International Journal of Forecasting 38 (2022) 74–96

Contents lists available at ScienceDirect

International Journal of Forecasting

journal homepage: www.elsevier.com/locate/ijforecast

Forecasting realized volatility of agricultural commodities

Stavros Degiannakis [a,*], George Filis [b], Tony Klein [c], Thomas Walther [d,e]

[a] Department of Economics and Regional Development, Panteion University of Social and Political Sciences, Greece
[b] Department of Accounting, Finance and Economics, Bournemouth University, UK
[c] Queen's Management School, Queen's University Belfast, UK
[d] Utrecht School of Economics, Utrecht University, The Netherlands
[e] Faculty of Business and Economics, Technische Universität Dresden, Germany

ARTICLE INFO

Keywords:
Agricultural commodities
Realized volatility
Median realized volatility
Heterogeneous autoregressive model
Forecast

ABSTRACT

We forecast the realized and median realized volatility of agricultural commodities using variants of the heterogeneous autoregressive (HAR) model. We obtain tick-by-tick data on five widely-traded agricultural commodities (corn, rough rice, soybeans, sugar, and wheat) from the CME/ICE. Real out-of-sample forecasts are produced for between 1 and 66 days ahead. Our in-sample analysis shows that the variants of the HAR model which decompose volatility measures into their continuous path and jump components and incorporate leverage effects offer better fitting in the predictive regressions. However, we demonstrate convincingly that such HAR extensions do not offer any superior predictive ability in their out-of-sample results, since none of these extensions produce significantly better forecasts than the simple HAR model. Our results remain robust even when we evaluate them in a Value-at-Risk framework. Thus, there is no benefit from including more complexity, related to the volatility decomposition or relative transformations of the volatility, in the forecasting models.

1. Introduction and a brief review of the literature

Examining the behaviours of agricultural commodity prices and volatilities is of significant importance, since they represent a major component of household consumption. They also have a pronounced impact on food security, which affects primarily the poorer parts of the population (Ordu, Oran, & Soytas, 2018).

The Food and Agricultural Organisation (FAO) of the United Nations claims that food prices had rarely experienced any significant volatility prior to 2008 (FAO, 2010); however, agricultural commodities have experienced enormous price swings over the last decade (2008–2018), resulting in both high and low volatility regimes (Greb & Prakash, 2015). This new normal suggests that the food system is becoming progressively more vulnerable to price volatility (FAO, 2010), and this led the G20 to request a report from several international bodies (including the World Bank, IMF, UNCTAD, OECD, and FAO, among others) in order "to develop options for G20 consideration on how to better mitigate and manage the risks associated with the price volatility of food and other agriculture commodities, without distorting market behaviour, ultimately to protect the most vulnerable". (FAO, 2011, p. 3).

The Council on Foreign Relations (Johnson, 2011) promotes the idea that such increased volatility is the result of extreme weather events, the production of biofuels, and market speculation, but also of rising demand coupled with declines in food stocks. von Braun and Tadesse (2012) also show that the price volatility of agricultural commodities is impacted by the increasing linkages among agricultural prices, energy commodities, and financial markets. Ordu et al. (2018) further suggest that the agricultural market is becoming financialized, since institutional investors are increasing their holdings in

* Corresponding author.
E-mail addresses: sdegiannakis@panteion.gr (S. Degiannakis), gfilis@bournemouth.ac.uk (G. Filis).

https://doi.org/10.1016/j.ijforecast.2019.08.011

commodity markets, which further suggests an increase in speculative activity in this market. It is easy to understand that such cross-market linkages and financialization processes could have destabilizing effects on agricultural food prices.

The proper modeling and detection of long-memory dynamics in the volatility of commodity futures improves risk-management techniques, such as volatility forecasting and hedging performances, and better characterizes equilibrium relationships. Over the last few years there has been increasing interest in modelling the agricultural price volatility (focusing primarily on GARCH-type and wavelet-based modelling approaches) and providing evidence of potential predictors of such volatility in an in-sample setting (Anderluh & Borovkova, 2008; Egelkraut & Garcia, 2006; Elder & Jin, 2007; Li, Ker, Sam, & Aradhyula, 2017; Triantafyllou, Dotsis, & Sarris, 2015).

Given the aforementioned market conditions and previous research efforts to model the agricultural volatility, it has become important to develop the necessary frameworks that would enable successful forecasting of the agricultural commodity price volatility, so that policy institutions can prepare for high price volatility periods or design preventative policies, as was also implied by Greb and Prakash (2017).

Despite the recent evidence provided by policy institutions of the need for successful agricultural price volatility forecasts, the fact that modelling approaches for agricultural price volatility have been being developed for over 15 years now, and the fact that the first effort to produce real out-of-sample forecasts was by Giot and Laurent (2003), we observe the paradox that there are only four other recent studies in this strand of the literature: those by Luo, Klein, Ji, and Hou (2019), Tian, Yang, and Chen (2017a, 2017b), and Yang, Tian, Chen, and Li (2017).

Starting with the first of these studies, Giot and Laurent (2003) focus on the price volatility of cocoa, coffee, and sugar futures and use GARCH-type models to generate the forecasts. In contrast, Tian et al. (2017a, 2017b) and Yang et al. (2017) utilize the increased availability of ultra-high-frequency data and extend the heterogeneous autoregressive (HAR) model of Corsi (2009) to produce short-run volatility forecasts (up to 20 days ahead).

More specifically, Tian et al. (2017a) use two regime-switching Markov models to forecast the realized volatility for five agricultural commodities traded in the Chinese market, namely soybeans, soybean oil, white sugar, gluten wheat and cotton. They find evidence that regime-switching dynamics offer predictive gains compared to both a simple AR(1) and a Markov-switching AR(1) model. Yang et al. (2017) also use intra-day data from the Chinese commodity futures markets (Zhenzhou Commodity Exchange and Dalian Commodity Exchange) of soybean, cotton, gluten wheat and corn futures prices and employ a strategy similar to that of Tian et al. (2017b), where the HAR model is extended with potential predictors (such as day-of-the-week dummies, past cumulative returns and the jump component) and forecasts are generated based on bagging and combination methods. Their conclusions suggest that the forecasts based on the HAR models with bagging and principal component combination methods are able to outperform the AR model. Finally, Tian et al. (2017b) use soybean, cotton, gluten wheat, corn, early Indica rice and palm futures prices, traded in the Chinese market, to construct and forecast their realized volatility measure. Furthermore, they use several other realized volatility measures (such as the daily log-range volatility, the realized threshold multi-power variation and the realized threshold bi-power variation) and the jump component as potential predictors of the realized volatility. Their predictive models allow both the predictors and the coefficients to vary over time. Their findings show that the dynamic model average and Bayesian model average models are able to exhibit superior predictive abilities relative to the simple HAR model. More importantly, they show that the HAR model with time-varying sparsity produces the most accurate forecasts for all of the commodities chosen.

Given the limited research efforts on agricultural price volatility forecasting and the importance of such forecasts, it is imperative that this line of research be extended further. Currently, there are three rather important issues that the limited number of studies have not considered when it comes to agricultural commodities volatility forecasting. First, all previous papers have used data from the Chinese futures markets, with no efforts having been made to forecast the volatility of agricultural commodities traded in the U.S., though the latter is the most established market, as well as the market with the highest penetration by both speculators and hedgers.[1] Second, the main focus has been on realized volatility forecasting, with other intra-day volatility measures having been ignored. Finally, while the current literature focuses on the aggregation of the information on agricultural commodities volatility (through bagging, combination techniques, or time-varying approaches), it does not provide any answer as to whether specific volatility components, such as the jump component, the continuous component, the signed jumps, and the volatility or return leverage, can provide better forecasts than simple HAR models. Thus, this study fills these voids and provides clear evidence as to whether the aforementioned components can provide predictive gains. This is rather important, given that the complexity of forecasting models should only be increased if this provides material predictive gains.

Succinctly, we add to this extremely sparse strand of the literature by applying several HAR-type models that accommodate the jump and continuous components, the signed jumps, and the volatility or return leverage (namely the HAR-J, HAR-CJ, HAR-PS and LHAR-CJ) to forecast different realized volatility measures (such as the realized volatility *RV* and the median realized volatility *MedRV*). For this study we focus on five important agricultural commodities that are traded in the Chicago Mercantile Exchange (CME) and the Intercontinental Exchange (ICE), namely corn, rough rice, soybeans, sugar and wheat, and produce forecasts for 1 to 66 days ahead.

Our choice of the *RV* and *MedRV* volatility measures stems from the fact that the former is the most well-known volatility measure both within past research and among practitioners, whereas the latter is a more robust

[1] See for example Bloomberg (2019).

measure, compared to multipower variations, as the median operators tend to eliminate from the calculation the large absolute returns that are associated with jumps. In addition, the *MedRV* offers a number of advantages over alternative measures of the integrated variance in the presence of infrequent jumps, and is less sensitive to the presence of occasional zero intra-day returns (Theodosiou & Zikes, 2011).

Our in-sample analysis shows that variants of the HAR model which decompose the volatility measure in its continuous path and jump component and take the volatility or return leverage effects into consideration (and in particular the LHAR-CJ model) are capable of offering a better fit of the predictive equation for both the *RV* and *MedRV* volatility measures. Turning to the out-of-sample results, these suggest strongly that the simple HAR model outperforms the random walk and AR models significantly. However, contrary to the in-sample findings, none of the HAR extensions is able to generate forecasts that are statistically significantly better than those of the simple HAR model. Hence, we cannot support the view that the decomposition of the volatility measure into its continuous path and jump component, or even taking into consideration the volatility or return leverage effect in a HAR-type model, adds any incremental predictive accuracy. These results hold for both *RV* and *MedRV*, and hence, the results are not volatility measure specific. Finally, we show that all HAR models have marginally better directional accuracies than the random walk and AR models for the shorter forecasting horizons.

The remainder of this study is structured as follows. Section 2 describes the construction of the volatility measures, the predictive models and the loss functions for the forecast evaluations. Section 3 presents the data and their descriptive statistics. Section 4 presents the results followed by a thorough discussion of the in-sample and real out-of-sample evaluations. Section 5 discusses the results from a risk management application. Finally, Section 6 concludes the study and provides avenues for further research.

2. Methodology

2.1. Realized variance measures and jump detection

Let the number of intraday observations be m and the total number of observation days be M. The intraday returns are then defined as the log-difference of two consecutive prices

$$r_{t,i} = \left(\log P_{t,i} - \log P_{t,i-1}\right) * 100, \qquad (1)$$

at day $t = 1, \ldots, M$ for $i = 2, \ldots, m$. The realized volatility of a given day t is then defined as

$$RV_t = \sum_{i=1}^{m} r_{t,i}^2. \qquad (2)$$

Following Andersen and Bollerslev (1998) and under the assumption of no serial correlation and other noise[2] in this discrete return data sampling, it holds that

$$\underset{m\to\infty}{\text{p-lim}} \left(\int_0^1 \sigma_{t+\tau}^2 \mathrm{d}\tau - \sum_{i=1}^{m} r_{t,i}^2 \right) = 0, \qquad (3)$$

where the integral describes the daily, continuous time volatility and the sum is the estimator of the daily realized volatility.

Discretizing the data by equidistant sampling, where Eq. (3) no longer holds, might introduce intra-day price jumps which translate into higher realized variances. In order to obtain a more robust measure of the realized volatility, Barndorff-Nielsen and Sheppard (2004) introduce the concept of the bi-power variation (BPV_t), which is defined as

$$BPV_t = \frac{\pi}{2} \left(\frac{m}{m-1} \right) \sum_{j=1}^{m-1} |r_{t,j}||r_{t,j+1}|. \qquad (4)$$

This bi-power variation is being used to separate the realized variance in a continuous part and discontinuous (jump) part. We use the approach of Huang (2004) to identify the jump component

$$J_t = I_{\{Z_t > \Phi_\alpha\}} \left(RV_t - BPV_t\right), \qquad (5)$$

where $\Phi(\cdot)$ refers to the density of a standard normal distribution with excess value

$$Z_t = \sqrt{m} \frac{1 - BPV_t \cdot RV_t^{-1}}{\sqrt{\left(\mu_1^{-4} + 2\mu_1^{-2} - 5\right) \max\left(1, TQ_t \cdot BPV_t^{-2}\right)}}, \qquad (6)$$

and $\mu_1 = \mathbb{E}(Z) = \sqrt{2/\pi}$. The tri-power quarticity TQ_t is defined as

$$TQ_t = m\mu_{4/3}^{-3} \sum_{j=1}^{m-2} |r_{t,j}|^{4/3} |r_{t,j+1}|^{4/3} |r_{t,j+2}|^{4/3}, \qquad (7)$$

where $\mu_p = 2^{p/2} \cdot \Gamma(1/2 \cdot (p+1)) \cdot \Gamma(1/2)$. We set $\alpha = 0.99$. The continuous component C_t is then calculated as

$$C_t = I_{\{Z_t > \Phi_\alpha\}} BPV_t + I_{\{Z_t \le \Phi_\alpha\}} RV_t. \qquad (8)$$

As the BPV_t is not free of flaws, such as a downward-bias if there are zero-return ticks, an alternative is introduced by Andersen, Dobrev, and Schaumburg (2012). This median realized volatility $MedRV_t$ is defined as

$$MedRV_t = \frac{\pi}{6 - 4\sqrt{3} + \pi} \frac{m}{m-2} \times \sum_{j=2}^{m-1} \text{median}\left(|r_{t,j-1}|, |r_{t,j}|, |r_{t,j+1}|\right)^2, \qquad (9)$$

which yields alternative continuous and jump components

$$J_{t,\alpha}^{MedRV} = I_{\left\{Z_t^{MedRV_t} > \Phi_\alpha\right\}} \left(RV_t - MedRV_t\right), \text{ and} \qquad (10)$$

$$C_t^{MedRV} = I_{\{Z_t > \Phi_\alpha\}} MedRV_t + I_{\{Z_t \le \Phi_\alpha\}} RV_t, \qquad (11)$$

with

$$Z_t^{MedRV} = \sqrt{m} \frac{1 - MedRV_t \cdot RV_t^{-1}}{\sqrt{0.96 \max\left(1, MedRQ_t \cdot MedRV_t^{-2}\right)}}, \qquad (12)$$

[2] We use tick-data of 5-minute price intervals to circumvent some of the microstructure issues.

$$MedRQ_t = \frac{3\pi}{9\pi + 72 - 52\sqrt{3}} \frac{m}{m-2} \times \sum_{j=2}^{m-1} \text{median}\left(|r_{t,j-1}|, |r_{t,j}|, |r_{t,j+1}|\right)^4. \quad (13)$$

We disaggregate the realized volatilities further in order to account for asymmetries by also applying realized semi-variances which are based on the work of Barndorff-Nielsen, Kinnebrock, and Shephard (2010) and Patton and Sheppard (2015):

$$RS_t^+ = \sum_{j=1}^{m} I_{\{r_{t,j}>0\}} r_{t,j}^2, \quad (14)$$

$$RS_t^- = \sum_{j=1}^{m} I_{\{r_{t,j}<0\}} r_{t,j}^2, \quad (15)$$

and it naturally holds that $RV_t = RS_t^+ + RS_t^-$.

2.2. RV models

This section presents the forecasting models for the realized volatility (RV), where we can obtain the equivalent predictive models for the $MedRV$ by replacing the RV with the $MedRV$. We follow the formulations of Corsi and Renò (2012). Thus, we generate a different regression estimation for each forecasting horizon h and each forecasting model. This allows us to circumvent the use of recursive long-term forecasts based on the relative weights for 1-day-ahead predictions for $h > 1$.[3] In particular, we define

$$\log(RV_{t+h}^{(h)}) = \frac{1}{h} \sum_{j=1}^{h} \log(RV_{t+h-j+1}) \quad \text{and} \quad (16)$$

$$\log(RV_t^{(h)}) = \frac{1}{h} \sum_{j=1}^{h} \log(RV_{t-j+1}), \quad (17)$$

where $h \in \{1, \ldots, 66\}$ denotes the forecasting horizon in number of days ahead. Note that $\log(RV_{t+h}^{(h)})$ is the average realized volatility for times $t+1$ to $t+h$, $\log(RV_t^{(h)})$ is the average realized volatility for times $t-h+1$ to t, and $\log(RV_t)$ is the realized volatility at time t and is equivalent to $\log(RV_t^{(1)})$.

As a baseline estimation, we use a simple random walk (RW), defined as:

$$\log(RV_{t+h}^{(h)}) = \log(RV_t^{(h)}) + \varepsilon_{t+h}^{(h)}, \quad (18)$$

a simple autoregressive model of order one (AR(1)), defined as:

$$\log(RV_{t+h}^{(h)}) = \beta_0^{(t)} + \beta_1^{(t)} \log(RV_t^{(h)}) + \varepsilon_{t+h}^{(h)}, \quad (19)$$

and an autoregressive moving average model of order one (ARMA(1,1)), defined as:

$$\log(RV_{t+h}^{(h)}) = \beta_0^{(t)} + \beta_1^{(t)} \log(RV_t^{(h)}) + \beta_2^{(t)} \varepsilon_t^{(h)} + \varepsilon_{t+h}^{(h)}. \quad (20)$$

[3] As was pointed out by Ederington and Guan (2010), the recursive forecast procedure introduces a bias to longer-term forecasts.

In addition to the three aforementioned naive and simple models, we focus on the standard HAR model of Corsi (2009) and a number of extensions. The standard HAR model is

$$\log(RV_{t+h}^{(h)}) = \beta_0^{(t)} + \beta_1^{(t)} \log(RV_t) + \beta_2^{(t)} \log(RV_t^{(5)}) + \beta_3^{(t)} \log(RV_t^{(22)}) + \varepsilon_{t+h}^{(h)}, \quad (21)$$

where RV_t denotes the previous day's volatility, $RV_t^{(5)}$ denotes the averaged volatility during the previous week, and $RV_t^{(22)}$ denotes the averaged volatility over the previous month.

Next, we account for possible jumps by augmenting the standard HAR with the simple jump measure J_t to define the HAR-J model:

$$\log(RV_{t+h}^{(h)}) = \beta_0^{(t)} + \beta_1^{(t)} \log(RV_t) + \beta_2^{(t)} \log(RV_t^{(5)}) + \beta_3^{(t)} \log(RV_t^{(22)}) + \beta_4^{(t)} \log(J_t + 1) + \varepsilon_{t+h}^{(h)}. \quad (22)$$

Andersen, Bollerslev, and Diebold (2007) further proposed the use of bi-power variations to separate the realized volatilities into continuous and jump components, which we subsequently labeled HAR-CJ:

$$\begin{aligned}\log(RV_{t+h}^{(h)}) = {} & \beta_0^{(t)} + \beta_1^{(t)} \log(J_t + 1) + \beta_2^{(t)} \log(J_t^{(5)} + 1) \\ & + \beta_3^{(t)} \log(J_t^{(22)} + 1) \\ & + \beta_4^{(t)} \log(C_t) + \beta_5^{(t)} \log(C_t^{(5)}) \\ & + \beta_6^{(t)} \log(C_t^{(22)}) + \varepsilon_{t+h}^{(h)}. \end{aligned} \quad (23)$$

In analogy to the definition of $RV_t^{(h)}$ above, we define $\log\left(C_t^{(h)}\right) = \frac{1}{h}\sum_{j=1}^{h} \log\left(C_{t-j+1}\right)$ and $J_t^{(h)} = \sum_{j=1}^{h} J_{t-j+1}$. Note that the jumps are aggregated, not averaged.

The next model is one of the HAR specifications outlined by Patton and Sheppard (2015), who separated realized volatilites into semi-variances to include measures for positive and negative daily log-returns (r_t), as well as possible leverage effects. This model is labeled HAR-PS:

$$\begin{aligned}\log(RV_{t+h}^{(h)}) = {} & \beta_0^{(t)} + \beta_1^{(t)} \log(RS_t^+) \\ & + \beta_2^{(t)} \log(RS_t^-) + \beta_3^{(t)} I_{\{r_t<0\}} \log(RV_t) \\ & + \beta_4^{(t)} \log(RV_t^{(5)}) + \beta_5^{(t)} \log(RV_t^{(22)}) + \varepsilon_{t+h}^{(h)}. \end{aligned} \quad (24)$$

Finally, we use a leverage variant of the HAR-CJ, which was proposed by Corsi and Renò (2012). This model separates the aggregated negative daily log-returns over the corresponding periods to account for leverage effects. The LHAR-CJ reads:

$$\begin{aligned}\log(RV_{t+h}^{(h)}) = {} & \beta_0^{(t)} + \beta_1^{(t)} \log(J_t + 1) + \beta_2^{(t)} \log(J_t^{(5)} + 1) \\ & + \beta_3^{(t)} \log(J_t^{(22)} + 1) \\ & + \beta_4^{(t)} \log(C_t) + \beta_5^{(t)} \log(C_t^{(5)}) + \beta_6^{(t)} \log(C_t^{(22)}) \\ & + \beta_7^{(t)} r_t^- + \beta_8^{(t)} r_t^{(5)-} + \beta_9^{(t)} r_t^{(22)-} + \varepsilon_{t+h}^{(h)}, \end{aligned} \quad (25)$$

with

$$r_t^{(h)-} = \frac{1}{h} I_{\{(r_t+\cdots+r_{t-h+1})<0\}} \left(r_t + \cdots + r_{t-h+1}\right). \tag{26}$$

The choice of the HAR model and its extensions is motivated by the fact that the existing literature has shown convincingly that this model class is the most appropriate framework for modeling and forecasting the intra-day volatility (such as the realized volatility and the median realized volatility). This has been shown not only for agricultural commodities (Tian et al., 2017a, 2017b; Yang et al., 2017), but also for other commodities, such as crude oil, copper and aluminum, as well as stock market indices (Corsi & Renò, 2012; Degiannakis & Filis, 2017; Sévi, 2014; Zhang, 2017).

2.3. Forecasting and evaluation

As was outlined in Section 2.2, we use a different regression model for each forecasting horizon h. For example, when estimating the HAR model for $h = 66$, i.e., $\log(RV_{t+66}^{(66)})$, we obtain a prediction of the average RV for the next 66 days and use it as an estimate for the realized volatility in 66 days. Doing so allows us, firstly, to circumvent any iterative forecasting procedure and, secondly, to use the one-day-ahead prediction for each model regardless of the forecasting horizon h. The idea is taken directly from Corsi and Renò (2012).

We evaluate our forecasting results from the presented models over the h-day-ahead horizons, for $h = 1, 5, \ldots, 66$, by employing three widely-used loss functions, namely the mean squared prediction error (MSPE), the mean absolute percentage error (MAPE), and the QLIKE (Patton, 2011):

$$MSPE = \sqrt{N^{-1} \sum_{t=1}^{N} \left(RV_t - \widehat{RV}_t\right)^2}, \tag{27}$$

$$MAPE = N^{-1} \sum_{t=1}^{N} \frac{\left|RV_t - \widehat{RV}_t\right|}{RV_t}, \tag{28}$$

$$QLIKE = N^{-1} \sum_{t=1}^{N} \left(\log(\widehat{RV}_t) + \frac{\widehat{RV}_t}{RV_t}\right), \tag{29}$$

where RV_t and $\widehat{RV}_t$ are the actual realized volatility and the forecasted RV, respectively, at the different forecasting horizons, and N is the number of real out-of-sample forecasts. The forecasting errors are then compared using the model confidence set (MCS, Hansen, Lunde, & Nason, 2011). The MCS is built by iteratively comparing all forecasts under consideration, the set $\mathcal{M}^0$, and creating a subset of models with a performance that is statistically indistinguishable from that of the best model, $\mathcal{M}^*$. Here, the best model refers to the one with the lowest loss function (MSPE, MAPE, and QLIKE). Thus, all models that belong to the set $\overline{\mathcal{M}^*}$, which are not part of the MCS, perform statistically worse than all models that are included in the MCS. Following Hansen et al. (2011), we calculate two MCS sets, the $\mathcal{M}^*_{90\%}$ for $\alpha = 10\%$ and $\mathcal{M}^*_{75\%}$ for $\alpha = 25\%$; i.e., we construct a larger set of models with a confidence level of 90% and a more restrictive subset of the best models at the cost of a lower confidence of 75%. We calculate the MCS using the T_R statistic and 10,000 bootstraps with a block length of three.[4]

Moreover, we evaluate the directional accuracy of the predicted RV. To this end, we calculate the success ratio (SR) by

$$SR = N^{-1} \sum_{t=1}^{N} \mathbf{I}_{RV_t \cdot \widehat{RV}_t > 0}, \tag{30}$$

where $\mathbf{I}_{RV_t \cdot \widehat{RV}_t > 0}$ is an indicator function that takes a value of one if $RV_t \cdot \widehat{RV}_t > 0$ and zero otherwise.

Thus, SR displays the ratio of a model's success in correctly predicting the directional movement of the actual time series. We obtain directions from non-negative volatility forecasts by de-meaning the actual realized volatility RV_t and its forecast ($\widehat{RV}_t$) by their corresponding overall mean beforehand. SR is then tested using the test statistic presented by Pesaran and Timmermann (1992).[5]

We should note here that the same loss functions and evaluation methods are utilized for the $MedRV$ forecasts.

3. Data

Our data set consists of tick-by-tick prices of the most liquid front month futures contracts of corn, rough rice, soybean, sugar, and wheat, traded at the CME and ICE, sampled from January 4, 2010, to June 30, 2017. The time period is dictated by the data availability of these futures contracts. We circumvent microstructure noise by aggregating our data to 5 min prices; see also Andersen and Bollerslev (1998), Degiannakis (2008), and Liu, Patton, and Sheppard (2015). Subsequently, we obtain data on $M = 1\,898$ trading days, with a total number of intra-day prices ranging from $m_{\text{total}} = 234\,798$ (sugar) to $m_{\text{total}} = 399\,190$ (rice). For our in-sample analysis we use the full number of daily observations, whereas for the real out-of-sample forecasts we use the period from January 4, 2010, to December 31, 2012, for our estimation period and the period from January 2, 2013, to June 30, 2017, for the out-of-sample forecasts, based on a rolling window approach with a fixed window length of three years (roughly 750 observations). We opt for a rolling window approach because of its superior ability to capture changes in the market conditions, as suggested by Degiannakis and Filis (2017), Degiannakis, Filis, and Hassani (2018), and Engle, Hong, and Kane (1990).

Table 1 provides an overview of the sampling times and data sources, while descriptive statistics and test

---

[4] Our code for the estimation and forecasting is based on the code provided by Andrew Patton (http://public.econ.duke.edu/~ap172/). The calculations of the MCS are performed using the MFE MatLab toolbox of Kevin Sheppard, available from his personal webpage https://www.kevinsheppard.com/MFE_Toolbox. All estimations, forecasts, and calculations are carried out in Matlab 2018a using an Intel i7-7700 and 32 GB RAM.

[5] Pesaran and Timmermann (1992) provide the test statistic $\frac{SR - SR^*}{\sqrt{\text{var}(SR) - \text{var}(SR^*)}} \overset{a}{\sim} N(0,1)$, where $SR^* = P \cdot \widehat{P} + (1-P) \cdot (1-\widehat{P})$, $\text{var}(SR) = SR^* \cdot (1 - SR^*)/N$, $\text{var}(SR^*) = \left(2\widehat{P} - 1\right)^2 \cdot P \cdot (1-P)/N + (2P-1)^2 \cdot \widehat{P} \cdot (1-\widehat{P})/N + 4P \cdot \widehat{P} \cdot (1-P) \cdot (1-\widehat{P})/N^2$, $P = N^{-1} \sum_{t=1}^{N} \mathbf{I}_{RV_t > 0}$, and $\widehat{P} = N^{-1} \sum_{t=1}^{N} \mathbf{I}_{\widehat{RV}_t > 0}$.

Table 1
Overview of the acquired data, its source for each agricultural commodity's futures, and sampling times.

Commodity	Exchange	Ticker	Sampling times (GMT)	Trading pauses (GMT)
Corn	CBOT/CME	CN	Monday (01:00:05)–Friday (23:59:59)	20:01-22:00
Rough rice	CBOT/CME	RR	Monday (08:15:05)–Friday (23:59:59)	20:01-22:00
Soybeans	CBOT/CME	SY	Monday (01:00:05)–Friday (23:59:59)	20:01-22:00
Wheat	CBOT/CME	WC	Monday (11:00:05)–Friday (23:59:59)	14:01-17:00
Sugar	ICE futures U.S.	SB	Monday (05:31:00)–Friday (19:00:00)	–

statistics of the Ljung–Box test for five, ten, and 22 lags (trading days), corresponding to the aggregation in the HAR-type models, are presented in Tables 2–6. We report statistics for the realized volatility (RV_t), the discontinuous jump component (J_t), and the continuous component (C_t) according to the definitions given in Eq. (2) and Eqs. (5)–(8), respectively. Statistics for the alternative measure of the realized volatility, $MedRV$, defined in Eq. (9), are given in the rightmost columns of those tables.

Sugar futures (Table 5) present the highest mean of realized volatilities, at 3.8498, as well as the highest maximum daily volatility, 44.1071, which is almost double the second-highest value of the maximum of RV_t (wheat). Soybean futures (Table 4) show the lowest values of the mean and maximum of RV_t, as well as the lowest standard deviation. The statistics for corn, rough rice, and wheat are all quite similar, and less extreme than those for either sugar or soybeans. The results for the alternative measure of the realized volatility, $MedRV_t$, are qualitatively the same.

We find that the measures for realized volatilities for all five commodities show significant autocorrelations on all lags, tested with the Ljung–Box test. This further motivates the application of autoregressive models such as the HAR and its extensions. Surprisingly, even the jump components J_t for all commodities show autoregressive behaviour, indicating that agricultural commodity futures are indeed a special case relative to the high-frequency prices of crude oil or metal futures. Albeit with lower test statistics than its measures for the realized volatilities, the autocorrelated jump measures suggest that jumps in realized volatilities are a very common occurrence. We work on the idea that high intra-day price movements are the rule rather than the exception for agricultural prices in our sample period. This is supported by the relatively high kurtosis of the realized volatility measures for all commodities. As the continuous component C_t refers to the remaining realized volatility after removing jumps, the Ljung–Box test statistics are naturally much higher and take dimensions similar to RV_t. The findings for $MedRV_t$ and its jump and continuous part decomposition are qualitatively the same. Since $MedRV_t$ is more robust to small and high jumps than RV_t, we would expect a better forecasting performance given this highly volatile data set.

Fig. 1 visualizes two measures of the realized volatility (RV_t and $MedRV_t$) and the jump measure ($J_{t,\alpha}$) for corn, rough rice, soybean, sugar, and wheat in our sample period, January 4, 2010, to June 30, 2017. Interestingly enough, we show that, while the two volatility measures are related closely, there are certain peaks, especially in the case of rice, that are not observed for both measures. This is due to the fact that the $MedRV$ measure is more robust to jumps. Similarly, the jump component behaves rather differently for the different commodities, with a common feature that fewer jumps are apparent during 2013–2014.[6]

4. Results and discussion

4.1. In-sample results

Our in-sample results are presented in Tables 7–11 for RV and in Tables A.1–A.5 (in Appendix A) for $MedRV$, given that the results are qualitatively similar for both volatility measures. Each table shows the parameter estimates and loss functions for all seven models over all five forecasting horizons.

The best model over all commodities and horizons appears to be the LHAR-CJ, which consistently has the highest R^2 and (with a few exemptions) the lowest loss functions; i.e., it always belongs to the $\mathcal{M}^*_{75\%}$. Comparing the class of HAR models with the naive random walk and the AR(1), we conclude that the HAR models are superior with regard to model fit, except in a few instances. This shows that a long-term component in the volatility helps to explain the variance of the volatility. The high t-statistics for the RV and C parameters for horizons of five and 22 days support this assessment. For the random walk, we notice that it performs even worse than the sample mean for forecasting horizons greater than one day, indicated by a negative R^2.

Another interesting observation is that the leverage effect appears weak. Thus, the interaction term between the dummy variable of a negative return and the RV in the in-sample series of corn, rice, soybeans, sugar, and wheat is merely of statistical importance. For the negative return parameters in the LHAR-CJ model, we find that the lag of r_t^- corresponds somewhat to the forecasting horizon h; i.e., we observe higher t-statistics for short forecasting horizons and decreasing t-statistics for longer horizons for the first lag. However, we find the reverse behaviour for the fifth and twenty-second lags. We presume that this association is rooted in the way in which the regression models for the different forecasting horizons are constructed, e.g. for $h = 22$ the model forecasts the average volatility over 22 days, and the leverage component for 22 days of average negative returns contains more information for this regression than the last leverage component for the preceding day.

A similar pattern is noticeable in the jump components of the HAR-CJ and LHAR-CJ models. Again, we see

[6] We note that the daily data for RV, $MedRV$, and their jump components are available from the authors upon request.

Table 2
Descriptive statistics for corn, sampled from January 4, 2010, to June 30, 2017, with $M = 1\,898$ trading days and a total of $m_{total} = 399\,114$ prices at a five-minute interval.

	RV_t	J_t	C_t	$MedRV_t$	J_t^{MedRV}	C_t^{MedRV}
Mean	2.4523	0.2565	2.1958	2.1194	0.1880	2.2644
Minimum	0.2171	0.0000	0.0750	0.0905	0.0000	0.2171
Maximum	18.4265	5.9690	16.4022	13.2742	6.4750	16.4022
StD	1.7878	0.5188	1.6563	1.4810	0.5805	1.6324
Skewness	2.7020	4.5461	2.6810	2.7628	5.3108	2.8505
Kurtosis	14.2612	34.5191	14.0081	14.4542	39.8801	15.4021
Q(5)	1987.95***	18.83***	1883.92***	1955.56***	24.07***	1818.43***
Q(10)	3119.27***	23.68***	3009.55***	3047.09***	45.80***	2854.76***
Q(22)	4696.17***	47.82***	4686.03***	4564.83***	96.88***	4318.17***

Table 3
Descriptive statistics for rough rice, sampled from January 4, 2010, to June 30, 2017, with $M = 1\,898$ trading days and a total of $m_{total} = 399\,190$ prices at a five-minute interval.

	RV_t	J_t	C_t	$MedRV_t$	J_t^{MedRV}	C_t^{MedRV}
Mean	3.1809	1.3842	1.7967	1.8069	0.9439	2.2370
Minimum	0.1245	0.0000	0.0158	0.0040	0.0000	0.0040
Maximum	19.7251	10.1585	18.6148	17.2740	11.1076	18.6148
StD	2.6145	1.4413	1.9326	1.7684	1.4327	2.2589
Skewness	2.0028	2.1103	2.8934	2.6134	2.4035	2.4388
Kurtosis	8.5347	9.0724	16.1702	13.9032	10.5472	11.5642
Q(5)	1395.49***	349.95***	737.04***	940.26***	69.50***	799.13***
Q(10)	2486.75***	632.27***	1332.10***	1687.71***	101.03***	1474.60***
Q(22)	4434.15***	1137.62***	2352.03***	3050.09***	169.53***	2693.43***

Table 4
Descriptive statistics for soybean, sampled from January 4, 2010, to June 30, 2017, with $M = 1\,898$ trading days and a total of $m_{total} = 399\,126$ prices at a five-minute interval.

	RV_t	J_t	C_t	$MedRV_t$	J_t^{MedRV}	C_t^{MedRV}
Mean	1.5387	0.1475	1.3912	1.2902	0.1471	1.3916
Minimum	0.0201	0.0000	0.0043	0.0019	0.0000	0.0019
Maximum	8.4025	5.4881	8.2409	10.7046	5.2553	8.2409
StD	1.0307	0.3581	0.9419	0.8652	0.4306	0.9196
Skewness	2.4411	6.0922	2.4766	2.9417	5.8652	2.5342
Kurtosis	11.4026	61.5027	12.1233	18.7540	50.2153	12.9593
Q(5)	1680.15***	22.01***	1976.96***	2052.24***	16.96***	2172.94***
Q(10)	2479.40***	29.62***	2916.09***	3037.15***	19.63***	3234.40***
Q(22)	3581.27***	43.12***	4120.91***	4289.34***	33.76***	4518.27***

Table 5
Descriptive statistics for sugar, sampled from January 4, 2010, to June 30, 2017, with $M = 1\,898$ trading days and a total of $m_{total} = 234\,798$ prices at a five-minute interval.

	RV_t	J_t	C_t	$MedRV_t$	J_t^{MedRV}	C_t^{MedRV}
Mean	3.8498	0.2875	3.5623	3.2655	0.3095	3.5403
Minimum	0.2853	0.0000	0.2665	0.3312	0.0000	0.2853
Maximum	44.1071	5.3501	44.1071	46.5043	6.5751	44.1071
StD	3.1993	0.6453	3.0801	2.8760	0.8004	3.0541
Skewness	3.2517	3.1877	3.5814	4.3797	3.5174	3.6207
Kurtosis	24.5723	15.5835	28.9848	43.1246	17.7357	29.5813
Q(5)	3260.05***	22.47***	3081.98***	2775.52***	34.32***	2987.32***
Q(10)	5641.97***	42.31***	5320.00***	4792.44***	56.22***	5193.60***
Q(22)	10486.96***	107.35***	9812.76***	8760.67***	119.38***	9588.06***

a correlation of the components' lag with the forecasting horizon for most commodities. However, the statistical significance for the HAR-J, i.e., for the model with only one lagged jump, varies over the five commodities. While we observe slightly statistically significant parameters for corn, rice, sugar, and wheat over all horizons from 1 to 66 days ahead, the parameter is not distinguishable from zero for soybeans.[7]

We conclude from the in-sample analysis that the best-performing model is the most complex one: the

7 Note that this finding is only robust for higher horizons if we look at the RV measure.

Table 6
Descriptive statistics for wheat, sampled from January 4, 2010, to June 30, 2017, with $M = 1\,898$ trading days and a total of $m_{\text{total}} = 399\,114$ prices at a five-minute interval.

	RV_t	J_t	C_t	$MedRV_t$	J_t^{MedRV}	C_t^{MedRV}
Mean	3.2421	0.3139	2.9282	2.7216	0.2813	2.9608
Minimum	0.1040	0.0000	0.1040	0.0601	0.0000	0.1040
Maximum	26.0959	6.4052	26.0959	24.4544	6.7609	26.0959
StD	2.2858	0.6015	2.1958	1.9768	0.6948	2.1531
Skewness	2.8804	3.3899	3.1174	3.2825	3.6660	3.1371
Kurtosis	17.5920	21.0279	20.2421	22.2619	20.6146	20.9127
Q(5)	2343.74***	48.49***	2104.90***	2076.85***	71.31***	2124.42***
Q(10)	3413.07***	66.45***	3022.29***	3007.03***	103.52***	3007.07***
Q(22)	5421.44***	101.57***	4755.90***	4833.95***	162.93***	4705.53***

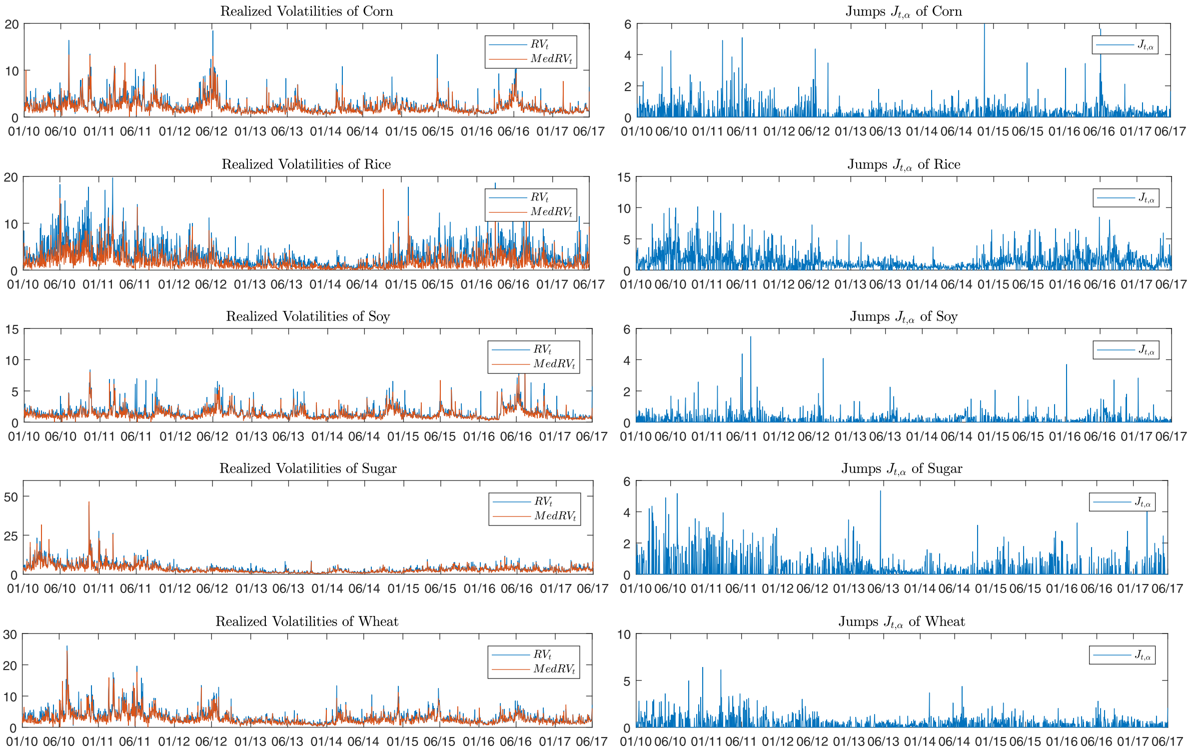

Fig. 1. Realized volatility measures (RV_t and $MedRV_t$) and jump measure ($J_{t,\alpha}$) for corn, rough rice, soybean, sugar, and wheat for the sample period January 4, 2010, to June 30, 2017.

LHAR-CJ depicting long memory, a leverage effect, and a differentiation between continuous and jump components. Moreover, the importance of the lags of the leverage and the jump parameters appears to be associated positively with the forecasting horizon. Thus, we conclude that stylized facts are important for describing the in-sample volatility of agricultural commodities. The fact that LHAR-CJ includes all of those components at different time horizons makes it consistently superior to its peer over all horizons.

4.2. Real out-of-sample forecasting results

The in-sample evaluation shows that the LHAR-CJ is the best-performing model for all agricultural commodities, across all horizons, and for both volatility measures. Nevertheless, to be able to generate solid conclusions we need to assess the performance of our models in real out-of-sample forecasts.

Thus, we now turn our attention to a real out-of-sample forecasting evaluation based on the MSPE, MAPE, and QLIKE. Furthermore, we use the MCS test to identify the set of the best models with equal predictive accuracies. The results are presented in Tables 12–16 for RV.[8] It is clear at first glance that none of the competing models can consistently beat the forecast accuracy that we obtain from the simple HAR model.

More specifically, the random walk, AR, and ARMA models largely underperform the HAR-type models under any loss function and for all commodities, although they

8 The results for $MedRV$ are presented in Tables A.6–A.10 Appendix A.

Table 7
In-sample regression results for corn with RV.

h	1	5	10	22	44	66
Random walk						
adj. R^2	0.2291	0.4768	0.4601	0.3986	0.1035	−0.2900
MSPE	1.6701	1.6512	1.6991**	1.7574*	1.9139	1.9736
MAPE	0.4281	0.4417	0.4640	0.4954	0.5877	0.6530
QLIKE	1.8564	1.8607**	1.8720**	1.9001*	1.9708	2.0336
AR(1)						
c	0.2715	0.1828	0.1888	0.2056	0.3070	0.4549
	(13.7709)	(14.1551)	(15.1709)	(14.9843)	(19.4514)	(24.9167)
$RV^{(h)}$	0.6144	0.7377	0.7296	0.7006	0.5538	0.3460
	(26.6586)	(44.3740)	(44.8092)	(36.9599)	(28.4631)	(15.8790)
adj. R^2	0.3770	0.5452	0.5329	0.4874	0.2972	0.1109
MSPE	1.4961	1.6007	1.6591**	1.7216*	1.8356	1.8628
MAPE	0.3763	0.4121*	0.4324*	0.4630**	0.5186*	0.5340**
QLIKE	1.8214**	1.8384**	1.8489**	1.8636**	1.8969**	1.9134**
ARMA						
c	0.0361	0.0886	0.1202	0.2298	0.5748	0.7806
	(4.4106)	(7.4290)	(8.6521)	(11.4874)	(22.7837)	(16.3591)
$RV^{(h)}$	0.9485	0.8733	0.8279	0.6692	0.1860	−0.1078
	(98.4321)	(60.7486)	(51.8560)	(28.6283)	(5.8400)	(1.7522)
$\varepsilon^{(h)}$	−0.6590	−0.3186	−0.2148	0.0671	0.6195	0.5319
	(31.1119)	(11.5396)	(7.4564)	(1.9298)	(21.7651)	(10.2136)
adj. R^2	0.4574	0.5645	0.5441	0.4908	0.3950	0.1507
MSPE	1.4134**	1.5866*	1.6557**	1.7181**	1.8065**	1.8751
MAPE	0.3493**	0.4043**	0.4300**	0.4614**	0.5113*	0.5362**
QLIKE	1.8098**	1.8351**	1.8483**	1.8632**	1.8987**	1.9177**
HAR						
c	0.0769	0.1143	0.1485	0.1974	0.2830	0.3627
	(3.9033)	(8.2035)	(11.2609)	(15.1118)	(21.7301)	(25.6239)
$RV^{(1)}$	0.2710	0.1642	0.1352	0.0931	0.0723	0.0559
	(8.4593)	(7.4805)	(6.4997)	(4.6027)	(3.7074)	(2.7557)
$RV^{(5)}$	0.3677	0.3480	0.2780	0.2294	0.2333	0.2096
	(7.1703)	(9.9696)	(8.5140)	(7.3187)	(7.5987)	(6.5342)
$RV^{(22)}$	0.2507	0.3220	0.3723	0.3915	0.2867	0.2130
	(5.2222)	(9.5482)	(11.5066)	(12.6777)	(9.8721)	(6.8432)
adj. R^2	0.4616	0.5829	0.5719	0.5378	0.4416	0.3271
MSPE	1.4138**	1.5823	1.6542**	1.7199**	1.8160	1.8440
MAPE	0.3474**	0.4036**	0.4299*	0.4611**	0.5101*	0.5271**
QLIKE	1.8094**	1.8347**	1.8475**	1.8635**	1.8910**	1.9091**
HAR-J						
c	0.0803	0.1228	0.1562	0.2069	0.2860	0.3600
	(3.8114)	(8.0783)	(10.9821)	(14.8998)	(20.6688)	(24.1734)
$RV^{(1)}$	0.2767	0.1788	0.1485	0.1095	0.0776	0.0512
	(7.7882)	(7.2318)	(6.3356)	(4.7209)	(3.5889)	(2.3196)
$RV^{(5)}$	0.3672	0.3466	0.2768	0.2280	0.2329	0.2100
	(7.1720)	(9.9612)	(8.4759)	(7.2561)	(7.5777)	(6.5449)
$RV^{(22)}$	0.2496	0.3190	0.3695	0.3880	0.2856	0.2139
	(5.1870)	(9.4131)	(11.3890)	(12.5545)	(9.8227)	(6.8864)
$J^{(1)}$	−0.0204	−0.0522	−0.0473	−0.0583	−0.0187	0.0169
	(−0.3689)	(−1.3986)	(−1.4217)	(−1.8507)	(−0.5884)	(0.5274)
adj. R^2	0.4614	0.5832	0.5721	0.5385	0.4414	0.3268
MSPE	1.4137**	1.5804*	1.6531**	1.7181**	1.8163	1.8437
MAPE	0.3475**	0.4035**	0.4296*	0.4613**	0.5103*	0.5271**
QLIKE	1.8095**	1.8345**	1.8473**	1.8636**	1.8911**	1.9091**
HAR-CJ						
c	0.1979	0.2560	0.2925	0.3037	0.2720	0.2804
	(4.4140)	(8.1272)	(10.0820)	(11.4628)	(10.7127)	(10.4344)
$J^{(1)}$	0.1488	0.0859	0.0595	0.0366	0.0223	0.0142
	(3.2641)	(2.8191)	(2.1244)	(1.4198)	(0.8341)	(0.5198)
$J^{(5)}$	0.0730	0.0575	0.0326	−0.0206	−0.0183	−0.0133
	(2.3276)	(2.6926)	(1.6555)	(−1.0230)	(−0.9383)	(−0.6589)
$J^{(22)}$	−0.0291	−0.0381	−0.0331	0.0076	0.0769	0.1126
	(−0.9481)	(−1.6990)	(−1.6055)	(0.3973)	(4.1672)	(5.9815)

(*continued on next page*)

Table 7 (*continued*).

h	1	5	10	22	44	66
$C^{(1)}$	0.2383	0.1439	0.1178	0.0816	0.0654	0.0516
	(7.8100)	(6.9921)	(6.1939)	(4.3552)	(3.6248)	(2.7543)
$C^{(5)}$	0.3260	0.3144	0.2675	0.2477	0.2479	0.2211
	(6.8119)	(9.6263)	(8.8319)	(8.5036)	(8.4374)	(7.1935)
$C^{(22)}$	0.2685	0.3373	0.3702	0.3501	0.2074	0.1179
	(5.6877)	(9.5194)	(11.0729)	(11.4272)	(6.9175)	(3.6910)
adj. R^2	0.4609	0.5863	0.5783	0.5435	0.4410	0.3314
MSPE	1.4159**	1.5747**	1.6495**	1.7179**	1.8133	1.8432
MAPE	0.3480**	0.4036**	0.4268**	0.4612**	0.5086*	0.5245**
QLIKE	1.8089**	1.8337**	1.8458**	1.8637**	1.8907**	1.9079**
HAR-PS						
c	0.2720	0.2315	0.2404	0.2625	0.3322	0.4021
	(8.8286)	(10.3589)	(10.9672)	(12.3914)	(16.5556)	(18.8381)
RS^+	0.0985	0.0574	0.0376	0.0207	0.0117	0.0009
	(3.6287)	(3.1694)	(2.1823)	(1.2009)	(0.6690)	(0.0485)
RS^-	0.1751	0.1069	0.0912	0.0708	0.0574	0.0545
	(5.0766)	(4.4604)	(3.8958)	(3.1795)	(2.6153)	(2.4125)
$\mathbf{I}_{r_t<0}RV^{(1)}$	−0.0152	−0.0076	0.0010	−0.0114	−0.0171	−0.0264
	(−0.5522)	(−0.3611)	(0.0521)	(−0.5884)	(−0.9656)	(−1.5331)
$RV^{(5)}$	0.3762	0.3537	0.2856	0.2385	0.2469	0.2256
	(7.3238)	(10.0583)	(8.6690)	(7.5252)	(7.9694)	(6.9823)
$RV^{(22)}$	0.2516	0.3226	0.3726	0.3914	0.2860	0.2117
	(5.2345)	(9.5383)	(11.4684)	(12.6516)	(9.8359)	(6.8047)
adj. R^2	0.4593	0.5815	0.5709	0.5366	0.4399	0.3258
MSPE	1.4157**	1.5840	1.6548**	1.7197**	1.8165	1.8439
MAPE	0.3477**	0.4040**	0.4305*	0.4611**	0.5099*	0.5270**
QLIKE	1.8096**	1.8350**	1.8479**	1.8633**	1.8909**	1.9092**
LHAR-CJ						
c	0.1869	0.2310	0.2741	0.2979	0.2578	0.2612
	(3.7655)	(6.8504)	(8.8028)	(10.1694)	(9.1067)	(8.7459)
$J^{(1)}$	0.1429	0.0806	0.0548	0.0343	0.0208	0.0139
	(3.1675)	(2.6713)	(1.9646)	(1.3321)	(0.7855)	(0.5176)
$J^{(5)}$	0.0732	0.0574	0.0324	−0.0207	−0.0181	−0.0129
	(2.3617)	(2.7158)	(1.6637)	(−1.0333)	(−0.9329)	(−0.6382)
$J^{(22)}$	−0.0382	−0.0337	−0.0323	0.0051	0.0848	0.1292
	(−1.1599)	(−1.4448)	(−1.4995)	(0.2468)	(4.2261)	(6.2994)
$C^{(1)}$	0.2224	0.1352	0.1085	0.0745	0.0593	0.0478
	(7.2915)	(6.5716)	(5.7081)	(3.9539)	(3.2836)	(2.5466)
$C^{(5)}$	0.3280	0.3064	0.2632	0.2499	0.2524	0.2274
	(6.8660)	(9.3713)	(8.6812)	(8.4827)	(8.5176)	(7.2767)
$C^{(22)}$	0.2793	0.3413	0.3749	0.3531	0.2008	0.1029
	(5.9710)	(9.6185)	(11.2086)	(11.4265)	(6.6458)	(3.1870)
$r_t^{-,(1)}$	−0.0417	−0.0225	−0.0240	−0.0188	−0.0171	−0.0116
	(−3.1915)	(−2.5805)	(−3.0373)	(−2.7349)	(−2.5435)	(−1.7253)
$r_t^{-,(5)}$	−0.0030	0.0009	−0.0001	−0.0009	0.0020	0.0044
	(−1.0386)	(0.4832)	(−0.0528)	(−0.5000)	(1.0786)	(2.2776)
$r_t^{-,(22)}$	−0.0601	−0.0789	−0.0632	−0.0123	0.0553	0.1119
	(−1.1275)	(−2.4668)	(−2.2226)	(−0.4630)	(2.1065)	(4.4947)
adj. R^2	0.4653	0.5896	0.5816	0.5447	0.4431	0.3379
MSPE	1.4050**	1.5757**	1.6520**	1.7181**	1.8090**	1.8375**
MAPE	0.3453**	0.4029**	0.4258**	0.4610**	0.5065**	0.5231**
QLIKE	1.8079**	1.8336**	1.8456**	1.8635**	1.8899**	1.9073**

Notes: * and ** indicate inclusion in the $\mathcal{M}^*_{90\%}$ and $\mathcal{M}^*_{75\%}$, respectively. The t-statistics for the parameter estimates are given in parentheses.

are among the best-performing models at the longer forecasting horizons for the RV measure under a specific loss function per commodity.

Turning to the HAR-type models, we observe that they outperform the random walk and AR models significantly based on the MCS test, except for the cases outlined earlier. The most important finding, though, is that the simple HAR model is not outperformed consistently by any of its extended versions, namely the HAR-J, HAR-CJ, HAR-PS and LHAR-CJ models, a finding that holds for both volatility measures. Hence, building forecasting models based on the jump component, the continuous component, the signed jumps, and the volatility or return leverage does not improve the forecasting accuracy. Thus, there is no scope for adding complexity to the predictive models without obtaining a significant predictive gain. This finding is in some contrast to those of Luo et al. (2019), Tian et al. (2017a, 2017b), and Yang et al. (2017), who maintain that the jump component and the introduction of time-varying HAR coefficients help to improve the forecast accuracy of agricultural commodities' price volatilities. However, these results are not contradictory.

Table 8
In-sample regression results for rough rice with RV.

h	1	5	10	22	44	66
Random walk						
adj. R^2	0.1138	0.5612	0.6559	0.6563	0.7404	0.7227
MSPE	2.7428	2.3759	2.3925**	2.4649	2.3974**	2.4587
MAPE	0.7216	0.6141	0.6208	0.6423	0.6306	0.6758
QLIKE	2.1942	2.1099**	2.1159**	2.1302**	2.1310**	2.1768
AR(1)						
c	0.3812	0.1890	0.1482	0.1475	0.1063	0.1066
	(15.2813)	(11.7710)	(9.6476)	(9.8653)	(8.2372)	(7.9070)
$RV^{(h)}$	0.5567	0.7807	0.8281	0.8281	0.8715	0.8640
	(26.5044)	(53.6456)	(57.8886)	(55.8951)	(71.8209)	(74.0386)
adj. R^2	0.3093	0.6088	0.6851	0.6854	0.7567	0.7413
MSPE	2.3864	2.3566	2.3908	2.4593	2.4157*	2.4768
MAPE	0.6134	0.5945	0.6074*	0.6284	0.6221	0.6592
QLIKE	2.1165**	2.0991**	2.1084**	2.1206**	2.1173**	2.1445**
ARMA						
c	0.0122	0.0364	0.0360	0.0458	0.0805	0.1260
	(2.7418)	(5.0655)	(5.0083)	(5.5321)	(7.7323)	(9.2143)
$RV^{(h)}$	0.9861	0.9584	0.9581	0.9451	0.8964	0.8344
	(217.6556)	(130.3651)	(134.2256)	(112.2272)	(81.1036)	(62.4972)
$\varepsilon^{(h)}$	−0.8385	−0.5577	−0.5131	−0.4122	−0.0849	0.3436
	(59.7307)	(23.9696)	(21.1455)	(16.0591)	(3.0020)	(11.7358)
adj. R^2	0.4393	0.6644	0.7069	0.7269	0.7705	0.8030
MSPE	2.2252	2.3104**	2.3725**	2.4179**	2.3997**	2.4170**
MAPE	0.5399	0.5713**	0.5949**	0.6118**	0.6186**	0.6470**
QLIKE	2.0656**	2.0848**	2.0996**	2.1092**	2.1195**	2.1481**
HAR						
c	0.0730	0.0962	0.1138	0.1427	0.1596	0.1599
	(2.8141)	(5.8371)	(7.4777)	(9.8667)	(12.1206)	(12.3609)
$RV^{(1)}$	0.1669	0.0724	0.0611	0.0513	0.0366	0.0316
	(5.7515)	(4.1456)	(3.9159)	(3.6719)	(2.7543)	(2.4538)
$RV^{(5)}$	0.2778	0.3124	0.3048	0.1901	0.1135	0.0986
	(4.9183)	(9.5792)	(10.5476)	(7.0905)	(4.3935)	(3.8385)
$RV^{(22)}$	0.4712	0.5036	0.5019	0.5920	0.6630	0.6755
	(8.6123)	(15.5121)	(17.5319)	(22.1786)	(27.9778)	(26.8721)
adj. R^2	0.4396	0.6576	0.7028	0.7034	0.7237	0.7347
MSPE	2.2208	2.3163*	2.3666**	2.4625	2.4473	2.4477
MAPE	0.5375	0.5739**	0.5939**	0.6301	0.6284	0.6483**
QLIKE	2.0651**	2.0867**	2.0979**	2.1221**	2.1235**	2.1378**
HAR-J						
c	0.1168	0.1137	0.1337	0.1700	0.1780	0.1739
	(3.2765)	(5.3059)	(6.9838)	(8.9676)	(10.1453)	(10.2858)
$RV^{(1)}$	0.2117	0.0904	0.0815	0.0794	0.0555	0.0459
	(5.2178)	(3.7525)	(3.9482)	(4.1602)	(3.0467)	(2.6313)
$RV^{(5)}$	0.2793	0.3130	0.3055	0.1911	0.1143	0.0992
	(4.9471)	(9.5988)	(10.5656)	(7.1195)	(4.4124)	(3.8529)
$RV^{(22)}$	0.4668	0.5019	0.4999	0.5892	0.6611	0.6740
	(8.5367)	(15.4413)	(17.4639)	(22.0114)	(27.7839)	(26.7343)
$J^{(1)}$	−0.0974	−0.0390	−0.0444	−0.0610	−0.0411	−0.0310
	(−1.6883)	(−1.2108)	(−1.5683)	(−2.1543)	(−1.5836)	(−1.2662)
adj. R^2	0.4402	0.6577	0.7030	0.7040	0.7239	0.7347
MSPE	2.2182	2.3174*	2.3657**	2.4615	2.4467*	2.4494
MAPE	0.5372	0.5743**	0.5942**	0.6303	0.6278	0.6486**
QLIKE	2.0652**	2.0869**	2.0980**	2.1221**	2.1232**	2.1381**
HAR-CJ						
c	−0.1526	−0.1556	−0.1641	−0.3002	−0.3468	−0.5027
	(−0.8698)	(−1.5025)	(−1.8874)	(−3.4272)	(−4.3784)	(−7.1070)
$J^{(1)}$	0.0606	0.0208	0.0223	0.0225	0.0138	0.0106
	(1.8315)	(1.0752)	(1.2972)	(1.3461)	(0.9314)	(0.7545)
$J^{(5)}$	0.1464	0.1650	0.1411	0.0490	0.0370	0.0162
	(2.9161)	(5.5419)	(5.4709)	(2.0006)	(1.6581)	(0.7645)
$J^{(22)}$	0.1885	0.1877	0.2042	0.2994	0.3231	0.3818
	(2.9139)	(4.9581)	(6.3064)	(9.3110)	(10.9483)	(14.5076)

(*continued on next page*)

Table 8 (*continued*).

h	1	5	10	22	44	66
$C^{(1)}$	0.1160	0.0503	0.0410	0.0340	0.0248	0.0212
	(5.4489)	(3.9183)	(3.7223)	(3.3817)	(2.6925)	(2.3856)
$C^{(5)}$	0.1461	0.1623	0.1675	0.1256	0.0698	0.0707
	(3.4427)	(6.8289)	(7.7370)	(5.9317)	(3.6895)	(3.8224)
$C^{(22)}$	0.2726	0.3013	0.2914	0.3022	0.3438	0.3145
	(5.2465)	(10.1374)	(11.1958)	(12.0409)	(15.0756)	(13.8898)
adj. R^2	0.4395	0.6592	0.7060	0.7104	0.7310	0.7435
MSPE	2.2207	2.3076**	2.3585**	2.4486	2.4377*	2.4330**
MAPE	0.5350	0.5753**	0.5947**	0.6279	0.6283	0.6452**
QLIKE	2.0642**	2.0884**	2.0980**	2.1209**	2.1238**	2.1352**
HAR-PS						
c	0.1780	0.1408	0.1541	0.1753	0.1798	0.1773
	(5.1370)	(6.7532)	(7.8460)	(9.4277)	(10.2804)	(10.4298)
RS^{+}	0.0559	0.0168	0.0151	0.0086	−0.0034	−0.0028
	(2.0366)	(0.9410)	(0.9657)	(0.6119)	(−0.2688)	(−0.2322)
RS^{-}	0.0851	0.0433	0.0394	0.0354	0.0308	0.0262
	(2.5813)	(2.1253)	(2.1929)	(2.1244)	(1.8406)	(1.7066)
$\mathbf{I}_{r_t<0}RV^{(1)}$	0.0384	0.0115	0.0034	0.0040	0.0090	0.0077
	(1.4279)	(0.6939)	(0.2324)	(0.2852)	(0.6788)	(0.6313)
$RV^{(5)}$	0.2861	0.3202	0.3107	0.1966	0.1203	0.1047
	(5.0307)	(9.7252)	(10.6517)	(7.2618)	(4.6319)	(4.0509)
$RV^{(22)}$	0.4685	0.5019	0.5008	0.5907	0.6609	0.6737
	(8.5650)	(15.4629)	(17.5027)	(22.1376)	(27.9160)	(26.7743)
adj. R^2	0.4394	0.6570	0.7023	0.7029	0.7237	0.7346
MSPE	2.2149	2.3176*	2.3669**	2.4628	2.4464*	2.4463
MAPE	0.5377	0.5742**	0.5943**	0.6303	0.6276	0.6480**
QLIKE	2.0649**	2.0870**	2.0980**	2.1221**	2.1232**	2.1378**
LHAR-CJ						
c	−0.1110	−0.0666	−0.0642	−0.1946	−0.2393	−0.3827
	(−0.6211)	(−0.6377)	(−0.7360)	(−2.2751)	(−3.1032)	(−5.4788)
$J^{(1)}$	0.0500	0.0156	0.0182	0.0181	0.0092	0.0065
	(1.5437)	(0.8158)	(1.0629)	(1.0906)	(0.6268)	(0.4656)
$J^{(5)}$	0.1410	0.1579	0.1333	0.0409	0.0292	0.0112
	(2.8643)	(5.4661)	(5.3211)	(1.7391)	(1.3563)	(0.5457)
$J^{(22)}$	0.1591	0.1491	0.1632	0.2543	0.2785	0.3336
	(2.4184)	(3.9173)	(5.0533)	(8.1537)	(9.7224)	(12.8497)
$C^{(1)}$	0.0984	0.0420	0.0351	0.0280	0.0189	0.0159
	(4.5401)	(3.2324)	(3.1438)	(2.7927)	(2.0501)	(1.7946)
$C^{(5)}$	0.1548	0.1647	0.1676	0.1237	0.0682	0.0693
	(3.6572)	(6.8945)	(7.7898)	(5.9659)	(3.7063)	(3.8737)
$C^{(22)}$	0.2811	0.3173	0.3099	0.3233	0.3653	0.3367
	(5.4272)	(10.7287)	(12.0586)	(13.2907)	(16.5240)	(15.2689)
$r_t^{-,(1)}$	−0.0790	−0.0228	−0.0086	−0.0072	−0.0069	−0.0058
	(−4.6098)	(−2.1229)	(−0.9357)	(−0.8101)	(−0.8565)	(−0.7414)
$r_t^{-,(5)}$	−0.0090	−0.0145	−0.0154	−0.0145	−0.0140	−0.0145
	(−1.8354)	(−5.0678)	(−6.0187)	(−5.7797)	(−6.2562)	(−6.5579)
$r_t^{-,(22)}$	−0.1337	−0.1607	−0.1905	−0.2825	−0.2508	−0.2010
	(−1.5981)	(−3.0681)	(−4.1927)	(−6.3198)	(−6.3700)	(−4.7859)
adj. R^2	0.4489	0.6691	0.7177	0.7279	0.7470	0.7572
MSPE	2.1821**	2.3030**	2.3561**	2.4436*	2.4423*	2.4380**
MAPE	0.5278**	0.5716**	0.5915**	0.6203*	0.6265	0.6430**
QLIKE	2.0595**	2.0852**	2.0953**	2.1156**	2.1227**	2.1346**

Notes: * and ** indicate inclusion in the $\mathcal{M}^*_{90\%}$ and $\mathcal{M}^*_{75\%}$, respectively. The t-statistics for the parameter estimates are given in parentheses.

The substantial findings of Tian et al. (2017a, 2017b) and Yang et al. (2017) are derived from data on Chinese futures markets, while our price data come from North American markets. A comparison of the realized volatility measures of these two markets, as well as of the results of the aforementioned studies, shows that Chinese and U.S. futures markets behave differently and may be driven by dissimilar factors. One of the most important reasons for this apparent difference of market behavior is the structure of investors in the two markets, where the Chinese market is driven by speculators much more than the U.S. market (Bloomberg, 2019; Fan & Zhang, 2018; Klein & Todorova, 2018).

However, we maintain that the expected outcome for the jump components is not to provide any forecasting gains; instead, they are built so as to capture surprise (sudden) changes in volatility. Hence, the jump components do not encompass any element of either long or short memory; they are simply non-autocorrelated zero-mean stochastic processes. This is the reason why the jump component is able to provide a better fit to the predictive regressions in the in-sample analysis, whereas

Table 9
In-sample regression results for soybean with RV.

h	1	5	10	22	44	66
Random walk						
adj. R^2	0.0878	0.4370	0.4079	0.2215	−0.2846	−0.8494
MSPE	1.0153	0.9843	1.0273	1.0670	1.1603	1.1986
MAPE	0.4792	0.4786	0.5046	0.5586	0.6631	0.7130
QLIKE	1.4582**	1.4631**	1.4777**	1.5210*	1.6081	1.6563
AR(1)						
c	0.1179	0.0706	0.0728	0.0942	0.1642	0.2599
	(7.8375)	(8.5864)	(9.2025)	(10.1223)	(13.6241)	(20.4670)
$RV^{(h)}$	0.5438	0.7186	0.7049	0.6131	0.3473	0.0198
	(17.3488)	(42.8571)	(43.0140)	(30.8879)	(13.4734)	(0.7105)
adj. R^2	0.2944	0.5156	0.4940	0.3681	0.1109	−0.0002
MSPE	0.9021	0.9486*	0.9933**	1.0341*	1.0843	1.0782**
MAPE	0.4357	0.4528**	0.4774**	0.5180**	0.5677**	0.5655**
QLIKE	1.4293**	1.4433**	1.4540**	1.4791**	1.5117**	1.5155**
ARMA						
c	0.0117	0.0388	0.0639	0.1324	0.2731	0.4155
	(2.9799)	(5.4589)	(6.8698)	(11.0727)	(20.3049)	(19.8041)
$RV^{(h)}$	0.9534	0.8434	0.7430	0.4764	−0.0653	−0.5738
	(92.6966)	(46.3489)	(33.2360)	(16.6055)	(1.4788)	(7.0828)
$\varepsilon^{(h)}$	−0.7161	−0.2685	−0.0735	0.2270	0.5765	0.7303
	(35.3722)	(9.4306)	(2.2693)	(6.6787)	(15.7752)	(10.3926)
adj. R^2	0.3857	0.5314	0.4957	0.3842	0.2013	0.0323
MSPE	0.8554*	0.9462*	0.9927**	1.0289**	1.0702**	1.0871
MAPE	0.4124**	0.4469**	0.4771**	0.5152**	0.5620**	0.5705*
QLIKE	1.4263**	1.4398**	1.4542**	1.4789**	1.5081**	1.5163**
HAR						
c	0.0340	0.0482	0.0633	0.0911	0.1399	0.1858
	(2.6427)	(5.6979)	(7.7652)	(10.4939)	(14.5342)	(18.7151)
$RV^{(1)}$	0.2191	0.1150	0.1053	0.0803	0.0586	0.0449
	(5.8359)	(4.2713)	(4.4042)	(3.5550)	(2.7998)	(2.2614)
$RV^{(5)}$	0.3918	0.4328	0.3734	0.3072	0.2986	0.2323
	(7.2888)	(11.8756)	(11.2228)	(9.0607)	(9.2428)	(7.2685)
$RV^{(22)}$	0.2530	0.2542	0.2623	0.2434	0.0897	0.0080
	(5.1857)	(7.6517)	(8.4722)	(7.7145)	(2.8859)	(0.2511)
adj. R^2	0.3866	0.5395	0.5253	0.4474	0.3028	0.1651
MSPE	0.8546*	0.9408**	0.9916**	1.0314**	1.0741**	1.0890
MAPE	0.4063**	0.4486**	0.4693**	0.5142**	0.5577**	0.5710*
QLIKE	1.4208**	1.4413**	1.4487**	1.4764**	1.5052**	1.5172**
HAR-J						
c	0.0563	0.0702	0.0824	0.1082	0.1502	0.1875
	(3.6376)	(6.1308)	(7.7444)	(10.0596)	(13.3946)	(16.4568)
$RV^{(1)}$	0.2540	0.1493	0.1351	0.1070	0.0747	0.0476
	(5.4865)	(4.5899)	(4.6437)	(3.9090)	(2.9985)	(2.0698)
$RV^{(5)}$	0.3817	0.4228	0.3647	0.2994	0.2939	0.2316
	(6.9829)	(11.4658)	(10.8152)	(8.7342)	(9.0113)	(7.2123)
$RV^{(22)}$	0.2488	0.2501	0.2587	0.2401	0.0878	0.0077
	(5.0893)	(7.5435)	(8.3703)	(7.6444)	(2.8324)	(0.2416)
$J^{(1)}$	−0.1484	−0.1460	−0.1265	−0.1135	−0.0682	−0.0113
	(−2.1328)	(−2.5815)	(−2.5356)	(−2.4237)	(−1.6642)	(−0.2858)
adj. R^2	0.3881	0.5422	0.5276	0.4497	0.3036	0.1647
MSPE	0.8521*	0.9398**	0.9903**	1.0312**	1.0744**	1.0891
MAPE	0.4048**	0.4467**	0.4687**	0.5128**	0.5579**	0.5711*
QLIKE	1.4199**	1.4399**	1.4485**	1.4749**	1.5057**	1.5173**
HAR-CJ						
c	0.0629	0.0640	0.0708	0.0657	0.0738	0.0732
	(1.6547)	(2.7843)	(3.4646)	(3.3161)	(3.5716)	(3.7030)
$J^{(1)}$	0.1111	−0.0006	0.0097	0.0063	0.0007	0.0033
	(1.7517)	(−0.0120)	(0.2279)	(0.1592)	(0.0205)	(0.0924)
$J^{(5)}$	−0.0011	0.0538	0.0536	0.0209	0.0348	0.0218
	(−0.0250)	(1.9818)	(2.1268)	(0.8225)	(1.4447)	(0.9746)
$J^{(22)}$	0.0438	0.0386	0.0392	0.0673	0.0799	0.1076
	(1.3187)	(1.8196)	(2.0924)	(3.5805)	(4.2185)	(6.4181)

(*continued on next page*)

Table 9 (*continued*).

h	1	5	10	22	44	66
$C^{(1)}$	0.2091	0.1211	0.1077	0.0806	0.0594	0.0454
	(5.2687)	(4.4631)	(4.4224)	(3.7131)	(3.0685)	(2.5548)
$C^{(5)}$	0.3870	0.4004	0.3429	0.2965	0.2870	0.2227
	(7.7566)	(11.2057)	(10.5988)	(9.3501)	(9.6499)	(7.5763)
$C^{(22)}$	0.2188	0.2306	0.2408	0.1992	0.0351	−0.0594
	(4.6569)	(7.1121)	(7.9743)	(6.6021)	(1.1755)	(−1.9651)
adj. R^2	0.3877	0.5396	0.5231	0.4467	0.3002	0.1737
MSPE	0.8522*	0.9403**	0.9912**	1.0317**	1.0747**	1.0846**
MAPE	0.4041**	0.4485**	0.4692**	0.5120**	0.5595**	0.5668*
QLIKE	1.4193**	1.4417**	1.4484**	1.4743**	1.5070**	1.5151**
HAR-PS						
c	0.2008	0.1454	0.1480	0.1496	0.1775	0.2161
	(6.2083)	(6.1117)	(6.7029)	(7.4499)	(9.0152)	(11.0303)
RS^+	0.1338	0.0621	0.0457	0.0490	0.0397	0.0325
	(4.4723)	(2.9348)	(2.2572)	(2.5062)	(2.1243)	(1.8151)
RS^-	0.0967	0.0726	0.0714	0.0317	0.0118	0.0091
	(2.6737)	(2.9442)	(3.1797)	(1.5702)	(0.6005)	(0.4607)
$\mathbf{I}_{r_t<0}RV^{(1)}$	−0.0119	−0.0271	−0.0173	0.0035	0.0172	0.0092
	(−0.2846)	(−0.9108)	(−0.6354)	(0.1329)	(0.6772)	(0.3761)
$RV^{(5)}$	0.3892	0.4281	0.3707	0.3057	0.2973	0.2316
	(7.1398)	(11.5419)	(10.9227)	(8.8975)	(9.0959)	(7.1841)
$RV^{(22)}$	0.2516	0.2542	0.2626	0.2428	0.0890	0.0074
	(5.1662)	(7.6552)	(8.4726)	(7.6823)	(2.8572)	(0.2313)
adj. R^2	0.3856	0.5394	0.5250	0.4468	0.3025	0.1645
MSPE	0.8553*	0.9403**	0.9915**	1.0313**	1.0741**	1.0893
MAPE	0.4064**	0.4481**	0.4693**	0.5139**	0.5570**	0.5713*
QLIKE	1.4212**	1.4411**	1.4487**	1.4762**	1.5046**	1.5174**
LHAR-CJ						
c	0.0337	0.0402	0.0429	0.0447	0.0508	0.0521
	(0.8559)	(1.6606)	(2.0116)	(2.1050)	(2.3320)	(2.4780)
$J^{(1)}$	0.0938	−0.0108	−0.0026	0.0005	−0.0025	0.0023
	(1.4934)	(−0.2260)	(−0.0609)	(0.0133)	(−0.0686)	(0.0644)
$J^{(5)}$	−0.0094	0.0456	0.0460	0.0143	0.0290	0.0165
	(−0.2084)	(1.7001)	(1.8452)	(0.5663)	(1.2010)	(0.7366)
$J^{(22)}$	0.0483	0.0446	0.0488	0.0771	0.0957	0.1242
	(1.4245)	(2.0762)	(2.6105)	(4.0645)	(5.0468)	(7.3908)
$C^{(1)}$	0.1988	0.1152	0.1007	0.0776	0.0583	0.0457
	(5.0947)	(4.3677)	(4.2943)	(3.6549)	(3.0807)	(2.6161)
$C^{(5)}$	0.3734	0.3869	0.3278	0.2829	0.2712	0.2080
	(7.5246)	(10.8508)	(10.2099)	(8.9297)	(9.1370)	(7.0235)
$C^{(22)}$	0.2215	0.2323	0.2424	0.2003	0.0367	−0.0573
	(4.7071)	(7.1369)	(7.9990)	(6.6144)	(1.2218)	(−1.8823)
$r_t^{-,(1)}$	−0.0300	−0.0158	−0.0198	−0.0069	−0.0015	0.0026
	(−2.2361)	(−1.6274)	(−2.3730)	(−0.8902)	(−0.2026)	(0.3687)
$r_t^{-,(5)}$	0.0076	0.0084	0.0106	0.0103	0.0140	0.0142
	(1.8421)	(3.0841)	(4.1333)	(4.0754)	(5.9767)	(6.4146)
$r_t^{-,(22)}$	−0.1018	−0.0816	−0.0459	−0.0222	0.0393	0.0605
	(−1.8492)	(−2.2507)	(−1.3506)	(−0.6758)	(1.2646)	(2.0464)
adj. R^2	0.3915	0.5440	0.5298	0.4517	0.3115	0.1886
MSPE	0.8476**	0.9403**	0.9921**	1.0328**	1.0721**	1.0829**
MAPE	0.4032**	0.4486**	0.4687**	0.5119**	0.5579**	0.5631**
QLIKE	1.4188**	1.4420**	1.4486**	1.4742**	1.5081**	1.5131**

Notes: * and ** indicate inclusion in the $\mathcal{M}^*_{90\%}$ and $\mathcal{M}^*_{75\%}$, respectively. The t-statistics for the parameter estimates are given in parentheses.

this ability no longer exists in a real out-of-sample exercise. Furthermore, the inability of the leverage effects, of either returns or volatility, to generate significant out-of-sample predictive gains, relative to the simple HAR model, could be explained by the fact that they are not powerful enough statistically to provide incremental predictive information relative to the heterogeneous beliefs of investors. Another possible explanation might be that the evidence that previous studies have found in favour of the predictive ability of the jump components in an out-of-sample setting is due to the incorporation of jump values that are not available to the forecasters at the time when the forecasts are generated, i.e., such studies do not produce real out-of-sample forecasts.

Next, we look at the success ratios of our competing models, as shown at the bottom of Tables 12–16. It is rather interesting that we cannot argue that there is any single model which is able to provide a superior directional accuracy. On the contrary, we conclude that even though the HAR-type models predict the direction of the volatility correctly at a high level (up to 75% depending on the volatility measure and commodity), these

Table 10
In-sample regression results for sugar with *RV*.

h	1	5	10	22	44	66
Random walk						
adj. R^2	0.5142	0.7405	0.7846	0.7966	0.7220	0.6699
MSPE	2.5965	2.5676	2.5859	2.4934**	2.5379	2.4903
MAPE	0.4287	0.4181	0.4196	0.4367	0.4922	0.5174
QLIKE	2.2141	2.2109**	2.2142**	2.2231**	2.2666	2.2889
AR(1)						
c	0.2624	0.1397	0.1160	0.1102	0.1514	0.1771
	(12.6261)	(9.3988)	(8.6776)	(7.5416)	(7.7898)	(9.1080)
$RV^{(h)}$	0.7571	0.8688	0.8897	0.8940	0.8503	0.8176
	(48.1471)	(73.1783)	(80.8939)	(79.3076)	(58.1268)	(55.4838)
adj. R^2	0.5728	0.7576	0.7966	0.8078	0.7451	0.7058
MSPE	2.3773	2.5252	2.5678	2.5120**	2.5158	2.4661
MAPE	0.4004	0.4062	0.4117	0.4317*	0.4800	0.4924**
QLIKE	2.1973**	2.2009**	2.2031**	2.2114**	2.2388**	2.2382**
ARMA						
c	0.0161	0.0310	0.0457	0.0839	0.0855	0.1003
	(3.0711)	(4.6030)	(6.0132)	(9.4439)	(10.0194)	(9.6682)
$RV^{(h)}$	0.9848	0.9703	0.9555	0.9159	0.9034	0.8844
	(232.3917)	(177.3654)	(153.7074)	(114.8710)	(116.1206)	(99.8488)
$\varepsilon^{(h)}$	−0.7445	−0.5094	−0.3604	−0.1249	−0.2625	−0.2042
	(44.5474)	(24.2486)	(16.9904)	(5.2419)	(10.8704)	(8.3140)
adj. R^2	0.6629	0.7903	0.8131	0.8188	0.7779	0.7517
MSPE	2.2555	2.4541*	2.4968**	2.4430**	2.4190**	2.3960**
MAPE	0.3419**	0.3858	0.4029*	0.4284**	0.4644**	0.4888**
QLIKE	2.1701**	2.1899**	2.1981**	2.2129**	2.2334**	2.2441**
HAR						
c	0.0445	0.0646	0.0799	0.1057	0.1501	0.1917
	(2.0806)	(4.3328)	(5.7612)	(7.6275)	(9.4248)	(10.9989)
$RV^{(1)}$	0.2458	0.1556	0.1084	0.0810	0.0679	0.0613
	(8.3251)	(7.4649)	(5.6673)	(4.3799)	(3.5851)	(3.0761)
$RV^{(5)}$	0.3288	0.2619	0.2388	0.1975	0.2058	0.1721
	(6.5406)	(7.4861)	(7.4609)	(6.0544)	(6.1533)	(4.9690)
$RV^{(22)}$	0.3834	0.5202	0.5760	0.6200	0.5780	0.5734
	(8.8657)	(17.0808)	(20.1447)	(21.8090)	(19.0863)	(18.0935)
adj. R^2	0.6686	0.7974	0.8185	0.8224	0.7950	0.7566
MSPE	2.2218	2.4251**	2.4923**	2.5080**	2.4745*	2.5002
MAPE	0.3401**	0.3855	0.4035	0.4298*	0.4717	0.5057
QLIKE	2.1685**	2.1895**	2.1975**	2.2106**	2.2346**	2.2479**
HAR-J						
c	0.0487	0.0743	0.0893	0.1136	0.1593	0.2012
	(2.1927)	(4.8667)	(6.2730)	(8.0528)	(9.9093)	(11.4917)
$RV^{(1)}$	0.2567	0.1812	0.1333	0.1021	0.0923	0.0862
	(8.1589)	(8.1053)	(6.4539)	(5.0589)	(4.4407)	(3.9588)
$RV^{(5)}$	0.3260	0.2552	0.2323	0.1920	0.1993	0.1655
	(6.4741)	(7.3201)	(7.2783)	(5.8774)	(5.9462)	(4.7642)
$RV^{(22)}$	0.3809	0.5147	0.5705	0.6154	0.5728	0.5681
	(8.7875)	(16.8263)	(19.8649)	(21.6509)	(18.9554)	(17.9948)
$J^{(1)}$	−0.0293	−0.0679	−0.0659	−0.0559	−0.0646	−0.0663
	(−0.7976)	(−2.7444)	(−2.8693)	(−2.6457)	(−3.0618)	(−2.9832)
adj. R^2	0.6685	0.7981	0.8193	0.8229	0.7957	0.7575
MSPE	2.2249	2.4224**	2.4930**	2.5085*	2.4734*	2.4957
MAPE	0.3399**	0.3853	0.4026	0.4301*	0.4713	0.5051
QLIKE	2.1684**	2.1893**	2.1972**	2.2106**	2.2344**	2.2474**
HAR-CJ						
c	0.1111	0.1307	0.1522	0.2102	0.2895	0.3364
	(3.4100)	(5.8602)	(7.4624)	(10.4620)	(13.6178)	(15.1940)
$J^{(1)}$	0.1089	0.0643	0.0431	0.0343	0.0309	0.0285
	(3.1018)	(2.8444)	(2.0590)	(1.8425)	(1.6940)	(1.4476)
$J^{(5)}$	0.0212	0.0123	0.0220	0.0344	0.0340	0.0258
	(0.9170)	(0.7570)	(1.4717)	(2.4911)	(2.4638)	(1.7723)
$J^{(22)}$	0.0304	0.0353	0.0272	−0.0027	−0.0325	−0.0383
	(1.3763)	(2.3602)	(2.0520)	(−0.2215)	(−2.6316)	(−2.9126)

(*continued on next page*)

Table 10 (*continued*).

h	1	5	10	22	44	66
$C^{(1)}$	0.2381 (8.2883)	0.1501 (7.3570)	0.1052 (5.6387)	0.0778 (4.2993)	0.0660 (3.5544)	0.0601 (3.0947)
$C^{(5)}$	0.3082 (6.2990)	0.2488 (7.3663)	0.2214 (7.1820)	0.1803 (5.6773)	0.1973 (6.0812)	0.1668 (4.9865)
$C^{(22)}$	0.3443 (7.9824)	0.4757 (15.7123)	0.5372 (19.3092)	0.5941 (21.5313)	0.5584 (19.1130)	0.5574 (18.2215)
adj. R^2	0.6693	0.7989	0.8210	0.8274	0.8031	0.7670
MSPE	2.2189	2.4303**	2.4938**	2.5134*	2.4712*	2.5054
MAPE	0.3392**	0.3832	0.4004*	0.4265**	0.4675	0.4991**
QLIKE	2.1681**	2.1888**	2.1962**	2.2087**	2.2323**	2.2450**
HAR-PS						
c	0.2053 (6.8309)	0.1710 (7.9936)	0.1532 (7.6708)	0.1621 (8.1335)	0.1994 (9.0974)	0.2396 (10.1543)
RS^+	0.1479 (5.5121)	0.1249 (6.9601)	0.1002 (5.9390)	0.0773 (4.7212)	0.0581 (3.3930)	0.0516 (2.8382)
RS^-	0.0691 (2.2775)	0.0159 (0.7312)	−0.0045 (−0.2302)	−0.0035 (−0.1888)	0.0073 (0.3675)	0.0125 (0.5846)
$\mathbf{I}_{r_t<0}RV^{(1)}$	0.0479 (2.5867)	0.0313 (2.3671)	0.0304 (2.5605)	0.0244 (2.1888)	0.0143 (1.2851)	0.0067 (0.5667)
$RV^{(5)}$	0.3336 (6.5851)	0.2624 (7.5075)	0.2376 (7.4136)	0.1932 (5.8944)	0.2017 (5.9728)	0.1666 (4.7523)
$RV^{(22)}$	0.3812 (8.8306)	0.5166 (17.0820)	0.5726 (20.1798)	0.6177 (21.8625)	0.5764 (19.1224)	0.5721 (18.0996)
adj. R^2	0.6684	0.7981	0.8196	0.8231	0.7952	0.7567
MSPE	2.2156	2.4238**	2.4911**	2.5052**	2.4744*	2.5000
MAPE	0.3402**	0.3852	0.4034	0.4294*	0.4714	0.5059
QLIKE	2.1685**	2.1894**	2.1975**	2.2103**	2.2345**	2.2480**
LHAR-CJ						
c	0.1247 (3.5722)	0.1399 (5.9190)	0.1477 (7.0830)	0.1861 (9.3628)	0.2467 (11.5448)	0.2915 (12.8981)
$J^{(1)}$	0.0989 (2.8223)	0.0623 (2.7713)	0.0423 (2.0152)	0.0337 (1.7848)	0.0299 (1.6133)	0.0269 (1.3371)
$J^{(5)}$	0.0214 (0.9338)	0.0099 (0.6192)	0.0184 (1.2644)	0.0311 (2.3204)	0.0313 (2.3030)	0.0232 (1.6024)
$J^{(22)}$	0.0296 (1.3549)	0.0366 (2.5127)	0.0307 (2.4201)	0.0025 (0.2135)	−0.0262 (−2.1867)	−0.0316 (−2.4473)
$C^{(1)}$	0.2124 (7.3584)	0.1398 (6.9047)	0.0979 (5.2432)	0.0724 (4.0049)	0.0625 (3.3902)	0.0557 (2.8811)
$C^{(5)}$	0.3074 (6.2662)	0.2384 (7.1383)	0.2067 (6.7955)	0.1648 (5.3172)	0.1837 (5.8124)	0.1542 (4.7191)
$C^{(22)}$	0.3423 (7.9402)	0.4734 (15.7642)	0.5375 (19.5300)	0.5977 (22.1264)	0.5654 (19.9294)	0.5647 (19.0181)
$r_t^{-,(1)}$	−0.0332 (−3.3033)	−0.0073 (−1.0424)	−0.0016 (−0.2670)	0.0010 (0.1981)	0.0018 (0.3312)	0.0001 (0.0236)
$r_t^{-,(5)}$	0.0058 (2.8862)	0.0049 (3.5960)	0.0035 (2.9363)	0.0011 (0.9473)	−0.0019 (−1.5736)	−0.0021 (−1.6513)
$r_t^{-,(22)}$	−0.0844 (−2.2615)	−0.1434 (−5.7516)	−0.1821 (−8.2723)	−0.1992 (−9.0427)	−0.1847 (−8.3511)	−0.1832 (−7.7072)
adj. R^2	0.6730	0.8024	0.8264	0.8349	0.8118	0.7763
MSPE	2.1443**	2.4123**	2.4760**	2.5191*	2.4946*	2.5341
MAPE	0.3377**	0.3805**	0.3974**	0.4239**	0.4621**	0.4964**
QLIKE	2.1674**	2.1874**	2.1945**	2.2066**	2.2296**	2.2429**

Notes: * and ** indicate inclusion in the $\mathcal{M}^*_{90\%}$ and $\mathcal{M}^*_{75\%}$, respectively. The $t-$statistics for the parameter estimates are given in parentheses.

are marginally higher (lower) than the random walk and AR models for the shorter (longer) forecasting horizons. In any case, however, any differences that are noticed in predicting the future direction of volatility are not statistically significant.

Overall, our findings are in line with those of Sévi (2014), who reaches the same conclusion as this study, despite the fact that he focuses on an energy commodity volatility (i.e. oil price volatility): namely, that sophisticated HAR-type models are not capable of outperforming the simple HAR in an out-of-sample exercise over different forecasting horizons, even though they outperform it in an in-sample setting.

4.3. Real out-of-sample forecasting results: further tests

This section proceeds with an evaluation of the average forecasts over the different horizons, against the actual average volatility over the same horizon. This comparison is motivated by the fact that a number of different

Table 11
In-sample regression results for wheat with RV.

h	1	5	10	22	44	66
Random walk						
adj. R^2	0.1756	0.4970	0.5112	0.5163	0.4174	0.2276
MSPE	2.0653	2.1759	2.1633**	2.1861	2.2311**	2.3436
MAPE	0.4737	0.4704	0.4849	0.4974	0.5393	0.5902
QLIKE	2.1772	2.1701**	2.1787**	2.1912**	2.2285	2.2750
AR(1)						
c	0.4086	0.2484	0.2413	0.2344	0.2770	0.3685
	(12.9311)	(14.4719)	(14.4099)	(14.3526)	(12.8627)	(15.0692)
$RV^{(h)}$	0.5877	0.7482	0.7551	0.7588	0.7128	0.6184
	(20.7364)	(45.0175)	(44.6687)	(47.0778)	(37.5835)	(28.5946)
adj. R^2	0.3446	0.5600	0.5708	0.5740	0.4984	0.3692
MSPE	1.9101	2.0802	2.1081**	2.1652**	2.2279	2.3096
MAPE	0.4188	0.4432	0.4569	0.4708**	0.5078**	0.5378**
QLIKE	2.1400**	2.1492**	2.1576**	2.1650**	2.1876**	2.2108**
ARMA						
c	0.0386	0.0857	0.1074	0.1901	0.4718	0.4090
	(4.4988)	(7.0134)	(7.5451)	(10.8720)	(19.1174)	(11.9579)
$RV^{(h)}$	0.9612	0.9126	0.8899	0.8060	0.5232	0.5799
	(123.1420)	(83.6537)	(69.8266)	(49.5912)	(21.8110)	(17.2683)
$\varepsilon^{(h)}$	−0.7114	−0.4264	−0.3405	−0.1030	0.3905	0.0640
	(39.6273)	(16.9608)	(11.9844)	(3.4798)	(12.6367)	(1.3506)
adj. R^2	0.4496	0.5878	0.5937	0.5820	0.5260	0.3708
MSPE	1.8055**	2.0460*	2.0984**	2.1601**	2.2052**	2.3110
MAPE	0.3884**	0.4337	0.4515	0.4704**	0.5076**	0.5392**
QLIKE	2.1248**	2.1451**	2.1556**	2.1650**	2.1948**	2.2150
HAR						
c	0.0978	0.1410	0.1791	0.2264	0.2970	0.3562
	(3.5555)	(7.6910)	(10.5290)	(14.3942)	(17.4647)	(19.2097)
$RV^{(1)}$	0.1949	0.1535	0.1083	0.0804	0.0613	0.0503
	(5.3468)	(5.9368)	(4.4552)	(3.5647)	(2.7974)	(2.3048)
$RV^{(5)}$	0.4178	0.3043	0.2502	0.1886	0.1718	0.1484
	(7.9222)	(8.3324)	(7.4342)	(5.8225)	(5.4687)	(4.6906)
$RV^{(22)}$	0.2885	0.3987	0.4589	0.4985	0.4627	0.4351
	(5.5246)	(11.7133)	(14.9318)	(18.3043)	(16.8009)	(15.2920)
adj. R^2	0.4549	0.6061	0.6090	0.6061	0.5612	0.4975
MSPE	1.7985**	2.0307**	2.1063**	2.1733	2.2318	2.2516
MAPE	0.3848**	0.4272*	0.4496	0.4702**	0.5022**	0.5300**
QLIKE	2.1241**	2.1412**	2.1534**	2.1635**	2.1852**	2.2047**
HAR-J						
c	0.0917	0.1397	0.1797	0.2268	0.2909	0.3451
	(3.3578)	(7.4358)	(10.3125)	(14.0392)	(16.9141)	(18.5417)
$RV^{(1)}$	0.1803	0.1504	0.1097	0.0814	0.0467	0.0240
	(4.4874)	(5.2974)	(4.1279)	(3.2821)	(1.9422)	(1.0154)
$RV^{(5)}$	0.4181	0.3044	0.2502	0.1885	0.1720	0.1490
	(7.9558)	(8.3380)	(7.4288)	(5.8194)	(5.5041)	(4.7586)
$RV^{(22)}$	0.2899	0.3990	0.4587	0.4984	0.4643	0.4381
	(5.5635)	(11.7119)	(14.8971)	(18.2686)	(16.9000)	(15.4672)
$J^{(1)}$	0.0510	0.0110	−0.0048	−0.0035	0.0507	0.0906
	(1.1025)	(0.3367)	(−0.1597)	(−0.1268)	(1.9526)	(3.5606)
adj. R^2	0.4551	0.6059	0.6088	0.6058	0.5619	0.5006
MSPE	1.7973**	2.0314*	2.1064**	2.1733	2.2299	2.2505
MAPE	0.3849**	0.4275*	0.4497	0.4701**	0.5013**	0.5304**
QLIKE	2.1241**	2.1414**	2.1534**	2.1635**	2.1844**	2.2057**
HAR-CJ						
c	0.1324	0.1557	0.1654	0.1499	0.0865	0.1017
	(2.9277)	(5.0306)	(5.4939)	(5.6053)	(3.4936)	(4.1700)
$J^{(1)}$	0.1112	0.0860	0.0511	0.0376	0.0234	0.0227
	(2.8383)	(3.0474)	(1.9466)	(1.5871)	(1.1023)	(1.1280)
$J^{(5)}$	0.0234	0.0007	0.0123	−0.0136	−0.0045	0.0057
	(0.8042)	(0.0325)	(0.6412)	(−0.8228)	(−0.3143)	(0.4109)
$J^{(22)}$	0.0522	0.0718	0.0868	0.1371	0.2224	0.2427
	(1.7119)	(3.3663)	(4.2404)	(7.7988)	(14.1275)	(15.9920)

(continued on next page)

Table 11 (*continued*).

h	1	5	10	22	44	66
$C^{(1)}$	0.1886	0.1444	0.1034	0.0767	0.0583	0.0466
	(5.6975)	(6.2422)	(4.7888)	(3.8145)	(3.1028)	(2.5009)
$C^{(5)}$	0.3912	0.2976	0.2427	0.1944	0.1700	0.1428
	(8.1138)	(8.8225)	(7.8325)	(6.5556)	(6.2051)	(5.1981)
$C^{(22)}$	0.2413	0.3340	0.3821	0.3869	0.3052	0.2685
	(4.8565)	(9.9894)	(12.5673)	(14.5925)	(11.9671)	(10.2734)
adj. R^2	0.4566	0.6095	0.6126	0.6126	0.5882	0.5374
MSPE	1.7950**	2.0249**	2.1039**	2.1589**	2.1943**	2.2210**
MAPE	0.3835**	0.4258**	0.4486	0.4697**	0.4968**	0.5250**
QLIKE	2.1231**	2.1403**	2.1529**	2.1645**	2.1833**	2.2043**
HAR-PS						
c	0.2400	0.2513	0.2554	0.2809	0.3341	0.3846
	(6.4359)	(9.1127)	(9.8467)	(11.9562)	(13.9554)	(15.4019)
RS^{+}	0.1301	0.0930	0.0711	0.0551	0.0344	0.0206
	(4.7287)	(4.9477)	(4.2080)	(3.2455)	(2.0982)	(1.2620)
RS^{-}	0.0649	0.0587	0.0330	0.0185	0.0156	0.0181
	(1.5032)	(1.7615)	(1.0594)	(0.6888)	(0.5884)	(0.7022)
$\mathbf{I}_{r_t<0}RV^{(1)}$	−0.0265	−0.0218	−0.0099	−0.0008	0.0058	0.0037
	(−1.0440)	(−1.1457)	(−0.5667)	(−0.0497)	(0.3853)	(0.2558)
$RV^{(5)}$	0.4304	0.3168	0.2590	0.1954	0.1801	0.1583
	(8.0612)	(8.4425)	(7.5256)	(5.9467)	(5.6262)	(4.9189)
$RV^{(22)}$	0.2901	0.3997	0.4595	0.4987	0.4625	0.4347
	(5.5336)	(11.7027)	(14.9139)	(18.2757)	(16.7910)	(15.2812)
adj. R^2	0.4552	0.6053	0.6085	0.6054	0.5599	0.4960
MSPE	1.7932**	2.0286**	2.1064**	2.1733	2.2328	2.2522
MAPE	0.3852**	0.4260**	0.4504	0.4701**	0.5024**	0.5301**
QLIKE	2.1244**	2.1403**	2.1538**	2.1636**	2.1852**	2.2047**
LHAR-CJ						
c	0.1186	0.1330	0.1413	0.1257	0.0569	0.0736
	(2.5508)	(4.2067)	(4.6576)	(4.6868)	(2.2814)	(2.9611)
$J^{(1)}$	0.1122	0.0870	0.0522	0.0375	0.0215	0.0203
	(2.8609)	(3.1014)	(1.9930)	(1.5880)	(1.0196)	(1.0065)
$J^{(5)}$	0.0185	−0.0073	0.0042	−0.0209	−0.0127	−0.0019
	(0.6362)	(−0.3484)	(0.2179)	(−1.2763)	(−0.8887)	(−0.1353)
$J^{(22)}$	0.0518	0.0721	0.0863	0.1364	0.2226	0.2427
	(1.7068)	(3.3859)	(4.2261)	(7.8382)	(14.3470)	(16.2348)
$C^{(1)}$	0.1885	0.1439	0.1029	0.0755	0.0560	0.0442
	(5.7192)	(6.2717)	(4.8431)	(3.8026)	(2.9911)	(2.4042)
$C^{(5)}$	0.3851	0.2878	0.2328	0.1853	0.1600	0.1333
	(8.0231)	(8.5897)	(7.6340)	(6.3103)	(5.8724)	(4.8952)
$C^{(22)}$	0.2527	0.3504	0.4009	0.4051	0.3242	0.2865
	(5.1051)	(10.5295)	(13.2915)	(15.3738)	(12.8772)	(11.0804)
$r_t^{-,(1)}$	0.0026	0.0017	0.0027	−0.0004	−0.0061	−0.0072
	(0.2422)	(0.2386)	(0.4048)	(−0.0588)	(−1.0668)	(−1.2123)
$r_t^{-,(5)}$	−0.0007	−0.0003	−0.0016	−0.0024	−0.0022	−0.0022
	(−0.2198)	(−0.1225)	(−0.8084)	(−1.2225)	(−1.1573)	(−1.1311)
$r_t^{-,(22)}$	−0.1093	−0.1662	−0.1799	−0.1700	−0.1813	−0.1696
	(−1.9617)	(−4.8605)	(−6.0103)	(−6.3813)	(−8.1063)	(−7.6402)
adj. R^2	0.4572	0.6143	0.6194	0.6200	0.5982	0.5471
MSPE	1.7909**	2.0198**	2.1030**	2.1556**	2.1955**	2.2211**
MAPE	0.3837**	0.4237**	0.4447**	0.4665**	0.4971**	0.5234**
QLIKE	2.1234**	2.1399**	2.1512**	2.1633**	2.1837**	2.2048**

Notes: * and ** indicate inclusion in the $\mathcal{M}^*_{90\%}$ and $\mathcal{M}^*_{75\%}$, respectively. The t-statistics for the parameter estimates are given in parentheses.

stakeholders who are interested in agricultural commodity volatility forecasting (agricultural firms, policy makers, international institutions, etc.) do not require point forecasts at a particular h-day-ahead horizon, but rather the expected average volatility over an h-day period. For the sake of brevity, we do not include these results in the main part of the study, but make them available in Appendix B.

Overall, the results based on the MCS test suggest that our main conclusions still hold, providing further evidence that the HAR extensions are not capable of generating any incremental predictive gains relative to the HAR model for U.S. agricultural commodity markets. This holds for both the *RV* and *MedRV* volatility measures. In addition, we report that the RW is also included in the set of the best forecasting models as we extend the forecasting horizon, particularly for the *MedRV*. This suggests that the ability of the HAR model to generate superior average volatility forecasts is of economic value primarily at shorter horizons.

Table 12
Forecasting evaluation for corn futures with *RV*.

	h	RW	AR	ARMA	HAR	HAR-J	HAR-CJ	HAR-PS	LHAR-CJ
MSPE	1	1.3038	1.1508	1.2400	1.0898**	1.0901**	1.0890**	1.0992	1.0993**
	5	1.2454**	1.2166**	1.2963	1.2045**	1.2036**	1.2031**	1.2079**	1.2035**
	10	1.2983	1.2651**	1.3346	1.2742	1.2726	1.2626**	1.2806	1.2636**
	22	1.3949	1.3423	1.3875	1.3248**	1.3241**	1.3197**	1.3240**	1.3282
	44	1.4981	1.3859	1.3376**	1.3747*	1.3746*	1.3667*	1.3739*	1.3768*
	66	1.5565	1.3870	1.4430	1.3753	1.3759	1.3665**	1.3753	1.3760
MAPE	1	0.6093	0.5899	0.5988	0.5516**	0.5515**	0.5509**	0.5550	0.5570*
	5	0.6232	0.6181	0.6389	0.6056**	0.6057**	0.6043**	0.6070**	0.6038**
	10	0.6325	0.6268**	0.6456	0.6282*	0.6288	0.6232**	0.6305	0.6240**
	22	0.6644	0.6593	0.6875	0.6505**	0.6506**	0.6483**	0.6503**	0.6541
	44	0.7217	0.7002**	0.7020**	0.6913**	0.6917**	0.6939**	0.6912**	0.7016
	66	0.7647	0.7313	0.7701	0.7031**	0.7039*	0.7094*	0.7032**	0.7155
QLIKE	1	1.6887	1.6600	1.6798	1.6517**	1.6519**	1.6520**	1.6535	1.6529**
	5	1.6925	1.6801**	1.7075	1.6770**	1.6768**	1.6771**	1.6770**	1.6775**
	10	1.7014	1.6906**	1.7123	1.6959	1.6955*	1.6933**	1.6968	1.6940**
	22	1.7340	1.7165**	1.7321	1.7113**	1.7113**	1.7111**	1.7114**	1.7139**
	44	1.7852	1.7320	1.7076**	1.7280	1.7278	1.7248	1.7278	1.7287
	66	1.8200	1.7205**	1.7371	1.7267	1.7267	1.7223**	1.7267	1.7265
SR	1	0.7606***	0.7389***	0.7597***	0.7597***	0.7578***	0.7635***	0.7540***	0.7588***
	5	0.6821***	0.6689***	0.6717***	0.6821***	0.6802***	0.6783***	0.6850***	0.6840***
	10	0.6774***	0.6689***	0.6471***	0.6481***	0.6414***	0.6462***	0.6518***	0.6462***
	22	0.6083***	0.5885***	0.5260	0.6140***	0.6140***	0.6140***	0.6121***	0.6159***
	44	0.4787	0.4437	0.5809***	0.5383**	0.5383**	0.5393**	0.5459**	0.5061
	66	0.4172	0.5676	0.5118	0.5307	0.5260	0.5506**	0.5203	0.5336

Notes: * and ** indicate inclusion in the $\mathcal{M}^{*}_{90\%}$ and $\mathcal{M}^{*}_{75\%}$, respectively. For the success ratio (SR), *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 13
Forecasting evaluation for rice futures with *RV*.

	h	RW	AR	ARMA	HAR	HAR-J	HAR-CJ	HAR-PS	LHAR-CJ
MSPE	1	2.4100	2.1404	2.3635	1.9934**	1.9968**	1.9967**	1.9943**	1.9838**
	5	2.1062**	2.1123*	2.1350*	2.0759**	2.0767**	2.0843**	2.0789**	2.0708**
	10	2.1401**	2.1503	2.1769	2.1142**	2.1144**	2.1258**	2.1165**	2.1047**
	22	2.1149**	2.1435*	2.1211**	2.1460*	2.1472*	2.1589	2.1460*	2.1264**
	44	2.1017**	2.1329	2.2183	2.1556	2.1575	2.1749	2.1570	2.1632
	66	2.1603**	2.2203	2.3428	2.2066	2.2043	2.2287	2.2063	2.2106
MAPE	1	0.8550	0.7907	0.8478	0.7343**	0.7327**	0.7354**	0.7359*	0.7355**
	5	0.7980	0.7789	0.7986	0.7624*	0.7619**	0.7656*	0.7610**	0.7707
	10	0.7905	0.7788**	0.8049	0.7740**	0.7734**	0.7815	0.7746**	0.7920
	22	0.7904**	0.7902**	0.7856**	0.7918**	0.7927**	0.7990*	0.7911**	0.8078
	44	0.7840**	0.7822**	0.8042*	0.7945**	0.7949**	0.7991*	0.7945**	0.8134
	66	0.8042**	0.8036**	0.8405	0.8082**	0.8074**	0.8127**	0.8086**	0.8305
QLIKE	1	2.0261	1.9471	2.0171	1.8804**	1.8811**	1.8829**	1.8807**	1.8781**
	5	1.9278	1.9234	1.9488	1.9089**	1.9096**	1.9130**	1.9096**	1.9076**
	10	1.9465	1.9422	1.9660	1.9264**	1.9275**	1.9299*	1.9268**	1.9185**
	22	1.9366**	1.9386**	1.9488*	1.9402**	1.9416*	1.9463*	1.9402**	1.9310**
	44	1.9414**	1.9537	2.0278	1.9522**	1.9540	1.9576	1.9526	1.9440**
	66	1.9851*	2.0320	2.1097	1.9874*	1.9869*	1.9947	1.9872*	1.9643**
SR	1	0.7011***	0.6556***	0.7030***	0.7353***	0.7268***	0.7353***	0.7315***	0.7334***
	5	0.7078***	0.6954***	0.7011***	0.7097***	0.7087***	0.7144***	0.7106***	0.7087***
	10	0.7144***	0.6917***	0.6869***	0.7011***	0.7049***	0.6973***	0.7097***	0.7030***
	22	0.7049***	0.6860***	0.6926***	0.6765***	0.6727***	0.6717***	0.6755***	0.6992***
	44	0.7021***	0.6954***	0.6945***	0.6917***	0.6879***	0.6831***	0.6926***	0.6907***
	66	0.6879***	0.6898***	0.6651***	0.6888***	0.6907***	0.6708***	0.6850***	0.6850***

Notes: * and ** indicate inclusion in the $\mathcal{M}^{*}_{90\%}$ and $\mathcal{M}^{*}_{75\%}$, respectively. For the success ratio (SR), *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

5. Value-at-risk backtesting results

We demonstrate the economic usefulness of the HAR model and its extensions in risk management applications further by calculating the Value-at-Risk (*VaR*) for the level α and the h-day-ahead forecasting horizon as

$$\text{VaR}^{(h)}_{t+h,\alpha} = \text{RV}^{(h)}_{t+h} z_{\alpha}, \tag{31}$$

where z_{α} is the α-quantile of the standard normal distribution. We then backtest the performances of the individual models based on this *VaR* forecast, using the

Table 14
Forecasting evaluation for soy futures with *RV*.

	h	RW	AR	ARMA	HAR	HAR-J	HAR-CJ	HAR-PS	LHAR-CJ
MSPE	1	0.9453	0.8394	0.9104	0.7848**	0.7833**	0.7841**	0.7857**	0.7843**
	5	0.8677*	0.8529*	0.8989	0.8493*	0.8452**	0.8475*	0.8495*	0.8525*
	10	0.9314	0.9085*	0.9421	0.9041*	0.9015**	0.9076	0.9041*	0.9144
	22	1.0220	0.9864	1.0355	0.9603**	0.9603**	0.9647*	0.9609**	0.9762
	44	1.1335	1.0377*	1.0193**	1.0207**	1.0216**	1.0256*	1.0208**	1.0336
	66	1.1765	1.0235**	1.0325**	1.0361**	1.0366**	1.0329**	1.0362**	1.0444
MAPE	1	0.6157	0.6015	0.6076	0.5549*	0.5531**	0.5554*	0.5550*	0.5581*
	5	0.6005	0.6005	0.6202	0.5958*	0.5942**	0.5968*	0.5968	0.6013
	10	0.6296**	0.6282**	0.6620	0.6261**	0.6246**	0.6284*	0.6265**	0.6295*
	22	0.6953	0.6875	0.7305	0.6735**	0.6733**	0.6766	0.6750	0.6826
	44	0.7691	0.7408	0.7513	0.7234**	0.7236**	0.7279	0.7237**	0.7345
	66	0.8075	0.7539	0.7613	0.7401**	0.7405*	0.7449*	0.7403**	0.7517
QLIKE	1	1.3287	1.2983	1.3209	1.2841**	1.2837**	1.2834**	1.2839**	1.2834**
	5	1.3113	1.3026*	1.3277	1.3021*	1.3010**	1.3015**	1.3020*	1.3029*
	10	1.3405	1.3250**	1.3462	1.3274**	1.3272**	1.3288*	1.3275**	1.3315
	22	1.3985	1.3642	1.3864	1.3500**	1.3501**	1.3506**	1.3501**	1.3562
	44	1.4695	1.3865	1.3714**	1.3786**	1.3790**	1.3800**	1.3786**	1.3853
	66	1.5064	1.3769**	1.3833**	1.3850**	1.3852**	1.3805**	1.3851**	1.3885
SR	1	0.7787***	0.7495***	0.7768***	0.7910***	0.7900***	0.7834***	0.7863***	0.7900***
	5	0.7589***	0.7580***	0.7354***	0.7561***	0.7571***	0.7589***	0.7524***	0.7571***
	10	0.7288***	0.7147***	0.6610***	0.7175***	0.7194***	0.7109***	0.7175***	0.7015***
	22	0.6252***	0.5979***	0.5490*	0.6412***	0.6450***	0.6525***	0.6431***	0.6478***
	44	0.5160	0.4595	0.5414**	0.5301	0.5264	0.5339	0.5273	0.5188
	66	0.4030	0.5075	0.4812	0.4699	0.4614	0.4859	0.4557	0.4492

Notes: * and ** indicate inclusion in the $\mathcal{M}^*_{90\%}$ and $\mathcal{M}^*_{75\%}$, respectively. For the success ratio (SR), *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 15
Forecasting evaluation for sugar futures with *RV*.

	h	RW	AR	ARMA	HAR	HAR-J	HAR-CJ	HAR-PS	LHAR-CJ
MSPE	1	1.6238	1.4626	1.5919	1.3174**	1.3168**	1.3167**	1.3188**	1.3190**
	5	1.4880	1.4721	1.4925	1.4265**	1.4223**	1.4225**	1.4258**	1.4279**
	10	1.4526**	1.4590**	1.5383	1.4582**	1.4564**	1.4519**	1.4571**	1.4528**
	22	1.5126**	1.5350**	1.5995	1.5378**	1.5349**	1.5329**	1.5373**	1.5356**
	44	1.5704**	1.6529	1.6063*	1.6275	1.6225	1.6265	1.6281	1.6441
	66	1.5623**	1.6836	1.6753	1.7081	1.7020	1.6944	1.7084	1.6723
MAPE	1	0.6537	0.6265	0.6480	0.5741**	0.5748**	0.5763*	0.5744**	0.5784*
	5	0.6427	0.6292	0.6403	0.6119**	0.6122**	0.6145**	0.6114**	0.6133**
	10	0.6358*	0.6304**	0.6515	0.6224**	0.6225**	0.6246**	0.6224**	0.6241**
	22	0.6603	0.6468**	0.6723*	0.6431**	0.6442**	0.6507*	0.6433**	0.6503**
	44	0.6878	0.6651**	0.6898*	0.6721**	0.6728**	0.6843	0.6724**	0.6846*
	66	0.6836	0.6659**	0.7222	0.6871	0.6872	0.6949	0.6876	0.6891
QLIKE	1	1.9622	1.9459	1.9591	1.9182**	1.9179**	1.9177**	1.9189**	1.9180**
	5	1.9610	1.9542	1.9604	1.9458**	1.9452**	1.9439**	1.9452**	1.9446**
	10	1.9529**	1.9508**	1.9833	1.9541**	1.9537**	1.9510**	1.9542**	1.9516**
	22	1.9824**	1.9879*	2.0484	1.9854*	1.9843*	1.9791**	1.9851*	1.9781**
	44	2.0311**	2.0622	2.0307**	2.0484	2.0461	2.0352**	2.0490	2.0366**
	66	2.0122**	2.0659	2.0453	2.0752	2.0732	2.0587	2.0762	2.0551
SR	1	0.7333***	0.7352***	0.7362***	0.7662***	0.7624***	0.7681***	0.7624***	0.7718***
	5	0.7352***	0.7277***	0.7211***	0.7343***	0.7352***	0.7390***	0.7399***	0.7390***
	10	0.7230***	0.7362***	0.7052***	0.7239***	0.7324***	0.7174***	0.7192***	0.7230***
	22	0.7108***	0.7146***	0.6854***	0.7221***	0.7080***	0.6977***	0.7239***	0.7136***
	44	0.7174***	0.7042***	0.7202***	0.6920***	0.6854***	0.6845***	0.6901***	0.6845***
	66	0.7484***	0.6723***	0.6704***	0.6563***	0.6516***	0.6638***	0.6516***	0.6714***

Notes: * and ** indicate inclusion in the $\mathcal{M}^*_{90\%}$ and $\mathcal{M}^*_{75\%}$, respectively. For the success ratio (SR), *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

unconditional coverage test of Kupiec (1995) and the conditional coverage test of Christoffersen (1998). Coverage means that, for example, a 99% *VaR* should have 1% of violations. A violation occurs if the actual returns exceed the *VaR* prediction (long) or turn out to be below the *VaR* forecast (short). Both tests compare the actual coverage with the theoretical coverage; however, while the Kupiec (1995) test assumes the violations to be independent of each other, the Christoffersen (1998) test has the alternative hypothesis of a first-order Markov chain.

The *VaR* results are provided in Appendix C. Clearly, they further confirm that the HAR extensions do not offer any material benefits in a risk management exercise relative to the simple HAR. Hence, our initial conclusion

Table 16
Forecasting evaluation for wheat futures with *RV*.

	h	RW	AR	ARMA	HAR	HAR-J	HAR-CJ	HAR-PS	LHAR-CJ
MSPE	1	1.4871	1.3285	1.4444	1.2476**	1.2497**	1.2575*	1.2418**	1.2579*
	5	1.4991	1.4300	1.5210	1.3900**	1.3899**	1.3962**	1.3908**	1.3894**
	10	1.4746**	1.4403**	1.4991	1.4297**	1.4299**	1.4362**	1.4335**	1.4220**
	22	1.4940**	1.4886**	1.5511	1.4867**	1.4876**	1.4864**	1.4886**	1.4839**
	44	1.5822**	1.5847**	1.6332	1.5589**	1.5591**	1.5622**	1.5597**	1.5555**
	66	1.6453*	1.6520	1.8056	1.6201**	1.6211**	1.6010**	1.6206**	1.5970**
MAPE	1	0.6271	0.6143	0.6204	0.5698**	0.5721	0.5689**	0.5682**	0.5744
	5	0.6329	0.6286	0.6371	0.6072*	0.6081	0.6047**	0.6078*	0.6090
	10	0.6202*	0.6225	0.6364	0.6185*	0.6192	0.6153**	0.6204	0.6214
	22	0.6355**	0.6423**	0.6613	0.6405**	0.6406**	0.6393**	0.6409**	0.6497
	44	0.6733**	0.6745*	0.7199	0.6739**	0.6745*	0.6762*	0.6744*	0.6887
	66	0.7032**	0.7190**	0.7816	0.7081**	0.7088**	0.7121**	0.7082**	0.7286
QLIKE	1	1.9467	1.9167	1.9393	1.9018**	1.9018**	1.9032*	1.9017**	1.9029**
	5	1.9429	1.9324	1.9494	1.9239**	1.9239**	1.9258*	1.9244**	1.9234**
	10	1.9389*	1.9328**	1.9499	1.9341**	1.9340**	1.9366*	1.9347**	1.9324**
	22	1.9574*	1.9544*	1.9915	1.9516*	1.9518*	1.9524*	1.9521*	1.9472**
	44	2.0036	2.0034	2.0022	1.9884	1.9880	1.9875	1.9884	1.9776**
	66	2.0194	2.0083	2.0441	2.0038*	2.0032*	1.9952*	2.0036*	1.9897**
SR	1	0.7124***	0.6805***	0.7143***	0.7105***	0.7077***	0.7049***	0.7180***	0.7068***
	5	0.6513***	0.6344***	0.6560***	0.6786***	0.6739***	0.6842***	0.6795***	0.6880***
	10	0.6692***	0.6363***	0.6541***	0.6673***	0.6692***	0.6729***	0.6664***	0.6758***
	22	0.6654***	0.6297***	0.6062***	0.6288***	0.6269***	0.6457***	0.6269***	0.6598***
	44	0.6071***	0.5470***	0.4643	0.5695***	0.5714***	0.5874***	0.5705***	0.6006***
	66	0.5536***	0.4464	0.4502	0.4812	0.4887	0.4887	0.4868	0.5122

Notes: * and ** indicate inclusion in the $\mathcal{M}^*_{90\%}$ and $\mathcal{M}^*_{75\%}$, respectively. For the success ratio (SR), *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

that the jump component, the continuous component, the signed jumps, and the volatility or return leverage do not offer any significant and economically useful forecasting gains remains robust.

6. Conclusion

The aim of this paper is to add to the extremely sparse literature on volatility forecasting for agricultural commodities. The existing studies have concentrated their attention on the Chinese futures markets and the benefits of developing a model averaging framework. Thus, they have not considered the U.S. market, which is the most established market, and they do not provide a clear answer as to whether specific volatility components, such as the jump component, the continuous component, the signed jumps and the volatility or return leverage, can provide incremental predictive gains. Finally, the current literature provides evidence based solely on the realized volatility measure. This study fills these voids by utilizing naive models (random walk, AR, ARMA) and several extensions of the simple HAR model (the simple HAR, HAR-J, HAR-CJ, HAR-PS and LHAR-CJ) to forecast two different realized volatility measures, namely the realized volatility (*RV*) and the median realized volatility (*MedRV*). For our study we obtain tick-by-tick data for five important agricultural commodities, namely corn, rough rice, soybeans, sugar and wheat, and produce forecasts for 1 to 66 days ahead. The period under study is from January 4, 2010, to June 30, 2017, and our out-of-sample period is January 2, 2013, to June 30, 2017.

Our in-sample analysis shows that the variants of the HAR model, which decompose the volatility measures into their continuous path and jump components, provide better fits in the predictive regressions. However, the real out-of-sample forecasts suggest strongly that such a decomposition does not offer any superior predictive ability, since none of the variants of the HAR model produce significantly better forecasts than the simple HAR model. Thus, there is no benefit in increasing the complexity in the forecasting models in regard to the volatility decomposition or its relative transformations. This finding holds for both the *RV* and *MedRV*, meaning that it is not specific a given volatility measure. We note that our findings hold for U.S. markets, whereas other studies, e.g. on Chinese futures markets (Tian et al., 2017a, 2017b; Yang et al., 2017), have found increased predictive power of jumps, structural breaks, and time variation of HAR coefficients. We conclude that differing driving factors, such as the motive and structure of market participants, could potentially affect the behaviour of the intra-day volatility, and hence its forecastability, differently.

Hence, we maintain that the search to improve the forecasting accuracy of the U.S. agricultural commodities volatility should not focus on the development of extended HAR models that take into account properties such as jump components, continuous components, signed jumps and the volatility or return leverage, but rather should look in other directions, such as the inclusion of exogenous predictors. Degiannakis and Filis (2017, 2018), and Nguyen and Walther (2019) have already shown that the incorporation of different asset classes' volatilities can help to improve the prediction of commodities prices and volatilities (oil prices and volatility in particular), and hence, further study should assess whether such asset classes could also help to improve forecasts for agricultural commodities. Furthermore, future research should consider how the inclusion of extreme weather events, food stocks, biofuels production or even market speculative activity could improve the agricultural commodity volatility forecasts further. Finally, an interesting avenue for further research would be the forecasting accuracy evaluation of alternative forecasting methods, such as machine learning.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

The authors would like to thank the Guest Editor Tao Hong and three anonymous reviewers for their helpful comments on a previous version of this paper. We are thankful for the comments and support of Matthias Fengler and Karl Frauendorfer. George Filis and Stavros Degiannakis acknowledge the support of Bournemouth University, which provided funding for the purchase of the data under the University's QR funds. Part of the work has been conducted during Thomas Walther's research time as Assistant Professor at the University of St. Gallen, Institute for Operations Research and Computational Finance.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.ijforecast.2019.08.011.

References

Anderluh, J., & Borovkova, S. (2008). Commodity volatility modelling and option pricing with a potential function approach. *The European Journal of Finance*, *14*(2), 91–113.

Andersen, T. G., & Bollerslev, T. (1998). Answering the skeptics: Yes, standard volatility models do provide accurate forecasts. *International Economic Review*, *39*(4), 885–905.

Andersen, T. G., Bollerslev, T., & Diebold, F. X. (2007). Roughing it up: Including jump components in the measurement, modeling, and forecasting of return volatility. *The Review of Economics and Statistics*, *89*(4), 701–720.

Andersen, T. G., Dobrev, D., & Schaumburg, E. (2012). Jump-robust volatility estimation using nearest neighbor truncation. *Journal of Econometrics*, *169*(1), 75–93.

Barndorff-Nielsen, O. E., Kinnebrock, S., & Shephard, N. (2010). Measuring downside risk — realized semivariance. In M. Watson, T. Bollerslev, & J. R. Russell (Eds.), *Volatility and time series econometrics: essays in honor of robert engle* (pp. 117–136). Oxford University Press, http://dx.doi.org/10.1093/acprof:oso/9780199549498.003.0007.

Barndorff-Nielsen, O. E., & Sheppard, N. (2004). Power and bipower variation with stochastic volatility and jumps. *Journal of Financial Econometrics*, *2*(1), 1–37. http://dx.doi.org/10.1093/jjfinec/nbh001.

Bloomberg (2019). There are three new ways to bet on Chinese commodity markets. URL https://www.bloomberg.com/news/articles/2019-01-28/there-are-three-new-ways-to-bet-on-chinese-commodity-markets. 28 January 2019.

von Braun, J., & Tadesse, G. (2012). Food security, commodity price volatility and the poor. In M. Aoki, T. Kuran, & G. Roland (Eds.), *IAE conference*: *Vol. 2012*, *Institutions and comparative economic development*. Palgrave Macmillan Publications.

Christoffersen, P. F. (1998). Evaluating interval forecasts. *International Economic Review*, *39*(4), 841–862. http://dx.doi.org/10.2307/2527341.

Corsi, F. (2009). A simple approximate long-memory model of realized volatility. *Journal of Financial Econometrics*, *7*(2), 174–196. http://dx.doi.org/10.1093/jjfinec/nbp001.

Corsi, F., & Renò, R. (2012). Discrete-time volatility forecasting with persistent leverage effect and the link with continuous-time volatility modeling. *Journal of Business & Economic Statistics*, *30*(3), 368–380. http://dx.doi.org/10.1080/07350015.2012.663261.

Degiannakis, S. (2008). ARFIMAX and ARFIMAX-TARCH realized volatility modeling. *Journal of Applied Statistics*, *35*(10), 1169–1180. http://dx.doi.org/10.1080/02664760802271017.

Degiannakis, S., & Filis, G. (2017). Forecasting oil price realized volatility using information channels from other asset classes. *Journal of International Money and Finance*, *76*, 28–49. http://dx.doi.org/10.1016/j.jimonfin.2017.05.006.

Degiannakis, S., & Filis, G. (2018). Forecasting oil prices: High-frequency financial data are indeed useful. *Energy Economics*, *76*, 388–402. http://dx.doi.org/10.1016/j.eneco.2018.10.026.

Degiannakis, S., Filis, G., & Hassani, H. (2018). Forecasting global stock market implied volatility indices. *Journal of Empirical Finance*, *46*, 111–129. http://dx.doi.org/10.1016/j.jempfin.2017.12.008.

Ederington, L. H., & Guan, W. (2010). Longer-term time-series volatility forecasts. *Journal of Financial and Quantitative Analysis*, *45*(4), 1055–1076. http://dx.doi.org/10.1017/S0022109010000372.

Egelkraut, T. M., & Garcia, P. (2006). Intermediate volatility forecasts using implied forward volatility: The performance of selected agricultural commodity options. *Australian Journal of Agricultural and Resource Economics*, *31*(3), 508–528.

Elder, J., & Jin, H. J. (2007). Long memory in commodity futures volatility: A wavelet perspective. *Journal of Futures Markets*, *27*(5), 411–437. http://dx.doi.org/10.1002/fut.20260.

Engle, R., Hong, C. -H., & Kane, A. (1990). *Valuation of variance forecast with simulated option markets*. Cambridge, MA: National Bureau of Economic Research, http://dx.doi.org/10.3386/w3350.

Fan, J. H., & Zhang, T. (2018). *Demystifying Commodity Futures in China*. http://dx.doi.org/10.2139/ssrn, SSRN 3124223.

FAO (2010). Price volatility in agricultural markets: Evidence, impact on food security and policy responses. URL http://www.fao.org/docrep/013/am053e/am053e00.pdf.

FAO (2011). Price volatility in food and agricultural markets: Policy responses. URL http://www.fao.org/fileadmin/templates/est/Volatility/Interagency_Report_to_the_G20_on_Food_Price_Volatility.pdf.

Giot, P., & Laurent, S. (2003). Market risk in commodity markets: a VaR approach. *Energy Economics*, *25*(5), 435–457. http://dx.doi.org/10.1016/S0140-9883(03)00052-5.

Greb, F., & Prakash, A. (2015). *Has price volatility changed? Food Outlook*, Rome, Italy: Food and Agriculture Organization of the United Nations.

Greb, F., & Prakash, A. (2017). Assessing volatility patterns in food crops. In *FAO commodity and trade policy research working paper series*, URL http://www.fao.org/3/a-i7066e.pdf.

Hansen, P. R., Lunde, A., & Nason, J. M. (2011). The model confidence set. *Econometrica*, *79*(2), 453–497. http://dx.doi.org/10.3982/ECTA5771.

Huang, H. -C. R. (2004). A flexible nonlinear inference to the Kuznets hypothesis. *Economics Letters*, *84*(2), 289–296. http://dx.doi.org/10.1016/j.econlet.2004.01.014.

Johnson, T. (2011). *Food price volatility and insecurity*. Council on Foreign Relations (CFR), URL https://www.cfr.org/backgrounder/food-price-volatility-and-insecurity.

Klein, T., & Todorova, N. (2018). *The impact of SHFE's night trading session on volume and realized volatility of aluminum and copper futures markets*. http://dx.doi.org/10.2139/ssrn.3249598, SSRN Working Paper 3249598.

Kupiec, P. H. (1995). Techniques for verifying the accuracy of risk measurement models. *The Journal of Derivatives*, *3*(2), 73–84. http://dx.doi.org/10.3905/jod.1995.407942.

Li, N., Ker, A., Sam, A. G., & Aradhyula, S. (2017). Modeling regime-dependent agricultural commodity price volatilities. *Agricultural Economics*, *48*(6), 683–691. http://dx.doi.org/10.1111/agec.12366.

Liu, L. Y., Patton, A. J., & Sheppard, K. (2015). Does anything beat 5-minute RV? A comparison of realized measures across multiple asset classes. *Journal of Econometrics*, *187*(1), 293–311. http://dx.doi.org/10.1016/j.jeconom.2015.02.008.

Luo, J., Klein, T., Ji, Q., & Hou, C. (2019). Forecasting realized volatility of agricultural commodity futures with infinite hidden Markov HAR models. *International Journal of Forecasting*, http://dx.doi.org/10.1016/j.ijforecast.2019.08.007.

Nguyen, D. K., & Walther, T. (2019). Modeling and forecasting commodity market volatility with long-term economic and financial variables. *Journal of Forecasting*, http://dx.doi.org/10.1002/for.2617, forthcoming.

Ordu, B. M., Oran, A., & Soytas, U. (2018). Is food financialized? Yes, but only when liquidity is abundant. *Journal of Banking & Finance*, *95*, 82–96. http://dx.doi.org/10.1016/j.jbankfin.2017.06.001.

Patton, A. J. (2011). Volatility forecast comparison using imperfect volatility proxies. *Journal of Econometrics*, *160*(1), 246–256. http://dx.doi.org/10.1016/j.jeconom.2010.03.034.

Patton, A. J., & Sheppard, K. (2015). Good volatility, bad volatility: Signed jumps and the persistence of volatility. *The Review of Economics and Statistics*, *97*(3), 683–697. http://dx.doi.org/10.1162/REST{_}a{_}00503.

Pesaran, M. H., & Timmermann, A. (1992). A simple nonparametric test of predictive performance. *Journal of Business & Economic Statistics*, *10*(4), 461–465. http://dx.doi.org/10.1080/07350015.1992.10509922.

Sévi, B. (2014). Forecasting the volatility of crude oil futures using intraday data. *European Journal of Operational Research*, *235*(3), 643–659. http://dx.doi.org/10.1016/j.ejor.2014.01.019.

Theodosiou, M., & Zikes, P. (2011). *A comprehensive comparison of alternative tests for jumps in asset prices*. Working Paper, Central Bank of Cyprus.

Tian, F., Yang, K., & Chen, L. (2017a). Realized volatility forecasting of agricultural commodity futures using long memory and Regime switching. *Journal of Forecasting*, *36*(4), 421–430. http://dx.doi.org/10.1002/for.2443.

Tian, F., Yang, K., & Chen, L. (2017b). Realized volatility forecasting of agricultural commodity futures using the HAR model with time-varying sparsity. *International Journal of Forecasting*, *33*(1), 132–152. http://dx.doi.org/10.1016/j.ijforecast.2016.08.002.

Triantafyllou, A., Dotsis, G., & Sarris, A. H. (2015). Volatility forecasting and time-varying variance risk premiums in grains commodity markets. *Journal of Agricultural Economics*, *66*(2), 329–357. http://dx.doi.org/10.1111/1477-9552.12101.

Yang, K., Tian, F., Chen, L., & Li, S. (2017). Realized volatility forecast of agricultural futures using the HAR models with bagging and combination approaches. *International Review of Economics and Finance*, *49*, 276–291. http://dx.doi.org/10.1016/j.iref.2017.01.030.

Zhang, D. (2017). Oil shocks and stock markets revisited: Measuring connectedness from a global perspective. *Energy Economics*, *62*, 323–333. http://dx.doi.org/10.1016/j.eneco.2017.01.009.