI component included in the models. The boxplot plotted in Panel B depicts the distribution (across the agricultural commodities in the sample) of the p-value (calculated using robust standard errors) of the 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.

Figure 2: In-sample results based on the financial origin of financial stress

Panel A: Coefficients



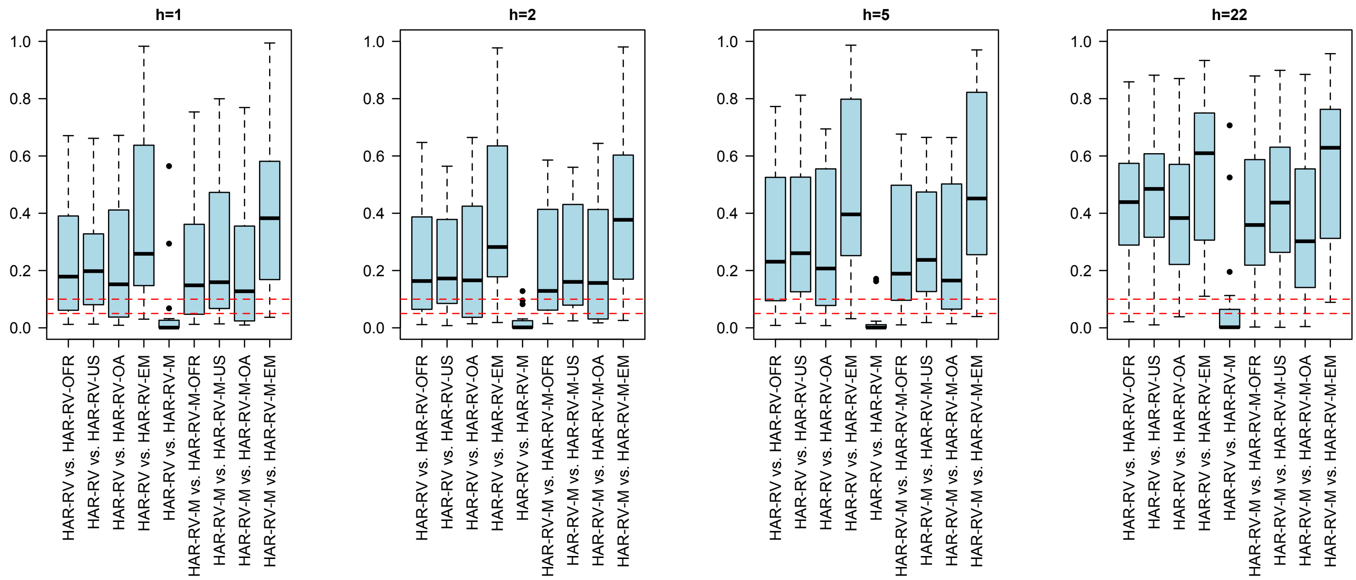
Panel B: p-values



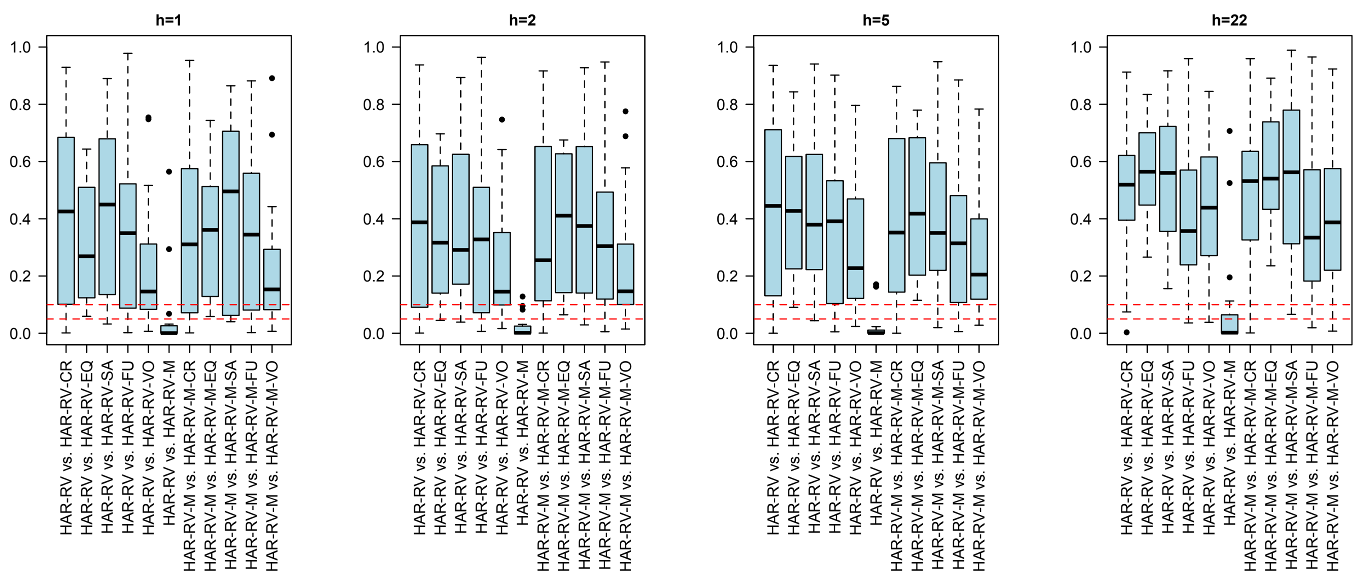
The models (horizontal axis) are estimated by the OLS technique. The boxplots plotted in Panel A depict the distribution (across the agricultural commodities in the sample) of the estimated coefficient of the FSI component included in the models. The boxplot plotted in Panel B depicts the distribution (across the agricultural commodities in the sample) of the p-value (calculated using robust standard errors) of the 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.

Figure 3: Out-of-sample results

Panel A: Regional origin of financial stress



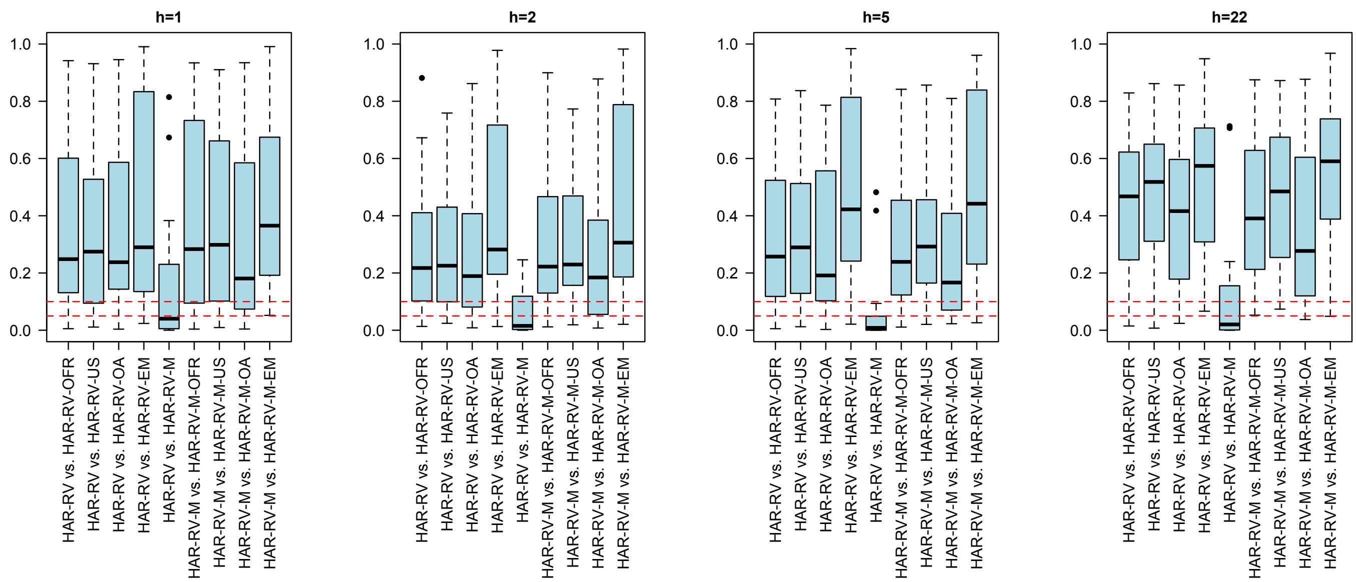
Panel B: Financial origin of financial stress



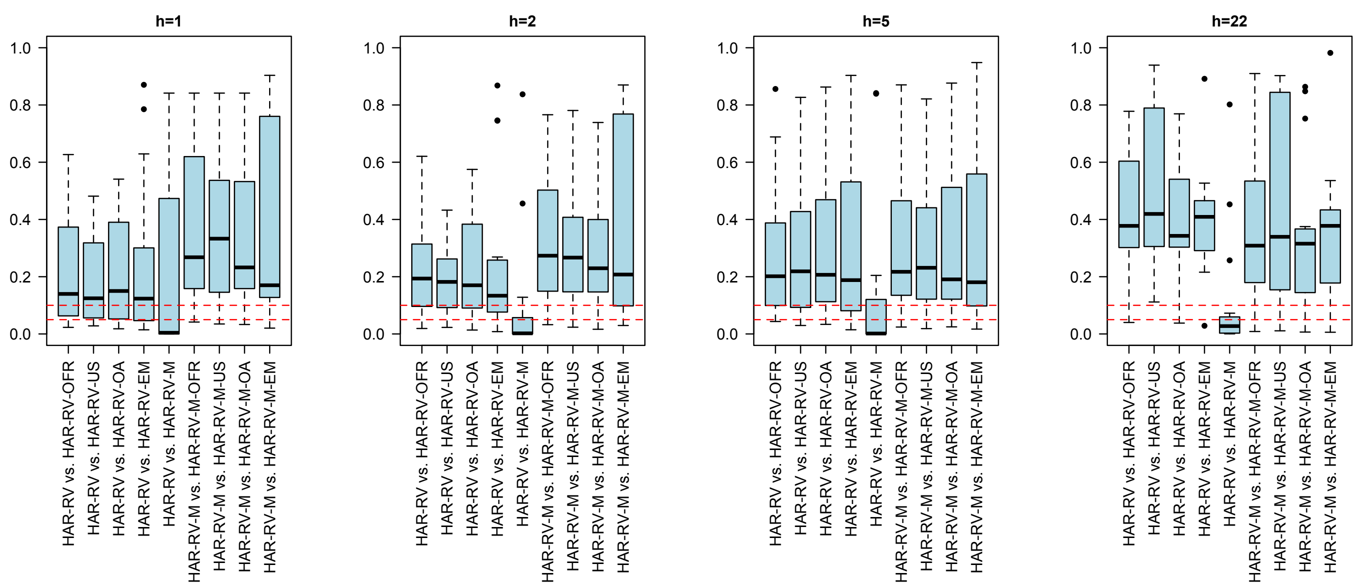
The forecasting models are estimated by the OLS technique using a recursive-estimation window (initialization period= 250 observations) and out-of-sample forecasts for the forecast horizon, h, are computed. The boxplots depict the distribution (across the agricultural commodities in the sample) of the 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 in 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.

Figure 4: Out-of-sample results: extensions

Panel A: Results for the realized variance



Panel B: Results for a rolling-estimation window



Panel A: 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. Panel B: The forecasting models are estimated by the OLS technique using a rolling-estimation window of length250 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 in 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.

Appendix

A1 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, RKU, are as follows:

$$RSK_t = \frac{\sqrt{M}\sum_{i=1}^{M} r_{(i,t)}^3}{RV_t^{3/2}}, \tag{A1}$$

$$RKU_t = \frac{M\sum_{i=1}^{M} r_{(i,t)}^4}{RV_t^2}. \tag{A2}$$

where the sum is computed over the intraday returns, $r_{i,t}, i = 1, ..., M$, 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:

$$\lim_{M\to\infty} RV_t = \int_{t-1}^{t} \sigma^2(s)ds + \sum_{j=1}^{N_t} k_{t,j}^2, \tag{A3}$$

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:

$$BV_t = \mu_1^{-2}\left(\frac{M}{M-1}\right)\sum_{i=2}^{M} |r_{t,i-1}||r_{i,t}| = \frac{\pi}{2}\sum_{i=2}^{M} |r_{t,i-1}||r_{i,t}|, \tag{A4}$$

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:

$$J_t = RV_t - BV_t. \tag{A5}$$

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

$$JT_t = \frac{RV_t - BV_t}{(v_{bb} - v_{qq})\frac{1}{N}QP_t}, \quad \text{(A6)}$$

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:

$$TP_t = M\frac{M}{M-2}\left(\frac{\Gamma(0.5)}{2^{2/3}\Gamma(7/6)}\right)\sum_{i=3}^{M}|r_{t,i}|^{4/3}|r_{t,i-1}|^{4/3}|r_{t,i-2}|^{4/3}, \quad \text{(A7)}$$

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:

$$RJ_t = \max(RV_t - BV_t; 0). \quad \text{(A8)}$$

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 $i, j = 1, \ldots, M$ where M is the number of observations per day. The positive tail risk estimator is computed as

$$H_t^{up} = \frac{1}{k}\sum_{j=1}^{k}\ln(X_{t,j}) - \ln(X_{t,k}) \quad \text{(A9)}$$

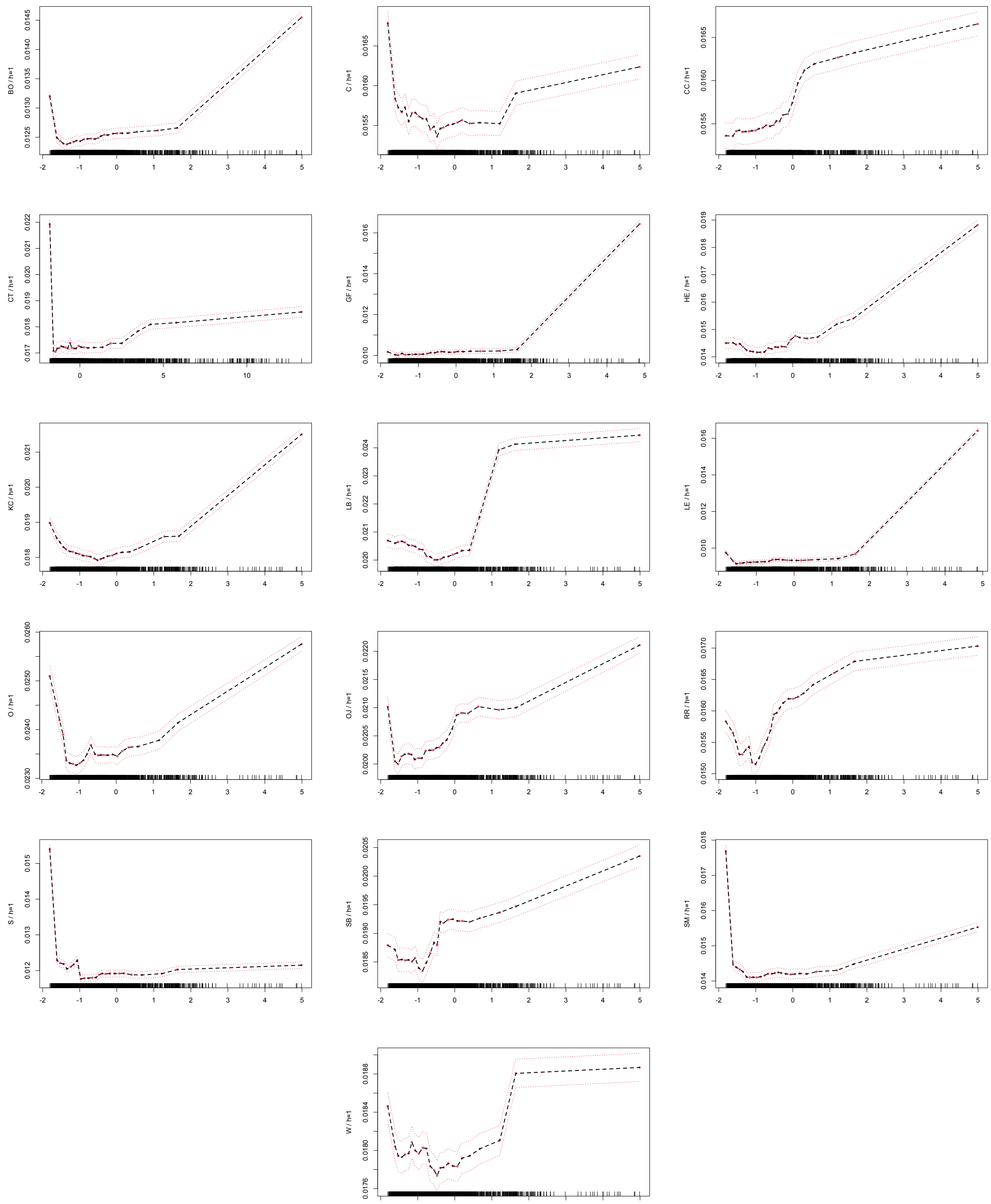
and the negative tail risk estimator as

$$H_t^{down} = \frac{1}{k}\sum_{j=n-k}^{M}\ln(X_{t,j}) - \ln(X_{t,M-k}) \quad \text{(A10)}$$

where $k =$ observation denoting the chosen α tail interval.

A2 Partial Dependence Functions

Figure A1: 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). The