Oil price volatility is effective in predicting food price volatility. Or is it?

Ioannis Chatziantoniou[1], Stavros Degiannakis[2], George Filis[3,*], Tim Lloyd[3]

[1]Economics and Finance Subject Group, University of Portsmouth, Portsmouth Business School, Portland Street, Portsmouth, PO1 3DE, United Kingdom.

[2]Department of Economics and Regional Development, Panteion University of Social and Political Sciences, 136 Syggrou Avenue, 17671, Greece.

[3]Bournemouth University, Department of Accounting, Finance and Economics, Executive Business Centre, 89 Holdenhurst Road, BH8 8EB, Bournemouth, UK.

*Corresponding author's email: gfilis@bournemouth.ac.uk

Abstract

Volatility spillovers between food commodities and oil prices have been identified in the literature, yet, there has been no empirical evidence to suggest that oil price volatility improves real out-of-sample forecasts of food price volatility. In this study we provide new evidence showing that oil price volatility does not improve forecasts of agricultural price volatility. This finding is based on extensive and rigorous testing of five internationally traded agricultural commodities (soybeans, corn, sugar, rough rice and wheat) and two oil benchmarks (Brent and WTI). We employ monthly and daily oil and food price volatility data and two forecasting frameworks, namely, the HAR and MIDAS-HAR, for the period 2nd January 1990 until 31st March 2017. Results indicate that oil volatility-enhanced HAR or MIDAS-HAR models cannot systematically outperform the standard HAR model. Thus, contrary to what has been suggested by the existing literature based on in-sample analysis, we are unable to find any systematic evidence that oil price volatility improves out-of-sample forecasts of food price volatility. The results remain robust to the choice of different out-of-sample forecasting periods and three different volatility measures.

Keywords: Forecasting, Food price volatility, Heterogeneous Autoregressive, Mixed-data sampling, Oil price volatility, Model Confidence Set.

JEL Classifications: C22, C53, Q02, Q17, Q47

1. Introduction

1.1 Context

Spikes in the prices of internationally traded agricultural commodities and oil in 2008 and 2011 and the associated food inflation – not seen since the 1970s – have raised concerns about the impact of food price volatility on both consumers and producers across the world (FAO-OECD, 2011). While recent research has emphasised a strengthening of links between oil and agricultural commodities both in levels and volatilities (see, for instance, Algieri and Leccadito, 2017; Zhang and Broadstock, 2018) this has been based on in-sample evidence. In contrast, the extent to which oil price volatility impacts on forecasts of agricultural price volatility has not been established. It is this gap that we aim to fill in this paper by investigating the incremental real out-of-sample predictive content of oil price volatility on the volatility forecasts of several important agricultural commodities for the global economy.

Understanding food price volatility is important for at least three reasons. First, volatile crop prices increase hedging costs of agricultural firms, deteriorating their financial position (Wu *et al*., 2011). Second, in recent years, commodity markets (including energy but also agricultural commodities) have attracted the interest of financial investors, and have become more financialised as a result (Irwin and Saunders, 2011). Wu *et al.* (2011) and Gardebroek and Hernandez (2013) document the recent upsurge in investment portfolios that comprise agricultural commodities. This financialisation of agricultural commodity markets has led, so the argument goes, to increased volatility in crop prices, retarding investment and raising costs to famers via higher option and insurance premiums. Ordu *et al*. (2017) further highlight the potential impact of the financialisation of agricultural commodities on household consumption and well-being, emphasizing the link between the price of food on one hand, and food security and malnutrition on the other. As the correlation between financial markets, energy and commodity markets becomes stronger, so does the impact from their interaction (see, *inter alia*, Vivian and Wohar, 2012; Silvernnoinen and Thorp, 2013; Sadorsky, 2014). Third, food price volatility is key concern for policy makers, particularly those whose focus is food security in poorer economies (FAO-OECD, 2011). For example, in the wake of recent agricultural price volatility, G20 leaders requested the development of mechanisms to mitigate the risks that are associated with food price volatility to protect both consumers and producers, particularly those in low-income countries. As a consequence, the Agricultural Market Information System

(AMIS) was established in 2011 to provide reliable market information and a forum to coordinate rapid responses to future crises (AMIS 2020). Even in relatively prosperous economies such as the UK, food price volatility is a pressing public policy concern owing to the importance of the agricultural industry to the rural economy and the cost of food for low income households (House of Lords, 2016).

The intensity and extent of agricultural price volatility also has implications for the formulation and implementation of policies designed to mitigate its effect, which by their very nature, lead to significant and widespread effects in both the short and long run (Byrne *et al*., 2013). While almost all agricultural policy has a price stabilisation objective, explicit market intervention to address commodity price volatility, at both the national and international scale, has a long and largely chequered history (Gilbert 2011) ranging from the buffer stock schemes characteristic of now-defunct International Commodity Agreements, to the export restrictions that typified the response of many governments to the 2007-2008 price spike, which merely served to amplify the volatility on intentional markets (FAO-OECD, 2011). Most recent policy aimed at ameliorating the effects of volatility does so either indirectly (e.g. decoupled payments of the Common Agricultural Policy) or involves more market-based risk management instruments, such as the crop insurance programme in US and the promotion of futures markets among farmers (see *inter alia* House of Lords 2016).

While the causes of agricultural price volatility are manifold, key among them is the linkage between the price of oil and agricultural commodities (Tyner, 2010, Tadesse *et al*., 2016) which Baffes (2013) argues has become stronger since 2005.

There are two main channels by which oil price volatility can exert impact on the volatility of food prices. On the one hand, there is a direct impact; in many parts of the world commercial agriculture is oil-intensive reflecting a reliance on fertilizers, irrigation and mechanisation in the pursuit of higher yields. For example, Lott (2011) claims that 10 calories of oil are required to produce 1 calorie of food in the US. While few agricultural systems are as oil-dependent as they are in the US, commercial farming would not exist without it, with the result that oil price volatility is transmitted into the markets of all internationally traded agricultural commodities whose production depends on it (see, Gardebroek and Hernandez, 2013; Ordu *et al*., 2017, among others).

On the other hand, there is an indirect channel arising from the demand for widely traded agricultural commodities (principally maize, soybeans, wheat and sugar) as biofuels (see, Harri *et al.*, 2009; Zhang *et al*., 2010; Du *et al*., 2011). Biofuel demand, particularly in times of high oil prices, has been significant. FAO-OECD (2011) report that during 2007-09, biofuels accounted for some 20% of the global consumption of sugar cane and 9% of vegetable oil. Furthermore, the adoption of biofuel mandates (mandatory obligations to blend fixed proportions of biofuels with fossil fuels) in both the US and European Union are widely thought to have hardened the inelasticity of demand that gives rise to agricultural price volatility in the first place. In countries where biofuel mandates were most aggressive, effects were stronger, Hertel and Beckman (2011) reporting that in 2010 about 40% of maize production in the US ended-up in biofuels. Other developments, such as the use of index investments (in which oil is an important component) in agricultural commodity market trading (Tang and Xiong 2012) and the fact that oil and agricultural commodities are typically traded in the US dollar (Harri *et al*. (2009), give credence to the view that the prices of oil and agricultural commodities and the variability of those prices are inextricably linked in international markets.

1.2 Commodities, volatilities and the futures market

Overall, while the linkage between the volatilities of oil and agricultural prices is widely discussed in the literature, evidence is still rather scarce. This view is highlighted by Serra (2011) and Gardebroek and Hernandez (2013) who are able to document only a handful of studies investigating the transmission of volatility between energy and commodity prices. Despite the scarce empirical literature, relevant studies occupy the full spectrum of potential linkages between oil and agricultural commodities, in the sense that the research relates to both spot and future prices and/or their respective volatilities. Focussing on the volatility of futures prices, the present study is positioned within an even scarcer strand of extant relevant work. Prominent in this literature is Algalith (2010) who provides evidence that higher levels of oil price volatility results in higher food prices. More particularly, Algalith (2010) argues that hedging oil quantities in futures contracts would likely reduce oil price uncertainty and as a consequence, reduce food commodity prices. In addition, Du *et al*. (2011) utilise crude oil, corn and wheat future contracts in order to investigate the impact of crude oil volatility on agricultural commodities, providing evidence of a positive link. More recently, Trujillo-Barrera *et al*. (2012) employ futures prices in order to examine spillovers from crude oil to a number of commodity markets in the US economy and show that there are important spillover effects running from oil price volatility to corn price volatility, which intensify during economic turbulent periods (specifically, the Global Financial Crisis of 2007-09).

1.3 Forecasting commodity price volatility in the futures market

Following from above, relevant studies that investigate the volatility of commodity prices in futures markets include Giot (2003) who was among the first to forecast agricultural commodity volatility – showing that implied volatilities of future contracts provide predictive gains to conditional volatility forecasts. Some fifteen years later, Tian *et al.* (2017a) forecasted the volatility of five agricultural commodity futures, namely Soybean, Soybean oil, White Sugar, Gluten Wheat and Cotton, using a two regime-switching Markov model. Their findings suggested that the dynamics of regime switching is capable of providing superior predictive accuracy relative to an AR(1) model or even a Markov-Switching AR(1) model.

In turn, Tian *et al.* (2017b) estimate Heterogeneous AutoRegressive (HAR) models, with both static and time-varying parameters, considering the daily realized volatility, the range estimator, jump components (i.e. discontinuities in the underlying process) and other realized volatility (RV) measures of agricultural commodity volatility, such as the realized threshold multi-power variation and the realized threshold bi-power variation, as potential predictors. Their study concentrates on China and comprises six of the most rapidly expanding agricultural commodity futures markets; namely, soybean, cotton, gluten wheat, corn, early Indica rice and palm. Their findings show that while jump components play a role, it is the HAR models with time-varying parameters that provide the highest predictive accuracy of agricultural volatility for 1- to 20-days ahead. Yang *et al.* (2017) also employ HAR models with jump components, lagged returns and days-of-the-week effects as exogenous variables. They then use bagging and principal component (PC) approaches in combination with HAR models (i.e. HAR, HAR with jumps, HAR with lagged returns and HAR with the days-of-the-week effects) to forecast price volatility of four agricultural commodity futures in China: soybean, cotton, gluten wheat and corn. Their findings show that both combination approaches yield improved predictions for 1-, 5- and 10-days ahead, relative to each individual HAR models.

What is apparent from this summary of the recent literature on commodity price volatility forecasting is that oil price volatility does not feature in it. Given the weight of evidence from a number of studies pointing to the important role of oil price volatility in commodity price volatility, we utilise out-of-sample forecasting techniques in order to investigate whether oil price volatility has any incremental predictive information with regard to food price volatility. The sample period for our analysis is January 1990 to March 2017 and we focus on five key food commodities, namely: corn, rough rice, soybeans, sugar #11 and wheat, as well as the two main crude oil benchmarks, i.e. West Texas Intermediate (WTI) and Brent. Unlike the previous research, our focus is on monthly volatility forecasts, reflecting the interest in food price volatility forecasting from a number of stakeholders with longer horizons (e.g. agricultural firms and policy makers). In the interest of comparison, we employ predictive models with and without the information from the oil market (i.e., oil volatility). In particular, we initially employ the HAR model developed by Corsi (2009) on monthly volatility, which we augment with oil price volatility. We further enhance our modelling approach by considering a mixed-data sampling model (MIDAS) so to assess whether the incremental predictive information of oil price volatility on monthly food price volatility forecasts is hidden in a higher frequency (i.e. daily oil price volatility). For robustness, we use three volatility measures, namely, realized volatility, price range volatility and realized range volatility.

The results from our out-of-sample forecasts show that the forecasting models which include the predictive information of oil price volatility do not systematically outperform models based on the autoregressive information of the food price volatilities, as suggested by the Mean Squared Forecasting Error and Mean Absolute Forecasting Error. This finding holds irrespective of type of the crude oil, crop forecast horizon or volatility measure that is used. Outcomes using directional accuracy also corroborate these findings. Finally, in order to evaluate whether the findings are robust across the sample period, we repeat the exercise considering three turbulent periods for commodity markets: the Food and Global Financial Crisis of 2007-2009, the second food crisis in 2010-2012 and the oil price collapse in 2014-2016. Overall, our results consistently show that oil price volatility does not add any incremental predictive information to food price volatility. Hence, we maintain that even though previous studies have suggested that there should be some predictive information stemming from oil price volatility on agricultural price volatility, that assertion relies on results obtained from in-sample exercises. Our findings suggest that when real-time out-of-sample forecasts of agricultural price volatility are evaluated, no evidence supporting the incremental predictive information of oil price volatility can be found.

The remainder of this study is structured as follows. Section 2 describes the data and the method employed in the paper. Section 3 presents the results followed by a thorough discussion. Finally, Section 4 concludes the study.

2. Data and Methods

2.1. Data Description

In this study we focus on the futures prices of five key agricultural commodities, namely, soybeans, corn, sugar #11, rough rice and wheat[1]. In addition, given that the aim of the study is to assess the incremental predictive ability of oil price volatility on the volatility of food prices, we use futures prices for the two main global oil benchmarks, namely, WTI and Brent[2]. Our dataset comprises open, high, low and close data on a daily frequency from 2nd of January, 1990 until 31st of March, 2017. The data are obtained from Bloomberg.

2.2. Estimating Monthly Food Price Volatility

As aforementioned, we focus on monthly food price volatility. In recent years the literature has provided both theoretical and empirical evidence in favour to the realized volatility as the most appropriate estimator of the actual but unobservable volatility[3]. The realized volatility is a consistent and asymptotically unbiased estimator under the assumption that the prices are observed in continuous time and without measurement errors; see for example Andersen *et al*. (2003) and Zhang *et al*. (2005) [4].

The annualized realized volatility on a monthly frequency is defined as the sum of the squared intra-day log-returns (see, i.e., Andersen and Bollerslev, 1998):

$$RV_t^{(M)} = \sqrt{\frac{252}{22}\sum_{i=0}^{21}\sum_{j=1}^{\tau}\left(logP_{t-i_j} - logP_{t-i_{j-1}}\right)^2}, \qquad (1)$$

---

[1] Soybean (SY), Corn (CN), Rough Rice (RR) and Wheat (WC) futures contracts are traded in the Chicago Board of Trade (CBOT). Sugar #11 (SB) is traded in Intercontinental Exchange (ICE).

[2] WTI (WT) and Brent (CO) crude oil futures contracts are traded in ICE.

[3] This also includes its subsequent variations; i.e. indicatively named the bipower variation of Barndorff-Nielsen and Shephard (2006), the median realized volatility of Andersen *et al.* (2012) as well as the realized semi variance of Barndorff-Nielsen *et al.* (2010).

[4] To confirm the validity of our $RV_t^{(M)}$ we compare our volatility measures against the conditional volatility constructed from the in-sample estimated standard deviations from an appropriately specified GARCH model variant fitted to daily data. Our volatility measures are closely related to the conditional volatility estimators and thus, they can be considered as valid proxies for our modelling framework. Details available upon request.

where t is the trading day, j is the intra-day point and τ is the number of equidistant intra-day points in time. Hence, $\left\{P_{t_j}\right\}_{j=1,\dots,t}^{t=1,\dots,T}$ denotes the intra-day observed prices of the commodity for T trading days.

We note, though, that in many cases accurate ultra-high frequency data are not easily available (either there are illiquid asset classes or high-quality intra-day data are available only for granular time periods or at high purchasing cost). Given these limitations, we focus on measures that analysts or researchers can construct with freely available data. Thus, with regard to the monthly realized volatility, we consider the daily sampling frequency during a calendar month as the intra-period sampling, defining the days as intra-points of the month. Then eq.(1) is computed for $\tau = 1$ intra-day point, as:

$$RV_t^{(M)} = \sqrt{\frac{252}{22}\sum_{i=1}^{22}(logP_{t-i} - logP_{t-i-1})^2}. \tag{2}$$

Despite the fact that analysts or researchers may not have access to ultra-high frequency data, it is rather common that the daily OHLC (open, high, low and close) price data are freely available and for lengthy time periods. Where this is the case, we can approximate volatility based on the range estimator, which justifies the choice of this alternative measure in our study. Garman and Klass (1980), extending Parkinson's (1980) high-low range estimator, proposed the four-data-points price range estimator including the opening and the closing daily prices. The annualized price-range volatility on a daily frequency is computed as:

$$PR_t^{(D)} = \sqrt{252\left(\frac{1}{2}\left(log\frac{\max_{j=1,\dots,\tau}\left(P_{t_j}\right)}{\min_{j=1,\dots,\tau}\left(P_{t_j}\right)}\right)^2 - (2log(2)-1)\left(log\frac{P_{t_\tau}}{P_{t_1}}\right)^2\right)}. \tag{3}$$

Degiannakis and Livada (2013) provide simulation evidence that the four-data-points price range is more accurate than the realized volatility estimator based on eight, or less, intra-period log-returns. Using the same notion, the annualized price-range volatility on a monthly frequency is estimated as:

$$PR_t^{(M)} =$$

$$\sqrt{12\left(\frac{1}{2}\left(log\frac{\max_{i=t,\dots,t-21,j=1,\dots,\tau}\left(P_{i_j}\right)}{\min_{i=t,\dots,t-21,j=1,\dots,\tau}\left(P_{i_j}\right)}\right)^2 - (2log(2)-1)\left(log\frac{P_{t_\tau}}{P_{t-21_1}}\right)^2\right)}. \tag{4}$$

For further evidence we choose to use an additional alternative volatility measure, which is also based on freely available data, i.e. the daily OHLC prices. Thus, we further propose the use of the realized range measure of monthly volatility:

$$RR_t^{(M)} = \sqrt{\frac{1}{22}\sum_{t=1}^{22} {PR_t^{(D)}}^2}, \tag{5}$$

as the summation of daily price-range variances instead of the monthly OHLC prices, used in $PR_t^{(M)}$. Naturally, the $RR_t^{(M)}$ incorporates much richer information set than the $PR_t^{(M)}$. The use of any other volatility measure would either require the use of ultra-high frequency data or would be less informative (e.g. the absolute monthly returns or the rolling window historical standard deviation).

2.3. Preliminary Analysis

Figures 1 to 3 illustrate the three different annualized volatility measures, whereas Table 1 presents their descriptive statistics.

[FIGURES 1 – 3 HERE]

[TABLE 1 HERE]

Evident in Figures 1 to 3 is that despite the obvious discrepancies in the manifestation of volatility across the five crops included in our analysis, all three different measures of volatility accentuate similar points of interest for each individual crop. For instance, Soybeans volatility reaches a peak in 1997, 2004, as well as 2008, a fact that is clearly captured irrespective of which measure of volatility we employ. The same is true when we consider the two different types of crude oil; that is, Brent crude oil and WTI, whereby, peak volatility values are obtained, irrespective of measure (i) during the Middle East conflicts in the early 1990s, (ii) following the Global Financial Crisis, as well as (iii), throughout the 2014-2016 oil price collapse. Two other observations are noteworthy, namely the absence of any clear synchronisation in the volatility statistics between oil and the commodity prices. Furthermore, the recent food crises of 2007-2008 and 2010-2012 do not correspond to the most pronounced spikes in commodity price volatility that have been observed over the sample period, highlighting the distinction between period of high prices and volatility.

Turning to the descriptive information presented in Table 1, sugar and wheat are the most volatile agricultural commodities considered, exhibiting the highest mean volatility, irrespective of the measure used. The statistics also suggest unusually high volatility and frequent extreme events, given the evident positive skewness and excess kurtosis. Furthermore, the three volatility measures indicate that WTI is the most volatile type of crude oil.

2.4. Modelling Food Price Volatility

Volatility measures are typically characterized by high autocorrelation, long memory and persistence (indicatively see, Andersen *et al*., 2001 and Degiannakis, 2008). These features are apparent in our commodity price data and suggest the use the Heterogeneous AutoRegressive (HAR) model proposed by Corsi (2009), which we adopt as our main forecasting tool. The HAR model relates the current realized volatility to the realized volatilities of previous time horizons at different sampling frequencies. For example, in the Corsi (2009) study, daily realized volatility was modelled as a function of the daily, weekly and monthly realized volatilities; the lower frequency data adeptly capturing the long memory property of volatility. For benchmarking purposes, we also use two naïve models, i.e. the random walk and the autoregressive models.

Recently, Degiannakis and Filis (2017) introduced the use of HAR models with exogenous variables to forecast realized volatility (HAR-X). We employ this modelling framework to investigate whether the inclusion of oil price volatility is able to provide any additional predictive information to food commodity price volatility. Furthermore, we extend the HAR model into the mixed data sampling frequency (MIDAS) framework in order to explore any possible relationship between monthly food volatility and oil price volatility at higher sampling frequency; i.e. on a daily basis.

In the following paragraphs, we set out the models that we will use to forecast monthly commodity price volatility, which is denoted as $V_t^{(M)}$ in its general form. Realized volatility, the price range and the realized range measures are obtained by replacing $V_t^{(M)}$ with $RV_t^{(M)}$, $PR_t^{(M)}$ and $RR_t^{(M)}$, respectively. We begin with standard benchmark models and then set out the HAR model and its extensions. In all models, it is assumed that $\varepsilon_t \sim N(0, \sigma_\varepsilon^2)$.

2.5. Random Walk (RW) model

It is rather typical in the volatility forecasting literature to use the Random Walk model (RW) as the most naïve forecasting model (see, for instance, Brailsford and Faff, 1996; Sadorsky, 2006; and more recently Kambouroudis *et al.*, 2016). The RW model without a drift is usually defined as the benchmark model in forecasting evaluation frameworks. The RW model lacks of forecasting ability and considers the most recently observed price as the best forecast:

$$log\left(V_t^{(M)}\right) = log\left(V_{t-1}^{(M)}\right) + \varepsilon_t, \tag{6}$$

where $\varepsilon_t \sim N(0, \sigma_\varepsilon^2)$.

2.6. Autoregressive (AR) model

Apart from the RW model, studies on volatility forecasting commonly use an AR model, as an additional benchmark (e.g. Tian *et al.*, 2017a). The most commonly applied model is the p^{th} order Autoregressive model, AR(p):

$$log\left(V_t^{(M)}\right) = w_0\left(1 - \sum_{i=1}^{p} w_i\right) + \sum_{i=1}^{p} w_i log\left(V_{t-i}^{(M)}\right) + \varepsilon_t. \tag{7}$$

The order p of the AR model is based on the Bayesian Information Criterion during the in-sample estimation period.

2.7. HAR model

We employ Corsi's (2009) HAR model, to fit monthly frequency data, so that similar to Degiannakis and Filis (2019), current monthly volatility is impacted by the previous month's, previous quarter's and previous year's volatility, such as that:

$$\begin{gathered} log\left(V_t^{(M)}\right) = w_0 + w_1 log\left(V_{t-1}^{(M)}\right) + w_2\left(3^{-1}\sum_{k=1}^{3} log\left(V_{t-k}^{(M)}\right)\right) + \\ w_3\left(12^{-1}\sum_{k=1}^{12} log\left(V_{t-k}^{(M)}\right)\right) + \varepsilon_t, \end{gathered} \tag{8}$$

where $\varepsilon_t \sim N(0, \sigma_\varepsilon^2)$. The main advantage of the HAR model is its ability to model the heterogeneous beliefs of market participants. It has been shown that models which consider the long-memory behaviour of volatility (e.g. HAR model) are able to generate superior forecasts (Bollerslev and Wright, 2001; Andersen *et al.*, 2007).

2.8. HAR-X model

Inspired by Degiannakis and Filis (2017), we augment the HAR model, incorporating exogenous information regarding the volatility of other assets. The HAR-X model can be presented as:

$$log\left(V_t^{(M)}\right) = w_0 + w_1 log\left(V_{t-1}^{(M)}\right) + w_2\left(3^{-1}\sum_{k=1}^{3} log\left(V_{t-k}^{(M)}\right)\right) + w_3\left(12^{-1}\sum_{k=1}^{12} log\left(V_{t-k}^{(M)}\right)\right) + w_4 log\left(V_{x,t-1}^{(M)}\right) + w_5\left(3^{-1}\sum_{k=1}^{3} log\left(V_{x,t-k}^{(M)}\right)\right) + w_6\left(12^{-1}\sum_{k=1}^{12} log\left(V_{x,t-k}^{(M)}\right)\right) + \varepsilon_t, \quad (9)$$

where $V_{x,t}^{(M)}$ denotes the volatility estimate of the exogenous assets; i.e. the WTI and Brent volatility measures.

2.9. MIDAS-HAR-X model

Thus far, all the models have been based on monthly frequency volatility measures. In this section, we entertain the possibility that the potential predictive information of oil price volatility to monthly food commodity price volatility is embodied in higher frequency data. This allows for the possibility that commodity market participants base their decisions on information affecting the market within the unit (monthly) frequency. The only model that related variables in different sampling frequencies is the MIDAS (Mixed-Data Sampling) model (see, Ghysels *et al.*, 2006; Andreou *et al.*, 2010, 2013). Thus, we expand the HAR model, in order to include predictive information available from explanatory variables at daily frequency. Denoting $\boldsymbol{X}_{(t)/s}^{(D)}$ as the WTI and Brent price volatility at the daily frequency, the MIDAS form of the model becomes as follows:

$$log\left(V_t^{(M)}\right) = w_0 + w_1 log\left(V_{t-1}^{(M)}\right) + w_2\left(3^{-1}\sum_{k=1}^{3} log\left(V_{t-k}^{(M)}\right)\right) + w_3\left(12^{-1}\sum_{k=1}^{12} log\left(V_{t-k}^{(M)}\right)\right) + \sum_{j=0}^{p}\sum_{\tau=0}^{q-1} \tau^j \boldsymbol{X}'^{(D)}_{(t-\tau-is)/s}\,\boldsymbol{\theta}_j + \varepsilon_t, \quad (10)$$

where $s = 22$ is the number of daily observations at each month and $\boldsymbol{\theta}_j$ is a vector of coefficients to be estimated from the data. Here q defines the number of lagged days that must be incorporated in the model and is not restricted by the s; i.e. the number of daily observations within each month. The p is the dimension of the lag polynomial in the vector parameters $\boldsymbol{\theta}_j$.[5]

[5] Every time that the model is re-estimated, new q and p that minimize the sum of squared residuals are adopted.

We handle the proposed MIDAS-HAR-X model in such a way that we will be able to produce s-months ahead volatility forecasts. For example, to predict the three-months ahead volatility forecast, the MIDAS-HAR-X model is adjusted for $i = 3$, and subsequently for $is = 66$.

Should monthly oil price volatility provide incremental forecasting accuracy for predicting commodity price volatility, models based on (9) and/or (10) will outperform those based on (6) to (8).

Given the daily data considered in the present study, another benchmark that could have been employed is the workhorse of volatility forecasting, the GARCH(1,1) or the recently developed GARCH-MIDAS model by Engle *et al.* (2013). We opt not to do so for a rather simple reason. Estimating volatility at daily frequency and forecasting it at a monthly frequency would result in an increase of the forecast error. For instance, let us assume that we would like to forecast next month's volatility. Based on the GARCH or GARCH-MIDAS daily models, we should compute daily volatility forecasts from 1- up to 22-steps-ahead. On the contrary, using the HAR or the HAR-MIDAS models we have to compute only the 1-step ahead monthly volatility forecast.

Before we proceed to the real out-of-sample forecasting, we compute the log-likelihood ratios between the oil price volatility-enhanced models (i.e. HAR-X and MIDAS-HAR-X models) and the standard HAR model, in order to gain some understanding of the performance of the former models, which can be regarded as extensions of the latter. Table 2 suggests that the MIDAS-HAR-X models are performing significantly better compared to the standard HAR model, although the findings for the HAR-X models paint the opposite picture. Thus, we maintain that the in-sample comparison promotes the MIDAS-HAR-X models as being the best performing models. Even though this in-sample analysis might provide us with some anticipation as to the models that could provide the best performing results, we maintain that it cannot certainly be regarded as a safe choice for the out-of-sample forecasting performance.

[TABLE 2 HERE]

2.10 Evaluating Food Price Volatility Forecasts

Turning to the three measures of volatility $RV_t^{(M)}$, $PR_t^{(M)}$ and $RR_t^{(M)}$ we begin by estimating the RW, AR(p) and HAR models. It is worth noting, each uses exclusively predictive information extracted from the past food price volatility itself. The HAR-X model with the WTI and the Brent volatility, as well as, the HAR-MIDAS model with the WTI and the Brent volatility at a daily sampling frequency are then estimated to investigate whether the oil volatility is able to provide any additional information in predicting food price volatility. Overall, we estimate seven (7) models for each of the five (5) food commodities and for each of three volatility measures. The initial sample size for estimation is set to $\tilde{T}$ =120 months (January 1990 – December 1999) so that the period for the real-time out-of-sample forecasting evaluation is January, 2000 up to March, 2017 (i.e. 207 months). The out-of-sample forecasts, for 1- up to 12-months ahead, are estimated iteratively, using a recursive approach.

Forecasting accuracy of the models is based on the Mean Squared Forecasting Error (MSFE) and the Mean Absolute Forecasting Error (MAFE):

$$MSFE^{(s)} = \left(T-\tilde{T}\right)^{-1} \sum_{t=1}^{T-\tilde{T}} \left(V_{t+s|t}^{(M)} - V_{t+s}^{(M)}\right)^2, \quad (11)$$

and

$$MAFE^{(s)} = \left(T-\tilde{T}\right)^{-1} \sum_{t=1}^{T-\tilde{T}} \left|V_{t+s|t}^{(M)} - V_{t+s}^{(M)}\right|, \quad (12)$$

where $V_{t+s|t}^{(M)}$ is the s-months-ahead volatility forecast, whereas $V_{t+s}^{(M)}$ is the volatility at month $t+s$. Using these measures, we test the forecasting accuracy of rival models with Hansen's *et al.* (2011) Model Confidence Set (MCS)[6]. The MCS test selects the set of models that comprise the best models in terms of the predefined function, $MSFE^{(s)}$ and $MAFE^{(s)}$. Here we apply the MCS test to identify which volatility model(s) (equations (6) to (10)) can produce the most accurate forecasts for each crop. Specifically, denoting $L_{i,t}$ as the loss function of model i at month t, and $d_{i,j,t} \equiv L_{i,t} - L_{j,t}$ the evaluation

[6] We opt for the use of the MCS test rather than alternatives, such as the Diebold-Mariano test (Diebold and Mariano, 1995), Equal Predictive Accuracy test (Clark and West, 2007), the Reality Check for Data Snooping (White, 2000) or the Superior Predictive Ability test (Hansen, 2005) because these alternatives compare forecasts against a predefined benchmark model, whereas we wish to identify the preferred model against the set of rivals.

differential, the null hypothesis $H_{0,M}: E(d_{i,j,t}) = 0$, for $\forall i, j \in M$, $M \subset M^0$ is tested against the alternative $H_{1,M}: E(d_{i,j,t}) \neq 0$, for some $i, j \in M$.[7]

Finally, given that there are situations in which the primary concern is the ability to correctly predict the direction of the movement (such as in the binary price options of derivatives' traders), we also consider the proportion of trading days that a model correctly predicts the direction (up or down) of the volatility movement. We refer to this variable as Directional Change (DC) in the following analysis.

3. Empirical Results and Discussion

3.1 Forecast Accuracy

In order to measure the incremental predictive contribution of oil price volatility-enhanced models to the forecasts of monthly food price volatility, we use the MSFE and MAFE of each model relative to that of the RW model, for comparative purposes. Hence, ratios below 1 imply forecasting improvement compared to the Random Walk model. Of key interest is the forecasting performance of the HAR-X and MIDAS-HAR-X models compared to the standard HAR model. We note that in the main analysis we focus on the $RV_t^{(M)}$ measure, whereas the results for the $PR_t^{(M)}$ and $RR_t^{(M)}$ measures serve as robustness tests. Tables 3 and 4 present the MSFE and MAFE ratios, respectively, for all five food commodities using the 1-, 3-, 6-, 9- and 12-month ahead forecasting horizons.

[TABLES 3 and 4 HERE]

We note that all forecasting models outperform the RW – with only a few marginal exceptions, most commonly, at the 12-month ahead horizons. This finding implies that the oil volatility-enhanced models are conducive to better forecasts of food price volatility when contrasted with the most naïve forecasting model[8].

Comparing the HAR-X and MIDAS-HAR-X models to the standard HAR model reveals that the latter demonstrates lower MSFE and MAFE ratios, suggesting that it outperforms almost any other oil volatility-enhanced alternative. To put it differently, on the basis of the $RV_t^{(M)}$ measure we find that incorporating oil price

[7] M^0 denotes the initial set of models under investigation.

[8] We note that we have also estimated our models assuming that disturbances are conditionally heteroscedastic. The results were either qualitatively similar or worse than those presented based on the normally distributed error terms. Details available upon request.

volatility either in monthly (HAR-X) or daily frequency (MIDAS-HAR-X) does not improve monthly food price volatility forecasting. On the rare occasion that the standard HAR falls short compared to the oil price volatility-enhanced models, the respective gains are not material. This finding applies irrespective of both forecast horizon and crop.

In terms of the MCS test, results show that the HAR model is invariably included in the set of the best forecasting models (i.e. the ones with the lowest forecasting errors), whereas this does not always hold true for the HAR-X and MIDAS-HAR-X. Results also fail to indicate any consistency in the improvement based on oil type or the frequency with which oil volatility is captured. In simple terms, there is not a specific HAR-X or MIDAS-HAR-X model that is consistently better among the family of the oil price volatility-enhanced models. Interestingly however, while there is no evidence that the oil-enhanced models improve forecasting accuracy *per se*, it is the case that Soy is the crop whose forecasting is the least improved by the adoption of oil price volatility-enhanced models, whereas corn seems to be the crop whose volatility forecasts benefit the most from the HAR-X and MIDAS-HAR-X models, although not systematically. While this may hint at the influence of biofuels, the evidence appears just too weak to justify any attribution.

To assess whether our findings remain robust at different time periods, we proceed with contrasting the evaluations of our forecasts across three recent turbulent periods, namely: (i) the period spanning 2007-2009 that includes the global food crisis of 2007-2008 and the oil price swings due to the global financial crisis; (ii) the 2010-2012 spike in food commodity prices, which resulted in a food crisis commonly attributed to the dry summer in the United States and Europe and the increased oil prices and increased demand for biofuels (Council on Foreign Relations, 2013), and; (iii) the oil price collapse period between 2014-2016.

Clearly, the choice of these three time periods, which specifically correspond to increased uncertainty in the prices of food and oil, aims to address the possibility that oil price volatility could provide any incremental predictive accuracy to food price volatility under different market conditions.

The results for the 2007-2009 period are shown in Tables 5 and 6, for the 2010-2012 food crisis results are presented in Tables 7 and 8, whereas the results for the 2014-2016 oil price collapse period are depicted in Tables 9 and 10.

[TABLES 5 – 10 HERE]

In general, results show that there is no consistent incremental contribution of oil price volatility to food price volatility forecasting, in any of the chosen turbulent periods, echoing the results from the full sample. It is rather clear that the oil-enhanced forecasting models cannot provide any significant incremental predicitive information, since in almost all cases, it is either the standard HAR model is also included in the set of the best forecasting models (along with the HAR-X and MIDAS-HAR-X) or that the HAR-X and MIDAS-HAR-X models cannot outperform the RW and AR(*p*) models. A notable exception holds for sugar during the oil price collapse period, where the oil price volatility-enhanced models (the HAR-X in particular) are the best performing models for the 3-month to 9-months horizons.

Overall, though, as with the full time period analysis, the fact that oil price volatility does not seem to provide incremental predictive accuracy for food price volatility holds regardless of forecast horizon, crop and loss function. Even in certain cases, whereby the enhanced specifications (either HAR-X or MIDAS-HAR-X) appear to outperform standard HAR model predictions, this does not really occur in a persistent or systematic way in order to justify the employment of a more complex model. To put it differently, when it comes to food price volatility forecasting, not much is lost if oil price volatility is ignored. In this regard, results point to the use of the parsimonious standard HAR model, as being the most efficient option. Hence, the modelling of heterogenous beliefs of the food commodity market only, is adequate to produce the best forecasts.

Even more, from the analysis undertaken, in this study at least, the argument put forward by the Council on Foreign Relations (2013) that the second food crisis period (2010-2012) was closely linked to developments and uncertainty in the market for oil, we opine that oil price volatility should not be held accountable for the developments in the food market of that period. Possibly the emphasis should be placed on increased oil prices *per se*, instead.

3.2 Directional Accuracy

Despite the fact that our HAR-X and MIDAS-HAR-X models do not provide any incremental predictive ability related to the point forecasts, it is worth examining whether they provide improved directional accuracy. More particularly, we are interested in making comparisons on the basis of the number of times (i.e., percentage) that any one of the competing models successfully predicts the direction of the food price volatility for 1- to 12-month ahead horizons. Results for the full out-of-sample period are given in Table 11, whereas the results for the three turbulent periods are shown in Tables 12 to 14.

[TABLES 11 – 14 HERE]

Prominent among the results presented in all directional accuracy tables (full-sample or turbulent periods) is that the HAR-X and MIDAS-HAR-X models provide significant gains in directional accuracy, compared to the RW model. Nevertheless, our findings also show that there is no systematic evidence that the standard HAR model falls short compared to HAR-X and MIDAS-HAR-X models in successfully predicting the direction of the change in food price volatility. To be more explicit, we note that irrespective of the measure of volatility under investigation, oil price volatility-enhanced models, neither consistently nor considerably outperform the standard HAR model (or even the AR(p) model in some cases). The finding holds irrespective of whether we consider monthly or daily oil price volatility or when we switch between Brent and WTI crude oil price volatility.

Thus, we can conclude that there is no systematic evidence that the oil price volatility-enhanced models can improve the directional accuracy of food price volatility of any crop.

Overall, our study finds no evidence that incorporating oil price volatility into a standard HAR model results in more accurate forecasts of food price volatility. Of all the HAR-X and MIDAS-HAR-X models that we employ in this study none offers any significant improvement over the standard HAR (or even the RW and AR(p) in many cases) when it comes to food price volatility forecasting. While the energy crops analysed here do not behave identically, the fact that they all appear to be similarly unaffected by oil price volatility offer a degree of consistency to what many may see as a surprising result.

As such, our findings are at odds with the views expressed in some existing literature (see, inter alia, the recent work by Rezitis, 2015; Dillon and Barrett, 2016; Zhang *et al*., 2018) that suggest the use of oil price volatility might in fact result in better forecasts of food price volatility. Bear in mind though, that, all such past studies have focused on in-sample estimation. Our results are the first to show that, in an out-of-sample forecasting exercise, the incremental predictive ability of oil price volatility cannot be detected.

3.3. Robustness

To add further validity to our findings we proceed with several robustness tests. In particular, we start our robustness section based on forecast averaging and subsequently we generate forecasts using two other volatility measures, namely the $PR_t^{(M)}$ and $RR_t^{(M)}$. All robustness results are available in the online appendix.

3.3.1. Forecast averaging

We estimate two different forecast averages, namely, the simple forecast average and forecast average weighted based on the inverse of the MSFE of the previous forecast. Our forecast averages are based on the HAR-X and the MIDAS-HAR-X models aiming to depict whether the combination of the oil price volatility-enhanced models could provide better results compared to the individual HAR-X and MIDAS-HAR-X models.

The results are available in Tables A1 to A4 and they clearly suggest that forecast averaging does not provide any significant improvement in the forecasting accuracy, relatively to the individual HAR-X and MIDAS-HAR-X models. The main exception is the 1-month ahead forecasts for all crops in the full out-of-sample period (see Table A1), although some additional scarce exceptions also exist in the first two turbulent periods, based on the weighted forecast average scheme (see Tables A2 and A3). Overall, we can confirm that our initial findings remain robust.

3.3.2. Alternative volatility measures

Next, we re-estimate our initial forecasts using two alternative volatility measures. The justification for the selection of these measures is reported in Section 2.2. The results are shown in the online appendix, in Tables A5 to A28. More specifically, Tables A5 to A10 refer to the full out-of-sample period, Tables A11 to A16 refer to the first food crisis period, Tables A17 to A22 refer to the second food crisis, whereas Tables A23 to A28 refer to the oil price collapse period.

It is evident that the results based on both alternative measures of volatility, $PR_t^{(M)}$ and $RR_t^{(M)}$, resemble those of the $RV_t^{(M)}$ measure. In short, the oil price volatility-enhanced models are capable of producing forecasts that are superior compared to the RW and the AR(p) models in the vast majority of the cases, yet, they cannot demonstrate a significant improved performance relatively to the standard HAR model. Once again, the MCS test suggests that the HAR model is always included in the set of the best models, which is something that does not apply to the HAR-X and MIDAS-HAR-X models.

These results strongly corroborate those obtained from the $RV_t^{(M)}$ measure, namely that oil price volatility does not provide significant incremental predictive ability to food price volatility.

It is also apparent from these results, that irrespectively of the volatility measure, there is little evidence that the oil price volatility-enhanced models that predicate upon daily frequency of the oil price volatility (i.e., the MIDAS-HAR-WTI and MIDAS-HAR-BRN models) are any better vis-à-vis their monthly counterparts (i.e., the HAR-WTI and HAR-BRN). At the same time, we find no evidence that results are any different when we use Brent crude oil price volatility as opposed to the Western Texas Intermediate.

As far as the directional accuracy is concerned, we note that in the cases of $PR_t^{(M)}$ and $RR_t^{(M)}$, the HAR-X and MIDAS-HAR-X models cannot consistently outperform those of the benchmark models (RW, AR(p) or HAR). The two main exceptions are the HAR-BRN and HAR-WTI models for sugar (only based on the $RR_t^{(M)}$ measure) for the full out-of-sample period, as well as, the MIDAS-HAR-BRN for the same crop during the oil price collapse period only, which generate the highest directional predictions for the majority of the forecasting horizons. However, since this result is primarily confined to the $RR_t^{(M)}$ measure, as well as, to a single crop, the evidence is weak confounding any generalisations. Thus, our overall findings remain robust to forecast averaging, alternative volatility measures, as well as, different market conditions (i.e. full out-of-sample versus turbulent periods).

4. Conclusion

The investigation of food price volatility is a critical economic issue with ramifications that extend from cost hedging in the agricultural sector to food security. At the same time, given both the oil-intensive character of the agricultural sector, the use of agricultural crops as biofuels and the importance of energy prices in transportation costs, the case for a linkage between food price volatility and the volatility in the price of oil seems strong. Nonetheless, thus far, the price volatility of agricultural commodities has not been investigated through the lens of the oil market volatility in a real out-of-sample forecasting setting. These specific observations practically delineate the framework of analysis of this study and highlight its main contribution; that is, to investigate whether oil price volatility has any incremental predictive information regarding the price volatility of five internationally traded agricultural commodities (i.e., soy, corn, sugar, rice and wheat).

In order to meet our objective, we utilize a HAR model, which we extend to include the predictive information of monthly oil price volatility on monthly food price volatility (HAR-X). In addition, in order to capture whether the predictive information of oil price could exist in higher frequency, we employ a MIDAS-HAR model, where we assess whether weekly oil price volatility could assist in forecasting monthly food price volatility (MIDAS-HAR-X). For robustness purposes we use (i) three realized volatility measures, namely, realized volatility, price range volatility and realized range volatility, (ii) forecasting averaging techniques, as well as, (iii) analysis during turbulent periods.

Prominent among the results of our study is that the HAR-X models that incorporate oil price volatility information, cannot systematically outperform the standard version of the HAR model that excludes information stemming from the oil market. In point of fact, any improvement that occurs in the out-of-sample forecasting of monthly food price volatility, based on the HAR-X or MIDAS-HAR-X models, is sporadic, despite the fact that the in-sample analysis suggested that the performance of the MIDAS-HAR-X models is superior compared to the standard HAR model. What is more, these findings hold irrespective of the crop, forecast horizon, volatility frequency or the type of oil market that is studied. Moreover, the findings apply to three widely used measures of volatility.

The results of Hansen's *et al*. (2011) Model Confidence Set tests to deduce whether there exist models that return equally successful forecasts yield a similar conclusion. In particular, we find that the standard HAR model is always included among the group of models that share significantly indifferent results; a fact which is indicative of the negligible contribution of the HAR-X and MIDAS-HAR-X models that incorporate oil market information. Therefore, the heterogeneous beliefs of food commodity market participants, as captured by the HAR model, is adequate to provide the most accurate forecasts.

We further investigate whether the models that we develop in this study contribute to better directional forecasts of food price volatility. Again, results indicate that the standard HAR model is persistently among the models with the best directional accuracy performance, along with the AR(p), thereby, rendering redundant the development of alternative enhanced versions. All aforementioned findings hold true even in turbulent periods for the agricultural and energy commodities.

The absence of evidence pointing to incremental forecasting gains from oil price volatility, which has been shown in the literature to possess in-sample explanatory power for food price volatility, may be explained by two potential reasons. First, in-sample predictions are regarded as pseudo-forecasts since they are obtained by considering data that fall beyond the time that the forecast is generated. By contrast, real out-of-sample forecasts, such as the ones produced in the current study, only consider the information that is available prior to the generation of the forecast. Second, the predictive information of oil price volatility on food price volatility may be present but at a higher frequency than the monthly forecasts considered here. Obviously, such high frequency forecasts would not be economically useful for policy makers but rather to financial investors.

Thus, potential avenues for future research might include the forecasting ability of the oil price volatility at higher frequency (i.e. at weekly or daily food price volatility) or the out-of-sample investigation of cross-market volatility spillovers among the different crops and their likely impact on their volatility forecasting. Explanations for the lack of correspondence between oil and commodity price volatility are also prompted by the results that have been obtained in the current study.

Finally, our findings are of importance given the strong implications from the existing literature that there is scope for developing models to predict food price volatility that make use of information on oil price volatility. Overall, we cannot provide any systematic and robust evidence that oil price volatility adds any incremental predictive information with regard to monthly food price volatility. In this regard, the development of oil price volatility-enhanced models does not offer any advantage to either policymakers or agricultural firms.

Acknowledgement

The authors would like to thank Prof. James L. Smith (the Editor) and three anonymous referees for their helpful comments on a previous version of the paper. The usual disclaimer applies.

References

AMIS (2020). *Agricultural Market Information System* [online] Available at: http://www.amis-outlook.org/amis-about/en/ [Accessed 25 Feb. 2020].

Alghalith, M. (2010). The interaction between food prices and oil prices. *Energy Economics,* 32, 1520-1522.

Algieri, B., and Leccadito, A. (2017). Assessing contagion risk from energy and non-energy commodity markets. *Energy Economics,* 62, 312-322.

Andersen, T., Bollerslev, T., Diebold, F. and Ebens, H. (2001). The distribution of realized stock return volatility. *Journal of Financial Economics*, 61(1), 43-76.

Andersen, T. G., Bollerslev, T., and 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., Bollerslev, T., Diebold, F. and Labys, P. (2003). Modeling and forecasting realized volatility. *Econometrica*, 71(2), 579-625).

Andersen, T., Dobrev, D. and Schaumburg, E. (2012). Jump-Robust Volatility Estimation Using Nearest Neighbor Truncation. *Journal of Econometrics,* 169(1), 75-93.

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

Andreou, E., Ghysels, E. and Kourtellos, A. (2010). Regression Models with Mixed Sampling Frequencies, *Journal of Econometrics*, 158, 246-261.

Andreou, E., Ghysels, E. and Kourtellos, A. (2013). Should macroeconomic forecasters use daily financial data and how? *Journal of Business and Economic Statistics*, 31, 240-251.

Baffes J. (2013). A framework for analysing the interplay among food, fuels and biofuels. *Global Food Security, 2*(2), 110-116.

Barndorff-Nielsen, O. and Shephard, N. (2006). Econometrics of Testing for Jumps in Financial Economics Using Bipower Variation. *Journal of Financial Econometrics*, 4, 1-30.

Barndorff-Nielsen, O., Kinnebrock, S., and Shephard, N. (2010). Measuring downside risk – Realised semivariance. In: T. Bollerslev, J. Russell and M. Watson (eds) Volatility and Time Series Econometrics: Essays in Honor of Robert F. Engle. Oxford University Press.

Bellemare, M.F. (2015). Rising food prices, food price volatility, and social unrest. *American Journal of Agricultural Economics,* 97(1), 1-21.

Bollerslev, T., and Wright, J. H. (2001). High-frequency data, frequency domain inference, and volatility forecasting. *Review of Economics and Statistics*, 83(4), 596-602.

Brailsford, T. J., and Faff, R. W. (1996). An evaluation of volatility forecasting techniques. *Journal of Banking & Finance*, 20(3), 419-438.

Byrne, J.P., Fazio, G., and Fiess, N. (2011). *Primary commodity prices: Co-movements, common factors and fundamentals*. World Bank Group, e-Library.

Clark, T.E. and West, K.D. (2007). Approximately normal tests for equal predictive accuracy in nested models. *Journal of Econometrics*, 138, 291–311.

Corsi, F. (2009). A simple approximate long-memory model of realized volatility. *Journal of Financial Econometrics*, 7, 174–196.

Council on Foreign Relations (2013). Food Price Volatility and Insecurity, https://www.cfr.org/backgrounder/food-price-volatility-and-insecurity

Creti, A., Joëts, M. and Mignon, V. (2013). On the links between stock and commodity markets' volatility. *Energy Economics*, 37, 16-28.

Degiannakis, S. (2008). ARFIMAX and ARFIMAX-TARCH realized volatility modelling, *Journal of Applied Statistics*, 35(10), 1169-1180.

Degiannakis, S. and Filis, G. (2017). Forecasting oil price realized volatility using information channels from other asset classes. *Journal of International Money and Finance*, 76, 28-49.

Degiannakis, S., & Filis, G. (2019). Forecasting European economic policy uncertainty. *Scottish Journal of Political Economy*, 66(1), 94-114.

Degiannakis, S. and Livada, A. (2013). Realized volatility or price range: Evidence from a discrete simulation of the continuous time diffusion process. *Economic Modelling*, *30*, 212-216.

Diebold, F. X., & Mariano, R. S. (1995). Comparing predictive accuracy. *Journal of Business & Economic Statistics*, 13, 253-263.

Dillon, B.M. and Barrett, C.B. (2016). Global oil prices and local food prices: Evidence from East Africa. *American Journal of Agricultural Economics*, 98(1), 154-171.

Du, X., Cindy, L. Y., and Hayes, D. J. (2011). Speculation and volatility spillover in the crude oil and agricultural commodity markets: A Bayesian analysis. *Energy Economics*, 33(3), 497-503.

Engle, R. F., Ghysels, E., and Sohn, B. (2013). Stock market volatility and macroeconomic fundamentals. *Review of Economics and Statistics*, 95(3), 776-797.

FAO-OECD (2011). Price Volatility in Food and Agricultural Markets: Policy Responses, June, available at www.worldbank.org/foodcrisis.

Gardebroek, C. and Hernandez, M.A. (2013). Do energy prices stimulate food price volatility? Examining volatility transmission between US oil, ethanol and corn markets. *Energy Economics*, 40, 119-129.

Garman, M. and Klass, M. (1980). On the Estimation of Security Price Volatilities from Historical Data. *Journal of Business*, 53(1), 67-78.

Ghysels, E., Santa-Clara, P. and Valkanov, R. (2006). Predicting volatility: Getting the most out of return data sampled at different frequencies, *Journal of Econometrics*, 131, 59–95.

Gilbert, C. (2011) *An Assessment of International Commodity Agreements for Commodity Price Stabilisation*. Ch. 4 in: “Safeguarding Food Security in Volatile Markets” by A. Prakash (ed), Rome, Food and Agriculture Organisation.

Giot, P. (2003). The information content of implied volatility in agricultural commodity markets. *Journal of Futures Markets*, 23(5), 441-454.

Hansen, P.R. (2005). A Test for Superior Predictive Ability. *Journal of Business and Economic Statistics*, 23, 365-380.

Hansen, P.R., Lunde, A. and Nason, J.M. (2011). The model confidence set, *Econometrica*, 79, 456–497.

Harri, A., Nalley, L., and Hudson, D. (2009). The relationship between oil, exchange rates, and commodity prices. *Journal of Agricultural and Applied Economics, 41*(2), 501-510.

Hertel, T.W., and Beckman, J. (2011). *Commodity price volatility in the biofuel era: An examination of the linkage between energy and agricultural markets*. Ch. 6 in: “The intended and unintended effects of US agricultural and biotechnology policies”, by J. Graff Zivin and J. Perloff (eds), University of Chicago Press for NBER, 189-221.

House of Lords (2016). Responding to Price Volatility: Creating a More Resilient Agricultural Sector Report of European Select Committee, Report HL146. House of Lords, London.

Irwin, S.H., and Sanders, D.R. (2011). Index funds, financialization, and commodity futures markets. *Applied Economic Perspectives and Policy*, 33(1), 1-31.

Kambouroudis, D. S., McMillan, D. G., and Tsakou, K. (2016). Forecasting stock return volatility: a comparison of GARCH, Implied volatility, and realized volatility models. *Journal of Futures Markets*, 36(12), 1127-1163.

Karatzas, I. and S.E. Shreve. (1988). Brownian Motion and Stochastic Calculus, Springer Verlag, New York.

Lott, M.C. (2011). 10 Calories in, 1 Calorie Out - The Energy We Spend on Food, *Scientific American*, August 11 2011.

Nazlioglu, S., Erdem, C. and Soytas, U. (2013). Volatility spillover between oil and agricultural commodity markets. *Energy Economics*, 36, 658-665.

Ordu, B.M., Oran, A., and Soytas, U. (2018). Is food financialized? Yes, but only when liquidity is abundant. *Journal of Banking and Finance, 95*, 82-96.

Parkinson, M. (1980). The Extreme Value Method for Estimating the Variance of the Rate of Return. *Journal of Business*, 53(1), 61-65.

Piesse, J. and Thirtle, C. (2009). Three bubbles and a panic: An explanatory review of recent food commodity price events. *Food policy*, 34(2), 119-129.

Roache, S.K. (2010). What explains the rise in food price volatility? *IMF Working Paper*, 10, 129.

Rezitis, A.N. (2015). The relationship between agricultural commodity prices, crude oil prices and US dollar exchange rates: A panel VAR approach and causality analysis. *International Review of Applied Economics*, 29(3), 403-434.

Sadorsky, P. (2006). Modeling and forecasting petroleum futures volatility. *Energy Economics*, 28(4), 467-488.

Serra, T. (2011). Volatility spillovers between food and energy markets: a semiparametric approach. *Energy Economics*, 33(6), 1155-1164.

Serra, T. and Gil, J.M. (2012). Price volatility in food markets: can stock building mitigate price fluctuations? *European Review of Agricultural Economics*, 40(3), 507-528.

Silvernnoinen, A., and Thorp, S. (2013). Financialization, crisis and commodity correlation dynamics. *Journal of International Financial Markets, Institutions and Money*, *24*, 42-65.

Tadasse, G., Algieri, B., Kalkuhl, M. and von Braun, J. (2016). Drivers and triggers of international food price spikes and volatility. In *Food Price Volatility and Its Implications for Food Security and Policy*. Springer International Publishing, 59-82.

Tang, K., Xiong, W. (2012). Index investment and the financialization of commodities. *Financial Analysts Journal* 68, 54–74.

Tian, F., Yang, K., & Chen, L. (2017a). Realized Volatility Forecasting of Agricultural Commodity Futures Using Long Memory and Regime Switching. *Journal of Forecasting*, 36, 421-430.

Tian, F., Yang, K. and 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.

Trujillo-Barrera, A., Mallory, M., and Garcia, P. (2012). Volatility spillovers in US crude oil, ethanol, and corn futures markets. *Journal of Agricultural and Resource Economics*, 247-262.

Tyner, W.E. (2010). The integration of energy and agricultural markets. *Agricultural Economics, 41*(s1), 193-201.

Vivian, A., and Wohar, M.E. (2012). Commodity volatility breaks. *Journal of International Financial Markets Institutions and Money, 22*(2), 395-422.

White, H. (2000). A Reality Check for Data Snooping. *Econometrica*, 68, 1097–1126.

Wu, F., Guan, Z., and Myers, R. (2011). Volatility spillover effects and cross hedging in corn and crude oil futures. *The Journal of Futures Markets, 31*(11), 1052-1075.

Yang, K., Tian, F., Chen, L. and Li, S. (2017). Realized volatility forecast of agricultural futures using the HAR models with bagging and combination approaches. *International Review of Economics & Finance*, 49, 276-291.

Zhang, D., and Broadstock, D. C. (2018). Global financial crisis and rising connectedness in the international commodity markets. *International Review of Financial Analysis*, online, https://doi.org/10.1016/j.irfa.2018.08.003.

Zhang, C., Liu, F., and Yu, D. (2018). Dynamic jumps in global oil price and its impact on China's bulk commodities. *Energy Economics*, 70, 297-306.

Zhang, Z., Lohr, L., and Escalante, C. (2010). Food versus fuel: What do prices tell us? *Energy Policy, 38*(1), 445-451.

Zhang, L., Mykland P.A. and Aït-Sahalia, Y. (2005). A tale of two time scales: Determining integrated volatility with noisy high-frequency data. *Journal of the American Statistical Association*, 100(472), 1394-1411.

Figures

Figure 1. The annualized realized volatility on a monthly frequency from January, 1990 up to March, 2017: $RV_t^{(M)} = \sqrt{\frac{252}{22}\sum_{i=1}^{22}(logP_{t-i} - logP_{t-i-1})^2}$.

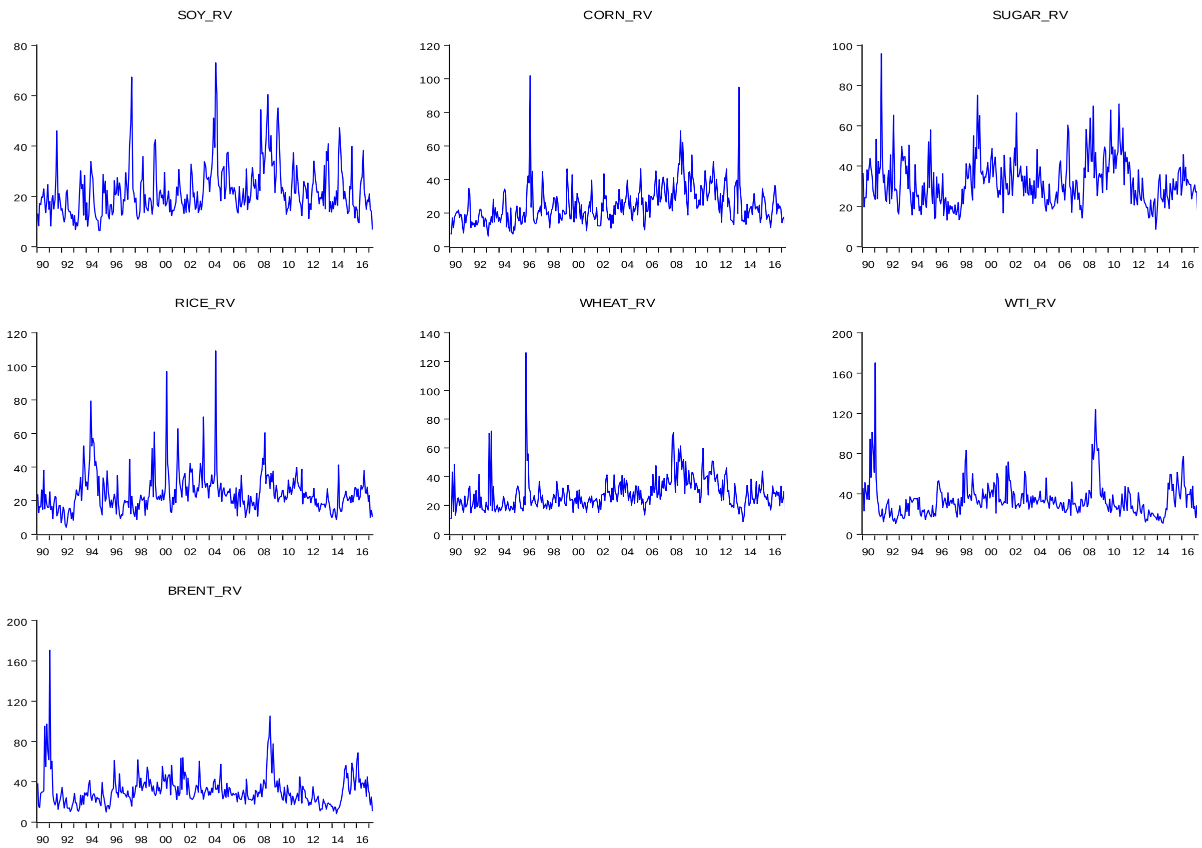


Figure 2. The annualized price-range volatility on a monthly frequency from January, 1990 up to March, 2017:

$$PR_t^{(M)} = \sqrt{12\left(\frac{1}{2}\left(log\frac{\max_{i=t,\dots,t-21,j=1,\dots,\tau}\left(P_{i_j}\right)}{\min_{i=t,\dots,t-21,j=1,\dots,\tau}\left(P_{i_j}\right)}\right)^2 - (2log(2)-1)\left(log\frac{P_{t_\tau}}{P_{t-21_1}}\right)^2\right)}.$$

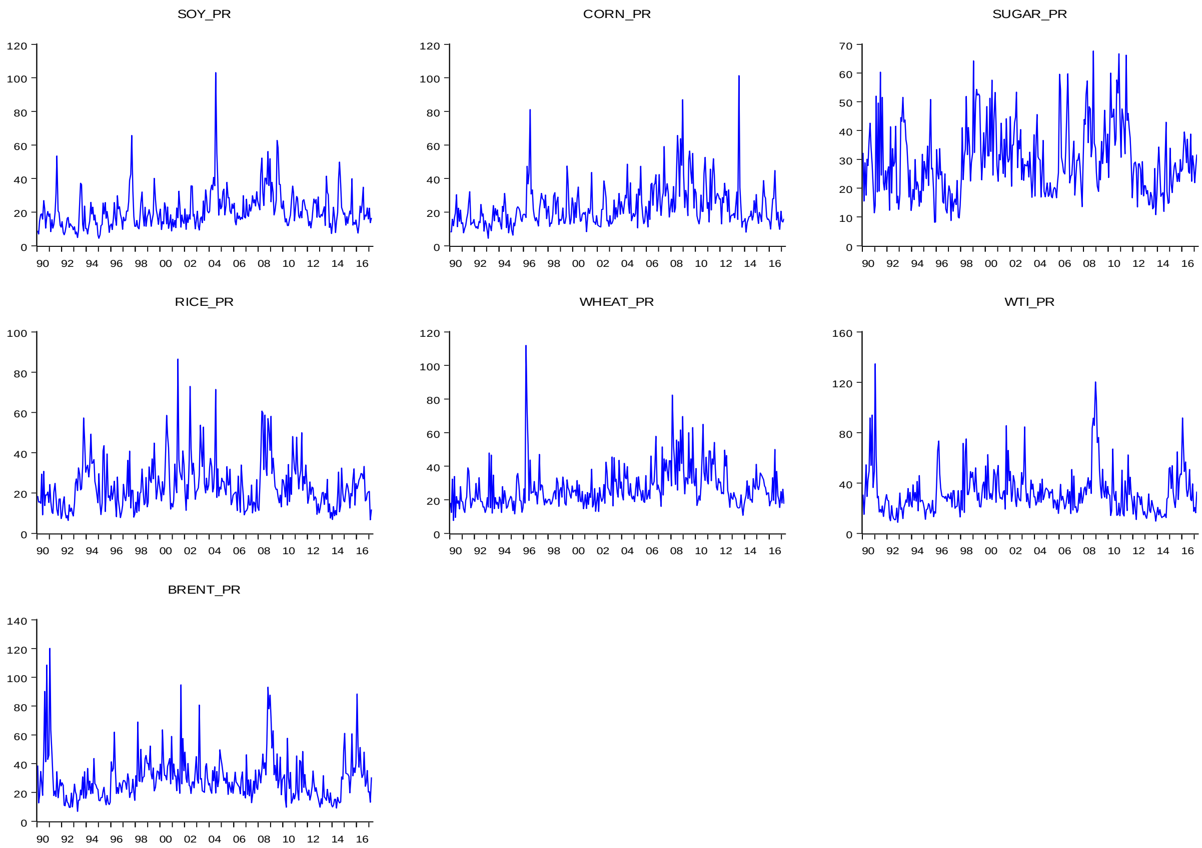
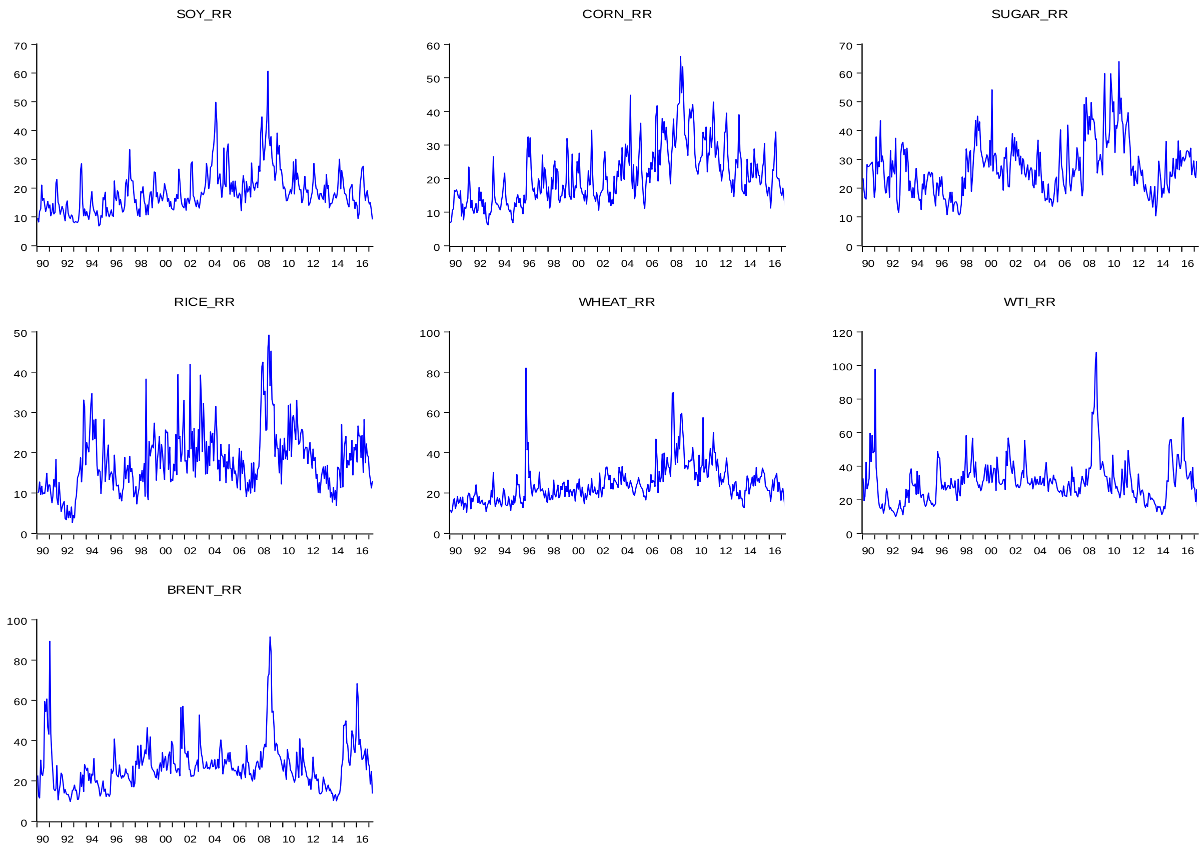


Figure 3. The annualized realized range on a monthly frequency from January, 1990 up to March, 2017:

$$RR_t^{(M)} = \sqrt{\frac{252}{22}\sum_{t=1}^{22}\left(\frac{1}{2}\left(log\,\frac{\max\limits_{j=1,\dots,\tau}\left(P_{t_j}\right)}{\min\limits_{j=1,\dots,\tau}\left(P_{t_j}\right)}\right)^2 - (2log(2)-1)\left(log\,\frac{P_{t_\tau}}{P_{t_1}}\right)^2\right)}$$



Tables

Table 1. Descriptive Statistics of the annualized volatility measures on a monthly frequency from January, 1990 up to March, 2017.

	Realized volatility						
	Soy	Corn	Sugar	Rice	Wheat	WTI	Brent
Mean	22.2347	24.8638	32.1326	24.6421	28.2819	34.5331	31.6853
Maximum	73.0180	101.7997	95.8561	109.3445	126.2147	170.1242	170.6803
Minimum	6.3847	6.2662	8.5554	4.0731	8.7428	10.4467	8.3053
Skewness	1.6264***	2.0902***	1.2105***	2.5596***	2.6316***	2.6830***	3.0226***
Kurtosis	6.8316***	12.1652***	5.8166***	14.9669***	17.8239***	15.7341***	20.8271***
	Price-range volatility						
	Soy	Corn	Sugar	Rice	Wheat	WTI	Brent
Mean	21.0418	23.2379	29.6329	23.6794	27.2884	32.6276	29.8406
Maximum	103.0825	101.2546	67.7072	86.4811	112.0038	134.6470	120.1278
Minimum	4.4292	4.3838	8.0961	6.4068	7.6568	8.6600	6.7942
Skewness	2.2534***	2.1292***	0.7497***	1.5491***	2.1451***	2.0769***	2.1130***
Kurtosis	12.9249***	10.3917***	3.1890	6.6714***	11.2324***	9.1190***	9.6386***
	Realized-range volatility						
	Soy	Corn	Sugar	Rice	Wheat	WTI	Brent
Mean	18.7647	20.9423	27.0910	18.0776	24.5476	31.1307	27.6205
Maximum	60.6418	56.3790	64.0112	49.1895	82.0796	107.9424	91.4836
Minimum	6.8455	6.2021	10.3500	2.6487	10.1694	9.8461	9.7385
Skewness	1.5764***	0.9606***	0.8732***	0.9643***	2.0000***	2.0057***	1.9457***
Kurtosis	7.0996***	3.8297**	4.0121***	4.4543***	9.6865***	10.3491***	9.3455***

Note: **,*** denote significance at 5% and 1% levels, respectively. The significance for skewness and kurtosis is gauged by the D'Agostino skewness test and Anscombe-Glynn kurtosis test, respectively.

Table 2. Log-likelihood ratios between the standard HAR model and the oil price volatility-enhanced models.

	HAR-WTI vs HAR	HAR-BRN vs HAR	HAR-MIDAS-WTI vs HAR	HAR-MIDAS-BRN vs HAR
		Realized volatility		
Corn	1.7482	4.8702	11.4170***	6.0458
Rice	4.8536	6.3745*	8.5470**	11.5899***
Soy	2.0517	4.8111	15.0796***	10.8752**
Sugar	4.5447	6.3975*	21.5725***	13.5739***
Wheat	1.1141	0.9185	8.8116**	10.0109**
		Price-range volatility		
Corn	2.1511	1.9241	5. 1856	8.1911**
Rice	6.5358*	6.7500*	6.8367*	8.4197**
Soy	1.6512	1.9732	5.3678	8.0922**
Sugar	4.4510	3.0064	6.4057*	7.1691*
Wheat	3.6186	3.4775	5.9932	8.1797**
		Realized-range volatility		
Corn	3.4150	3.5356	4.2988	9.2350**
Rice	7.7007**	6.0101	9.3739**	13.3987***
Soy	0.6242	1.8019	6.3682*	5.8159
Sugar	3.7805	4.7187	11.8618***	8.6197**
Wheat	3.2193	1.0121	6.2078	10.2892**

Note: ***, **, * denote significance at 1%, 5% and 10% level, respectively.

Table 3. The Mean Squared Forecasting Error (MSFE) evaluation function for 1-, 3-, 6-, 9-, 12- month ahead forecasting horizons. Volatility Measure: Monthly Realized Volatility; $RV_t^{(M)}$. Forecasting period: Jan 2000 – March 2017.

Months-ahead	RW	AR(p)	HAR	HAR-WTI	HAR-BRN	MIDAS-HAR-WTI	MIDAS-HAR-BRN
				SOY			
1	127.5	**0.5498***	**0.5043***	**0.5341***	**0.5286***	**0.4980***	**0.5216***
3	129.5	**0.9066**	**0.7954***	**0.8324**	**0.8309**	**0.8324**	**0.8039***
6	131.6	**0.9825**	**0.8389***	**0.8609**	**0.8670**	**0.8640***	**0.8982**
9	134.4	**0.9970**	**0.8728***	**0.9018***	**0.9063***	**0.8876***	**0.9152***
12	137.2	**0.9985**	**0.9060***	**0.9461***	**0.9512***	**0.9235***	**0.9169***
				CORN			
1	164.8	**0.6760**	**0.5686***	**0.5850***	**0.5910**	**0.5825***	**0.5941**
3	166.5	**0.9141**	**0.6967***	**0.7093***	**0.7051***	**0.7315***	**0.7213***
6	168.9	**0.9976**	**0.7501***	**0.7655***	**0.7649***	**0.7981***	**0.7780***
9	171.7	1.0035	**0.7094***	**0.7123***	**0.7082***	**0.7030***	**0.7239***
12	175.4	1.0034	**0.7269***	**0.7144***	**0.7098***	**0.7537***	**0.7269***
				SUGAR			
1	130.3	**0.6501***	**0.6285***	**0.6293***	**0.6447***	**0.6531***	**0.6447***
3	131.9	**0.8010***	**0.7589***	**0.7650***	**0.7801***	**0.8059***	**0.7885***
6	134.1	**0.9183**	**0.8762***	**0.8814***	**0.8963***	**0.8837***	**0.8494***
9	133.9	**0.9716***	**0.9589***	**0.9604***	**0.9731***	**0.9537***	**0.9089***
12	134.3	**0.9928***	1.0112	1.0015	1.0186	1.0171	1.0253
				RICE			
1	154.8	**0.7351***	**0.7125***	**0.7119***	**0.7190***	**0.7339***	**0.7222***
3	156.9	**0.8890**	**0.8515***	**0.8464***	**0.8458***	**0.8407***	**0.8764***
6	160.1	**0.9542**	**0.8919***	**0.8975***	**0.9119***	**0.9644**	**0.9225***
9	130.7	**0.9596**	**0.8768***	**0.9090***	**0.9151***	**0.8707***	**0.9166***
12	132.1	**0.9660**	**0.8902***	**0.9281***	**0.9349***	1.0666	1.0053
				WHEAT			
1	131.4	**0.5771***	**0.5175***	**0.5221***	**0.5221***	**0.5434***	**0.5342***
3	133.2	**0.7759**	**0.6126***	**0.6126***	**0.6156***	**0.6404***	**0.6231***
6	136.4	**0.9090**	**0.6972***	**0.6935***	**0.6994***	**0.6840***	**0.7104***
9	139.5	**0.9631**	**0.7505***	**0.7484***	**0.7548***	**0.7305***	**0.7799***
12	142.9	**0.9942**	**0.8411***	**0.8432***	**0.8530***	**0.8502***	**0.8901**

Note: WTI = WTI crude oil price volatility, BRN = Brent crude oil price volatility. The RW column shows the actual MSFE. All other columns show the MSFE ratios, for each forecasting model, that have been normalized relative to the monthly RW forecast. The order of the AR models for Soy and Corn is 1, whereas for Sugar, Rice and Wheat is 2, based on the Bayesian Information Criterion. Bold face numbers denote that the forecast outperforms the RW. * denotes that the model is included in the set of the best models according to the Model Confidence Set (MCS).

Table 4. The Mean Absolute Forecasting Error (MAFE) evaluation function for 1-, 3-, 6-, 9-, 12- month ahead forecasting horizons. Volatility Measure: Monthly Realized Volatility; $RV_t^{(M)}$. Forecasting period: Jan 2000 – March 2017.

Months-ahead	RW	AR(p)	HAR	HAR-WTI	HAR-BRN	MIDAS-HAR-WTI	MIDAS-HAR-BRN
				SOY			
1	7.55	**0.7603***	**0.7483***	**0.7629***	**0.7629***	**0.7589***	**0.7656***
3	7.65	**0.9608***	**0.9412***	**0.9725**	**0.9725**	**0.9647***	1.0013
6	7.71	**0.9935**	**0.9520***	**0.9663***	**0.9792**	**0.9520***	**0.9935**
9	7.83	**0.9987**	**0.9681***	**0.9872***	**0.9949**	**0.9732***	1.0000
12	7.93	**0.9987**	**0.9710***	1.0000	1.0038	**0.9823***	**0.9836***
				CORN			
1	9.20	**0.7859***	**0.7424***	**0.7500***	**0.7554***	**0.7370***	**0.7707***
3	9.28	**0.9580**	**0.8362***	**0.8513***	**0.8545***	**0.8556***	**0.8578***
6	9.34	**0.9979**	**0.8587***	**0.8715***	**0.8801***	**0.8747***	**0.8801***
9	9.42	1.0021	**0.8280***	**0.8386***	**0.8450***	**0.8461***	**0.8482***
12	9.55	1.0021	**0.8471***	**0.8440***	**0.8534***	**0.8691***	**0.8649***
				SUGAR			
1	8.67	**0.7931***	**0.7739***	**0.7797***	**0.7843***	**0.8028***	**0.7797***
3	8.72	**0.9001**	**0.8429***	**0.8406***	**0.8463***	**0.8911***	**0.8865***
6	8.79	**0.9455**	**0.9181***	**0.9283***	**0.9352***	**0.9238***	**0.8999***
9	8.76	**0.9889**	**0.9658***	**0.9600***	**0.9726***	**0.9680***	**0.9566***
12	8.74	**0.9912***	1.0092	**0.9954***	1.0080	**0.9954***	1.0137
				RICE			
1	7.41	**0.7981***	**0.7949***	**0.7895***	**0.7922***	**0.8205***	**0.8246***
3	7.54	**0.9101**	**0.8846***	**0.8886***	**0.8833***	**0.9058***	**0.9058***
6	7.64	**0.9731**	**0.9267***	**0.9411***	**0.9476***	**0.9830**	**0.9895**
9	7.26	**0.9918**	**0.9559***	**0.9959**	1.0000	**0.9311***	**0.9959**
12	7.29	**0.9973**	**0.9822***	1.0178	1.0288	1.1440	1.0796
				WHEAT			
1	8.31	**0.8172**	**0.7280***	**0.7329***	**0.7316***	**0.7485***	**0.7449***
3	8.39	**0.9128**	**0.7998***	**0.8010***	**0.8021***	**0.8129***	**0.7950***
6	8.51	**0.9372**	**0.8555***	**0.8555***	**0.8602***	**0.8555***	**0.8790**
9	8.61	**0.9712**	**0.8711***	**0.8722***	**0.8769***	**0.8757***	**0.8850***
12	8.74	**0.9991**	**0.9119***	**0.9062***	**0.9142***	**0.9291***	**0.9508**

Note: WTI = WTI crude oil price volatility, BRN = Brent crude oil price volatility. The RW column shows the actual MAFE. All other columns show the MAFE ratios, for each forecasting model, that have been normalized relative to the monthly RW forecast. The order of the AR models for Soy and Corn is 1, whereas for Sugar, Rice and Wheat is 2, based on the Bayesian Information Criterion. Bold face numbers denote that the forecast outperforms the RW. * denotes that the model is included in the set of the best models according to the Model Confidence Set (MCS).

Table 5. The Mean Squared Forecasting Error (MSFE) evaluation function for 1-, 3-, 6-, 9-, 12- month ahead forecasting horizons. Volatility Measure: Monthly Realized Volatility; $RV_t^{(M)}$. Forecasting period: 1st Food Crisis (2007-2009).

Months-ahead	RW	AR(p)	HAR	HAR-WTI	HAR-BRN	MIDAS-HAR-WTI	MIDAS-HAR-BRN
				SOY			
1	300.6379	**0.2279***	**0.1457***	**0.1697***	**0.1940***	**0.2115***	**0.1931***
3	303.8171	**0.7610**	**0.5384***	**0.5627***	**0.5427***	**0.5236***	**0.5557***
6	307.6376	**0.9532**	**0.6776***	**0.7391***	**0.7122***	**0.7586***	**0.7095***
9	311.1295	**0.9929**	**0.7819***	**0.8490***	**0.8185***	**0.8337***	**0.7793***
12	313.6337	1.0015	**0.8758***	**0.9455**	**0.9240***	**0.8829***	**0.9158***
				CORN			
1	400.0467	**0.3373**	**0.1833***	**0.1794***	**0.2047***	**0.2270***	**0.2263***
3	404.1275	**0.8568**	**0.4609***	**0.4330***	**0.4050***	**0.5031***	**0.4859***
6	409.5952	**0.9884**	**0.6307***	**0.6122***	**0.5886***	**0.6579***	**0.6220***
9	414.1244	1.0026	**0.6843***	**0.6607***	**0.6292***	**0.6188***	**0.6505***
12	418.0852	1.0039	**0.7286***	**0.6980***	**0.6618***	**0.7021***	**0.6232***
				SUGAR			
1	233.1784	**0.3639***	**0.3717***	**0.3308***	**0.3192***	**0.4655***	**0.3087***
3	235.8354	**0.9111**	**0.7551***	**0.7582***	**0.7639***	**0.7556***	**0.8065***
6	238.0399	**0.9839***	1.0158	1.0453	1.0296	1.0105	**0.9867***
9	238.7880	**0.9877***	1.0943	1.1221	1.1018	**0.9610***	1.0965
12	238.4474	**0.9894***	1.1287	1.1510	1.1293	1.0156	1.1282
				RICE			
1	163.0254	**0.2395***	**0.2535***	**0.2379***	**0.2247***	**0.1985***	**0.2338***
3	158.4992	**0.8212**	**0.6245***	**0.5516***	**0.5382***	**0.6205***	**0.6369***
6	160.4909	**0.9626**	**0.8101***	**0.8196***	**0.7617***	**0.8974***	**0.8926***
9	162.2005	**0.9902**	**0.9863***	**1.0696**	**0.9776***	**0.9904**	**0.9551***
12	163.1053	**0.9985***	1.1465	1.2778	1.1594	1.1947	1.2095
				WHEAT			
1	486.5897	**0.5942**	**0.2639***	**0.2621***	**0.2635***	**0.2818***	**0.2609***
3	491.8009	**0.9634**	**0.4423***	**0.4343***	**0.4369***	**0.4828***	**0.4624***
6	498.3697	**0.9912**	**0.5605***	**0.5392***	**0.5484***	**0.5067***	**0.5248***
9	504.9523	**0.9920**	**0.6838**	**0.6630**	**0.6725**	**0.5457***	**0.7095**
12	510.9423	**0.9921**	**0.8046***	**0.7841***	**0.7931***	**0.7851***	**0.8127***

Note: WTI = WTI crude oil price volatility, BRN = Brent crude oil price volatility. The RW column shows the actual MSFE. All other columns show the MSFE ratios, for each forecasting model, that have been normalized relative to the monthly RW forecast. The order of the AR models for Soy and Corn is 1, whereas for Sugar, Rice and Wheat is 2, based on the Bayesian Information Criterion. Bold face numbers denote that the forecast outperforms the RW. * denotes that the model is included in the set of the best models according to the Model Confidence Set (MCS).

Table 6. The Mean Absolute Forecasting Error (MAFE) evaluation function for 1-, 3-, 6-, 9-, 12- month ahead forecasting horizons. Volatility Measure: Monthly Realized Volatility; $RV_t^{(M)}$. Forecasting period: 1st Food Crisis (2007-2009).

Months-ahead	RW	AR(p)	HAR	HAR-WTI	HAR-BRN	MIDAS-HAR-WTI	MIDAS-HAR-BRN
			SOY				
1	13.9855	**0.4625***	**0.3352***	**0.3700***	**0.3936***	**0.4191***	**0.3911***
3	14.0689	**0.8490**	**0.6685***	**0.6980***	**0.6927***	**0.6666***	**0.7156***
6	14.1756	**0.9710**	**0.7774***	**0.8236***	**0.8286***	**0.8565**	**0.7989***
9	14.2718	**0.9944**	**0.8517***	**0.9058**	**0.8925**	**0.8939**	**0.8433***
12	14.3528	1.0011	**0.9126***	**0.9538**	**0.9499**	**0.9189***	**0.9417***
			CORN				
1	16.1422	**0.5704**	**0.4009***	**0.3906***	**0.4152***	**0.4317***	**0.4569***
3	16.2383	**0.9126**	**0.6641***	**0.6565***	**0.6455***	**0.7196***	**0.6972***
6	16.3790	**0.9933**	**0.7289***	**0.7062***	**0.6983***	**0.7316***	**0.7249***
9	16.5061	1.0016	**0.7611***	**0.7433***	**0.7277***	**0.7375***	**0.7398***
12	16.6270	1.0025	**0.8018**	**0.7815**	**0.7614***	**0.7691***	**0.7290***
			SUGAR				
1	11.8797	**0.5769***	**0.5432***	**0.5147***	**0.5263***	**0.6121***	**0.5321***
3	11.9633	**0.9451**	**0.8089***	**0.8040***	**0.8137***	**0.8165***	**0.8363***
6	12.0218	**0.9848**	**0.9599***	1.0048	1.0061	**0.9366***	**0.9485***
9	12.0591	**0.9868**	1.0031	1.0256	1.0282	**0.8780***	1.0195
12	12.0814	**0.9888***	1.0613	1.0442	1.0437	**0.9796***	1.0264
			RICE				
1	9.8313	**0.4628***	**0.4573***	**0.4415***	**0.4506***	**0.4045***	**0.4641***
3	10.4693	**0.8903**	**0.7449***	**0.7056***	**0.7015***	**0.7311***	**0.7677***
6	10.5569	**0.9735**	**0.8358***	**0.8457***	**0.8050***	**0.8634**	**0.8826**
9	10.6286	**0.9935**	**0.9473***	1.0011	**0.9470***	**0.9274***	**0.9171***
12	10.6728	**0.9978***	1.0526	1.1019	1.0378	1.0562	1.0679
			WHEAT				
1	18.7489	**0.7581**	**0.4443***	**0.4411***	**0.4432***	**0.4644***	**0.4570***
3	18.8665	**0.9727**	**0.5807***	**0.5747***	**0.5768***	**0.6102***	**0.5833***
6	19.0386	**0.9912**	**0.6885***	**0.6752***	**0.6823***	**0.6577***	**0.6521***
9	19.2019	**0.9917**	**0.7657**	**0.7514***	**0.7585***	**0.6837***	**0.7860**
12	19.3518	**0.9918**	**0.8590***	**0.8429***	**0.8527***	**0.8483***	**0.8733***

Note: WTI = WTI crude oil price volatility, BRN = Brent crude oil price volatility. The RW column shows the actual MAFE. All other columns show the MAFE ratios, for each forecasting model, that have been normalized relative to the monthly RW forecast. The order of the AR models for Soy and Corn is 1, whereas for Sugar, Rice and Wheat is 2, based on the Bayesian Information Criterion. Bold face numbers denote that the forecast outperforms the RW. * denotes that the model is included in the set of the best models according to the Model Confidence Set (MCS).

Table 7. The Mean Squared Forecasting Error (MSFE) evaluation function for 1-, 3-, 6-, 9-, 12- month ahead forecasting horizons. Volatility Measure: Monthly Realized Volatility; $RV_t^{(M)}$. Forecasting period: 2nd Food Crisis (2010-2012).

Months-ahead	RW	AR(p)	HAR	HAR-WTI	HAR-BRN	MIDAS-HAR-WTI	MIDAS-HAR-BRN
				SOY			
1	37.6543	**0.1400***	**0.2395***	**0.2567***	**0.2641***	**0.2115***	**0.2173***
3	38.0482	**0.9923***	1.3308	1.3461	1.3862	1.3600	1.5691
6	38.0289	1.0763	1.7627	1.7356	1.8758	1.5299	1.5894
9	37.7240	1.0197	1.7357	1.6591	1.8520	1.6089	1.9887
12	37.5260	1.0066	1.5667	1.5496	1.7478	1.6923	1.3475
				CORN			
1	155.9105	**0.2362***	**0.1824***	**0.1746***	**0.1901***	**0.1746***	**0.1692***
3	157.4761	**0.8200**	**0.5078***	**0.5259***	**0.5420***	**0.5803***	**0.4763***
6	159.2643	**0.9876**	**0.6395***	**0.6631***	**0.7027***	**0.6945***	**0.7062***
9	160.7444	1.0030	**0.5346***	**0.5412***	**0.5599***	**0.5528***	**0.5482***
12	162.6917	1.0069	**0.5199***	**0.5154***	**0.5275***	**0.5604***	**0.5665***
				SUGAR			
1	220.3728	**0.3252***	**0.2590***	**0.2758***	**0.2911***	**0.2592***	**0.2719***
3	222.6717	**0.8744**	**0.5451***	**0.5899***	**0.6166***	**0.6037***	**0.6395**
6	225.4427	**0.9731**	**0.7109***	**0.7750***	**0.8097***	**0.8410**	**0.6955***
9	228.1687	**0.9835**	**0.8335**	**0.9071**	**0.9525**	**0.7931***	**0.6705***
12	230.4773	**0.9855**	**0.9406***	**0.9861**	1.0410	**0.9904**	**0.9244***
				RICE			
1	37.6730	**0.1972***	**0.2306***	**0.2446***	**0.2583***	**0.3115***	**0.4411***
3	30.7237	**0.9270***	1.0573	1.1479	1.2242	1.1088	**0.9568***
6	30.8785	**0.9844***	1.1812	1.2997	1.4347	1.5187	2.3535
9	30.9521	**0.9972***	1.2972	1.3761	1.5224	1.4681	2.0246
12	30.8973	1.0015	1.4186	1.4107	1.5721	1.4367	2.0414
				WHEAT			
1	174.1139	**0.4091***	**0.2919***	**0.2807***	**0.2831***	**0.2907***	**0.3261***
3	175.9285	**0.9241**	**0.5267***	**0.5164***	**0.5202***	**0.5663***	**0.5457***
6	177.8176	**0.9926**	**0.5936***	**0.5759***	**0.5864***	**0.5658***	**0.5835***
9	179.5908	**0.9949**	**0.5508***	**0.5279***	**0.5391***	**0.5279***	**0.5238***
12	181.8405	**0.9950**	**0.6181***	**0.6047***	**0.6171***	**0.6187***	**0.6128***

Note: WTI = WTI crude oil price volatility, BRN = Brent crude oil price volatility. The RW column shows the actual MSFE. All other columns show the MSFE ratios, for each forecasting model, that have been normalized relative to the monthly RW forecast. The order of the AR models for Soy and Corn is 1, whereas for Sugar, Rice and Wheat is 2, based on the Bayesian Information Criterion. Bold face numbers denote that the forecast outperforms the RW. * denotes that the model is included in the set of the best models according to the Model Confidence Set (MCS).

Table 8. The Mean Absolute Forecasting Error (MAFE) evaluation function for 1-, 3-, 6-, 9-, 12- month ahead forecasting horizons. Volatility Measure: Monthly Realized Volatility; $RV_t^{(M)}$. Forecasting period: 2nd Food Crisis (2010-2012).

Months-ahead	RW	AR(p)	HAR	HAR-WTI	HAR-BRN	MIDAS-HAR-WTI	MIDAS-HAR-BRN
				SOY			
1	4.7843	**0.3576***	**0.5017**	**0.5021**	**0.5066**	**0.4662***	**0.4671***
3	4.8134	**0.9904***	1.1892	1.1814	1.1987	1.2028	1.2692
6	4.8178	1.0243	1.3816	1.3892	1.4272	1.3090	1.3407
9	4.7987	1.0119	1.3351	1.3254	1.3848	1.2840	1.4207
12	4.7790	1.0048	1.3174	1.3248	1.3905	1.3117	1.2002
				CORN			
1	10.2521	**0.4745***	**0.4251***	**0.4155***	**0.4327***	**0.4010***	**0.4060***
3	10.3104	**0.8847**	**0.7164***	**0.7225***	**0.7347***	**0.7566**	**0.6965***
6	10.3898	**0.9877**	**0.7939***	**0.8141***	**0.8405**	**0.8178***	**0.8111***
9	10.4606	1.0025	**0.7154***	**0.7163***	**0.7308***	**0.7112***	**0.7189***
12	10.5422	1.0044	**0.7170***	**0.7132***	**0.7219***	**0.7284***	**0.7673**
				SUGAR			
1	11.9224	**0.5427***	**0.4610***	**0.4677***	**0.4860***	**0.4997***	**0.4661***
3	11.9889	**0.9291**	**0.6783***	**0.7114***	**0.7209***	**0.6873***	**0.7267***
6	12.0726	**0.9808**	**0.8287***	**0.8615**	**0.8745**	**0.9133**	**0.7917***
9	12.1457	**0.9862**	**0.9048**	**0.9336**	**0.9518**	**0.8672***	**0.7884***
12	12.2098	**0.9877**	**0.9837**	**0.9991**	1.0212	1.0227	**0.9524***
				RICE			
1	4.5634	**0.4288***	**0.4519***	**0.4858***	**0.5044***	**0.5590***	**0.6425**
3	4.5440	**0.9592***	1.0655	1.0976	1.1343	1.0581	**0.9746***
6	4.5541	**0.9901***	1.1639	1.1692	1.2232	1.2879	1.5632
9	4.5586	1.0006	1.2145	1.1812	1.2391	1.2636	1.4657
12	4.5432	1.0019	1.2764	1.1932	1.2646	1.1552	1.4338
				WHEAT			
1	10.8431	**0.6214**	**0.5226***	**0.5154***	**0.5180***	**0.5073***	**0.5438**
3	10.9047	**0.9399**	**0.7137***	**0.7075***	**0.7100***	**0.7525**	**0.7419**
6	10.9799	**0.9914**	**0.7909***	**0.7760***	**0.7818***	**0.7837***	**0.7872***
9	11.0420	**0.9931**	**0.7509***	**0.7323***	**0.7380***	**0.7219***	**0.7183***
12	11.1124	**0.9932**	**0.7892***	**0.7550***	**0.7691***	**0.7958**	**0.7629***

Note: WTI = WTI crude oil price volatility, BRN = Brent crude oil price volatility. The RW column shows the actual MAFE. All other columns show the MAFE ratios, for each forecasting model, that have been normalized relative to the monthly RW forecast. The order of the AR models for Soy and Corn is 1, whereas for Sugar, Rice and Wheat is 2, based on the Bayesian Information Criterion. Bold face numbers denote that the forecast outperforms the RW. * denotes that the model is included in the set of the best models according to the Model Confidence Set (MCS).

Table 9. The Mean Squared Forecasting Error (MSFE) evaluation function for 1-, 3-, 6-, 9-, 12- month ahead forecasting horizons. Volatility Measure: Monthly Realized Volatility; $RV_t^{(M)}$. Forecasting period: Oil price collapse (2014-2016).

Months-ahead	RW	AR(p)	HAR	HAR-WTI	HAR-BRN	MIDAS-HAR-WTI	MIDAS-HAR-BRN
			SOY				
1	106.9064	**0.1885***	**0.2535***	**0.2905***	**0.2874***	**0.3058***	**0.2364***
3	107.8049	**0.9126***	**0.9726**	1.0899	1.0354	1.0103	1.1389
6	107.8909	1.0256	1.0818	1.2266	1.1687	1.3127	1.2641
9	107.4750	1.0105	1.0165	1.1509	1.0840	**0.9947***	1.0075
12	107.2496	**0.9964**	**0.8811***	**0.9913**	**0.9061**	**0.8461***	**0.8851***
			CORN				
1	32.8181	**0.1869***	**0.4174***	**0.4001***	**0.4103***	**0.4975***	**0.4188***
3	33.1169	1.0491	1.1726	1.1971	1.2161	1.5739	1.4307
6	33.0560	1.0150	1.1575	1.1237	1.0902	1.2672	1.4083
9	32.9217	**0.9992**	1.0066	**0.9479***	**0.9458***	1.0570	**0.8898***
12	32.9963	**0.9998***	1.3075	1.6895	1.8258	1.3955	1.4315
			SUGAR				
1	46.8132	**0.2223***	**0.4665***	**0.4183***	**0.4061***	**0.6353**	**0.5614***
3	47.1778	**0.9503**	**0.9094**	**0.8289***	**0.8368***	**0.7367***	1.0483
6	47.4482	**0.9816**	**0.8971**	**0.7494***	**0.7387***	**0.8828**	**0.6847***
9	47.8288	**0.9862**	1.0278	**0.9174***	**0.9110***	1.1198	1.1397
12	48.1264	**0.9868**	**0.9212**	**0.8746***	**0.8344***	1.2247	1.2463
			RICE				
1	34.4131	**0.1808***	**0.5004**	**0.5332**	**0.5668**	**0.5951**	**0.6213**
3	30.1598	**0.8828**	**0.6300***	**0.8050**	**0.9043**	**0.7356***	**0.8226**
6	30.5801	**0.9248**	**0.5793***	**0.7442**	**0.8400**	**0.6492***	**0.7393**
9	31.2431	**0.9627**	**0.6303***	**0.8292**	**0.9214**	**0.6517***	**0.6620***
12	31.8029	**0.9871**	**0.6477***	**0.8465**	**0.9927**	**0.7621***	**0.8192**
			WHEAT				
1	43.8732	**0.3126***	**0.6232**	**0.6005**	**0.5892**	**0.6438**	**0.6441**
3	44.1871	1.0002	1.1702	1.0821	1.1118	1.3833	1.1418
6	44.2864	1.0011	1.4146	1.2820	1.3342	1.5496	1.3944
9	44.1702	1.0034	1.6005	1.4335	1.5266	1.4885	1.6114
12	43.9806	1.0005	1.5052	1.3094	1.4287	1.4313	1.5105

Note: WTI = WTI crude oil price volatility, BRN = Brent crude oil price volatility. The RW column shows the actual MSFE. All other columns show the MSFE ratios, for each forecasting model, that have been normalized relative to the monthly RW forecast. The order of the AR models for Soy and Corn is 1, whereas for Sugar, Rice and Wheat is 2, based on the Bayesian Information Criterion. Bold face numbers denote that the forecast outperforms the RW. * denotes that the model is included in the set of the best models according to the Model Confidence Set (MCS).

Table 10. The Mean Absolute Forecasting Error (MAFE) evaluation function for 1-, 3-, 6-, 9-, 12- month ahead forecasting horizons. Volatility Measure: Monthly Realized Volatility; $RV_t^{(M)}$. Forecasting period: Oil price collapse (2014-2016).

Months-ahead	RW	AR(p)	HAR	HAR-WTI	HAR-BRN	MIDAS-HAR-WTI	MIDAS-HAR-BRN
				SOY			
1	8.0025	**0.4007***	**0.4668***	**0.4889***	**0.4738***	**0.4704***	**0.4536***
3	8.0377	**0.9323***	**0.9954**	1.0410	1.0206	1.0275	1.0463
6	8.0403	1.0123	1.0583	1.1127	1.0778	1.1092	1.1308
9	8.0215	1.0006	1.0256	1.0967	1.0559	1.0797	1.0594
12	8.0207	**0.9974**	**0.9913**	1.0215	**0.9690***	**0.9756***	1.0526
				CORN			
1	4.5887	**0.4297***	**0.6245***	**0.6098***	**0.6162***	**0.6918**	**0.6298***
3	4.6094	1.0169	1.0690	1.0768	1.0905	1.2531	1.1955
6	4.6040	1.0203	1.1268	1.1007	1.0749	1.1673	1.2324
9	4.5885	1.0032	1.0277	1.0190	1.0056	1.0901	**0.9662***
12	4.5936	1.0002	1.2054	1.3531	1.3823	1.2743	1.3034
				SUGAR			
1	5.7242	**0.4631***	**0.6638***	**0.6264***	**0.6382***	**0.7650**	**0.7130**
3	5.7415	**0.9403**	**0.9640**	**0.9315***	**0.9305***	**0.9027***	1.0781
6	5.7604	**0.9881**	**0.9075**	**0.8397***	**0.8346***	**0.8730**	**0.7617***
9	5.7876	**0.9873**	**0.9552**	**0.8680***	**0.8868***	**0.9909**	**0.9834**
12	5.8091	**0.9874**	**0.9058**	**0.9129**	**0.8657***	1.1078	1.0763
				RICE			
1	4.0212	**0.4022***	**0.5902***	**0.5689***	**0.5955**	**0.6291**	**0.6071**
3	4.5574	**0.8937**	**0.7518***	**0.8637**	**0.8877**	**0.8447**	**0.8979**
6	4.5917	**0.9813**	**0.6913***	**0.8547**	**0.8897**	**0.7627***	**0.8552**
9	4.6350	**0.9841**	**0.7927***	**0.9545**	1.0037	**0.7799***	**0.8358***
12	4.6682	**0.9944**	**0.7944***	**0.9398**	1.0267	**0.8819***	**0.9051**
				WHEAT			
1	5.1022	**0.5401***	**0.7117**	**0.6976**	**0.6853***	**0.7516**	**0.7436**
3	5.1220	**0.9914**	1.0448	**0.9897***	1.0046	1.1230	1.0391
6	5.1267	**0.9879***	1.1859	1.0991	1.1328	1.2129	1.1750
9	5.1265	**0.9913***	1.2334	1.1406	1.1931	1.2047	1.2284
12	5.1365	**0.9882***	1.1846	1.0878	1.1509	1.1506	1.1945

Note: WTI = WTI crude oil price volatility, BRN = Brent crude oil price volatility. The RW column shows the actual MAFE. All other columns show the MAFE ratios, for each forecasting model, that have been normalized relative to the monthly RW forecast. The order of the AR models for Soy and Corn is 1, whereas for Sugar, Rice and Wheat is 2, based on the Bayesian Information Criterion. Bold face numbers denote that the forecast outperforms the RW. * denotes that the model is included in the set of the best models according to the Model Confidence Set (MCS).

Table 11. Directional accuracy for 1-, 3-, 6-, 9-, 12- month ahead forecasting horizons. Volatility Measure: Monthly Realized Volatility; $RV_t^{(M)}$. Forecasting period: Jan 2000 – March 2017.

Months-ahead	RW	AR(p)	HAR	HAR-WTI	HAR-BRN	MIDAS-HAR-WTI	MIDAS-HAR-BRN
				SOY			
1	0.6359	0.8301	0.8301	**0.8398**	0.8252	0.8204	0.8107
3	0.7059	0.7255	0.7157	0.7010	0.6912	0.6814	0.6765
6	0.7363	0.7313	0.7065	0.7214	0.7313	0.7015	0.6567
9	0.6970	0.6970	0.7273	0.6919	0.7121	0.7222	0.7172
12	0.7026	0.7026	0.7128	0.7026	0.6821	0.6923	0.6923
				CORN			
1	0.6456	0.7961	0.8204	0.8204	0.8204	0.7864	0.8155
3	0.6618	0.6716	0.6863	0.6765	0.6765	0.6569	0.6569
6	0.6617	0.6617	0.7214	0.7164	**0.7264**	0.7114	0.7313
9	0.6919	0.6919	0.7677	0.7475	0.7273	0.7374	0.7475
12	0.6000	0.6000	0.6154	**0.6308**	**0.6256**	**0.6410**	**0.6256**
				SUGAR			
1	0.6456	0.7816	0.7621	0.7379	0.7379	**0.8107**	0.7379
3	0.6569	0.6961	0.7108	0.7010	0.6961	0.7108	0.7010
6	0.7114	0.7114	0.7114	0.7114	0.7065	0.7114	0.7015
9	0.7172	0.7172	0.6869	0.6869	0.6970	0.6869	0.6566
12	0.7487	0.7385	0.7231	0.7487	0.7385	0.7282	0.7128
				RICE			
1	0.6553	0.8738	0.8689	0.8592	0.8447	0.8495	0.8252
3	0.6716	0.6618	0.6225	0.6422	0.6569	0.6225	0.6176
6	0.6318	0.6318	0.5920	0.5771	0.5721	0.5771	0.5672
9	0.6919	0.6919	0.6263	0.6263	0.6212	0.6212	0.6010
12	0.6410	0.6410	0.5744	0.5641	0.5795	0.5795	0.5795
				WHEAT			
1	0.6311	0.7087	0.7670	0.7573	0.7524	0.7573	0.7524
3	0.6618	0.6667	0.6814	0.6765	0.6716	0.6520	0.6765
6	0.6368	0.6368	0.6866	0.6816	**0.6915**	0.6866	**0.6915**
9	0.6717	0.6717	0.7172	0.7020	0.7020	0.6616	0.6970
12	0.6513	0.6513	0.6821	0.6615	0.6718	0.6718	0.6513

Note: WTI = WTI crude oil price volatility, BRN = Brent crude oil price volatility. Bold face indicates improvement in directional accuracy relative to the benchmark models (RW, AR(p) or HAR). The order of the AR models for Soy and Corn is 1, whereas for Sugar, Rice and Wheat is 2, based on the Bayesian Information Criterion.

Table 12. Directional accuracy for 1-, 3-, 6-, 9-, 12- month ahead forecasting horizons. Volatility Measure: Monthly Realized Volatility; $RV_t^{(M)}$. Forecasting period: 1st Food Crisis (2007-2009).

Months-ahead	RW	AR(p)	HAR	HAR-WTI	HAR-BRN	MIDAS-HAR-WTI	MIDAS-HAR-BRN
				SOY			
1	0.4400	0.6400	0.7600	0.7200	0.6800	0.6800	0.6000
3	0.6800	0.7200	0.7200	0.6800	0.6400	0.7200	0.6400
6	0.6000	0.6000	0.6000	0.6000	0.6000	0.5600	0.6000
9	0.5600	0.5600	0.6400	0.5200	0.5200	0.5200	0.5600
12	0.4800	0.4800	0.5600	0.4400	0.4400	0.4800	0.4800
				CORN			
1	0.6000	0.7200	0.8800	0.8800	0.8400	0.7200	0.7600
3	0.5200	0.5600	0.5200	0.5200	0.4800	0.4800	0.4400
6	0.4400	0.4400	0.5600	0.5600	0.5600	0.5600	0.5600
9	0.4800	0.4800	0.6800	0.6800	0.6800	0.6400	0.6400
12	0.4800	0.4800	0.6000	0.6000	0.6000	**0.6400**	**0.6400**
				SUGAR			
1	0.6400	0.8400	0.8800	0.8400	0.8400	0.8400	0.8400
3	0.5600	0.6400	0.6400	**0.6800**	**0.6800**	0.6400	**0.6800**
6	0.7600	0.8000	0.8000	0.6800	0.6800	0.7600	0.7200
9	0.8000	0.8000	0.7600	0.7600	0.7600	**0.8800**	0.7600
12	0.8400	0.8400	0.8000	0.8400	0.8000	0.8400	0.8400
				RICE			
1	0.5200	0.7200	0.7200	**0.7600**	**0.7600**	**0.7600**	0.6800
3	0.7200	0.7200	0.8000	0.8000	0.8000	**0.8400**	0.6800
6	0.6800	0.7200	0.7600	0.7600	0.7600	0.7200	0.7200
9	0.8400	0.8400	0.7600	0.6800	0.6800	0.7600	0.7600
12	0.7600	0.7600	0.7600	0.7200	0.7600	**0.8000**	**0.8000**
				WHEAT			
1	0.4800	0.5600	0.7600	0.7600	0.7600	0.7600	0.7600
3	0.5200	0.5200	0.6800	**0.7200**	0.6800	0.6400	0.6400
6	0.4400	0.4400	0.5600	0.5600	0.5600	**0.6000**	**0.6000**
9	0.3600	0.3600	0.4000	0.4400	0.4000	0.4400	0.4400
12	0.3200	0.3200	0.4000	0.4000	0.4000	0.4400	0.4000

Note: WTI = WTI crude oil price volatility, BRN = Brent crude oil price volatility. Bold face indicates improvement in directional accuracy relative to the benchmark models (RW, AR(p) or HAR). The order of the AR models for Soy and Corn is 1, whereas for Sugar, Rice and Wheat is 2, based on the Bayesian Information Criterion.

Table 13. Directional accuracy for 1-, 3-, 6-, 9-, 12- month ahead forecasting horizons. Volatility Measure: Monthly Realized Volatility; $RV_t^{(M)}$. Forecasting period: 2nd Food Crisis (2010-2012).

Months-ahead	RW	AR(p)	HAR	HAR-WTI	HAR-BRN	MIDAS-HAR-WTI	MIDAS-HAR-BRN
				SOY			
1	0.7222	0.9167	0.8611	0.8611	0.8333	0.8889	0.8889
3	0.7778	0.7222	0.6667	0.6944	0.6944	0.6111	0.6667
6	0.8056	0.7778	0.6944	0.6944	0.7222	0.7500	0.7222
9	0.7778	0.7778	0.7500	0.7500	0.7222	**0.8056**	0.7222
12	0.8333	0.8333	0.8056	**0.8889**	**0.8611**	0.8056	0.8056
				CORN			
1	0.5556	0.7500	0.8333	**0.8611**	0.8333	**0.8611**	**0.8889**
3	0.6667	0.6389	0.6944	**0.7222**	0.6944	0.6667	**0.7222**
6	0.6389	0.6389	0.7500	**0.7778**	**0.7778**	0.7500	0.7500
9	0.5833	0.5833	0.7222	0.7222	0.6667	**0.7500**	**0.7500**
12	0.6111	0.6111	0.5556	0.5833	0.5833	**0.6389**	0.5556
				SUGAR			
1	0.5556	0.6967	0.6944	0.6667	0.6389	**0.7778**	0.6389
3	0.6944	0.6944	0.6667	0.6389	0.6667	0.6944	0.6667
6	0.7222	0.7222	0.7222	0.7222	0.7222	0.6944	0.7222
9	0.6667	0.6667	0.6667	0.6944	**0.7222**	0.6667	**0.7222**
12	0.6944	0.6944	0.6944	**0.7222**	**0.7222**	**0.7222**	**0.7222**
				RICE			
1	0.6667	0.9444	0.9444	0.8611	0.8333	0.8333	0.8611
3	0.6667	0.6667	0.5833	0.6111	0.6111	0.5278	0.6111
6	0.6111	0.6389	0.5833	0.5000	0.4722	0.4722	0.3889
9	0.6667	0.6389	0.5833	0.6111	0.6111	0.5278	0.5000
12	0.6667	0.6667	0.6389	0.5833	0.5556	0.6111	0.5278
				WHEAT			
1	0.5556	0.6111	0.6944	**0.7222**	0.6944	0.6944	0.6944
3	0.7222	0.7500	0.6389	0.6111	0.6111	0.5556	0.6111
6	0.5833	0.5833	0.6667	**0.6944**	**0.6944**	**0.7222**	**0.7222**
9	0.5833	0.5833	0.6667	0.6667	0.6667	0.6389	**0.6944**
12	0.6667	0.6667	0.6944	**0.7222**	**0.7222**	0.6944	0.6944

Note: WTI = WTI crude oil price volatility, BRN = Brent crude oil price volatility. Bold face indicates improvement in directional accuracy relative to the benchmark models (RW, AR(p) or HAR). The order of the AR models for Soy and Corn is 1, whereas for Sugar, Rice and Wheat is 2, based on the Bayesian Information Criterion.

Table 14. Directional accuracy for 1-, 3-, 6-, 9-, 12- month ahead forecasting horizons. Volatility Measure: Monthly Realized Volatility; $RV_t^{(M)}$. Forecasting period: Oil price collapse (2014-2016).

Months-ahead	RW	AR(p)	HAR	HAR-WTI	HAR-BRN	MIDAS-HAR-WTI	MIDAS-HAR-BRN
				SOY			
1	0.6190	0.8571	0.7619	0.7619	0.8095	0.8095	0.8095
3	0.6667	0.6667	0.5714	0.6190	0.6190	0.6190	0.6667
6	0.8571	0.8571	0.8571	0.8095	0.8095	0.7619	0.8095
9	0.6667	0.6667	0.6667	0.6190	0.6667	0.6190	**0.7143**
12	0.7619	0.7619	0.8095	0.7143	0.7619	0.8095	0.8095
				CORN			
1	0.7143	0.9524	0.7619	0.8571	0.8571	0.7619	0.8095
3	0.6190	0.6190	0.6667	0.6190	0.6190	0.6667	0.5714
6	0.7619	0.7619	0.7619	**0.8571**	**0.8571**	0.7619	0.7143
9	0.6667	0.6667	0.6667	0.6190	0.6190	0.6667	0.6667
12	0.7143	0.7143	0.6190	0.7143	0.6667	0.6667	0.5714
				SUGAR			
1	0.5714	0.7143	0.7143	**0.7619**	0.7143	**0.7619**	**0.7619**
3	0.7143	0.7619	0.7143	0.6667	0.7619	**0.8571**	**0.8095**
6	0.7143	0.7143	0.6667	0.6190	0.6190	0.6667	**0.7619**
9	0.9524	0.9524	0.8571	0.9048	0.8095	0.8571	0.8571
12	0.8571	0.8571	0.7619	0.8095	0.8571	0.7143	0.7143
				RICE			
1	0.7143	0.9048	0.8095	0.8571	0.8571	0.8571	0.6667
3	0.6667	0.7143	0.7143	0.6667	0.6667	0.7143	0.5714
6	0.8095	0.8095	0.8571	0.8095	0.8095	0.8571	0.8571
9	0.8095	0.8571	0.8571	0.8571	0.8571	0.8571	0.8571
12	0.8095	0.8095	0.8571	0.8571	0.8095	0.8571	0.8095
				WHEAT			
1	0.7143	0.9524	0.8571	0.8095	0.8571	0.8571	0.7619
3	0.6667	0.7143	0.6190	0.6667	0.6667	0.6190	0.6667
6	0.8571	0.8571	0.8571	0.8571	0.8571	0.7619	0.7619
9	0.8571	0.8571	0.9524	0.9524	0.9524	0.8571	0.9048
12	0.8571	0.8571	0.8571	0.8095	0.8571	0.8571	0.8095

Note: WTI = WTI crude oil price volatility, BRN = Brent crude oil price volatility. Bold face indicates improvement in directional accuracy relative to the benchmark models (RW, AR(p) or HAR). The order of the AR models for Soy and Corn is 1, whereas for Sugar, Rice and Wheat is 2, based on the Bayesian Information Criterion.

Online Appendix

Table A1. Forecast average measures. The Mean Squared Forecasting Error (MSFE) evaluation function for 1-, 3-, 6-, 9-, 12- month ahead forecasting horizons. Volatility Measure: Monthly Realized Volatility, $RV_t^{(M)}$. Forecasting period: Jan 2000 – March 2017.

Months-ahead	FA_BRN_1	FA_WTI_1	FA_BRN_2	FA_WTI_2
		SOY		
1	**0.1912**	**0.1832**	**0.1949**	**0.1843**
3	0.7539	0.7325	0.7532	0.7289
6	0.8622	0.8751	0.9803	0.9929
9	0.8831	0.8975	1.0088	1.0140
12	0.9036	0.8977	0.9020	0.9204
		CORN		
1	**0.3005**	**0.2987**	**0.2939**	**0.2962**
3	0.6758	0.6626	0.6654	0.6583
6	0.8049	0.7989	0.8497	0.8747
9	0.7491	0.7467	0.7667	0.7715
12	0.7388	0.7026	0.6830	0.6874
		SUGAR		
1	**0.3425**	**0.3546**	**0.3439**	**0.3521**
3	0.7231	0.7468	0.7208	0.7454
6	0.8567	0.8310	0.9106	0.8739
9	0.9432	0.9414	1.0296	1.0066
12	1.0045	1.0077	1.2323	1.1825
		RICE		
1	**0.2885**	**0.2995**	**0.2849**	**0.2979**
3	0.7927	0.7963	0.7855	0.8006
6	0.9129	0.9124	0.9682	0.9784
9	0.8763	0.9005	1.0216	1.0071
12	0.9710	0.9331	0.9342	0.9387
		WHEAT		
1	**0.3435**	**0.3474**	**0.3471**	**0.3501**
3	0.5881	0.5768	0.5846	0.5795
6	0.6555	0.6866	0.6586	0.6492
9	0.7226	0.7538	0.7047	0.7033
12	0.8111	0.8305	0.7720	0.7663

Note: FA_BRN_1 denotes the simple forecast average between HAR-BRN and MIDAS-HAR-BRN. FA_WTI_1 denotes the simple forecast average between HAR-WTI and MIDAS-HAR-WTI. FA_BRN_2 denotes forecast average between HAR-BRN and MIDAS-HAR-BRN weighted by the inverse of the mean squared forecast error of the previous forecast. FA_WTI_2 denotes forecast average between HAR-WTI and MIDAS-HAR-WTI weighted by the inverse of the mean squared forecast error of the previous forecast. Bold face numbers denote that the forecast average outperforms all other models according to the Model Confidence Set (MCS).

Table A2. Forecast average measures. The Mean Squared Forecasting Error (MSFE) evaluation function for 1-, 3-, 6-, 9-, 12- month ahead forecasting horizons. Volatility Measure: Monthly Realized Volatility, $RV_t^{(M)}$. Forecasting period: 1st Food Crisis (2007-2009).

Months-ahead	FA_1	FA_2	FA_3	FA_4
		SOY		
1	0.1850	0.1899	0.1871	0.1921
3	0.5392	0.5449	0.5360	0.5431
6	0.7451	0.7072	**0.5659**	**0.5564**
9	0.8381	0.7950	**0.6985**	**0.6865**
12	0.9107	0.9172	0.8132	0.8091
		CORN		
1	0.1938	0.2077	0.1919	0.2080
3	0.4627	0.4424	0.4669	0.4408
6	0.6313	0.5989	0.5492	0.5658
9	0.6360	0.6369	0.5850	0.5847
12	0.6974	0.6384	**0.5505**	**0.5413**
		SUGAR		
1	0.3881	0.3074	0.3710	0.2964
3	0.7495	0.7701	0.7314	0.7635
6	1.0212	0.9999	1.1053	1.1152
9	1.0342	1.0853	1.3059	1.3500
12	1.0768	1.1209	1.4708	1.5034
		RICE		
1	0.2112	0.2148	0.2094	0.2073
3	0.7499	0.6943	0.7460	0.6921
6	1.0882	1.0238	1.1275	1.1225
9	1.1358	1.0786	1.1644	1.1574
12	1.2193	1.1965	1.4019	1.4362
		WHEAT		
1	0.2699	0.2607	0.2722	0.2646
3	0.4550	0.4477	0.4494	0.4450
6	0.5215	0.5355	0.4630	0.4601
9	0.5988	0.6894	0.5323	0.5603
12	0.7843	0.8020	**0.6156**	**0.6269**

Note: FA_BRN_1 denotes the simple forecast average between HAR-BRN and MIDAS-HAR-BRN. FA_WTI_1 denotes the simple forecast average between HAR-WTI and MIDAS-HAR-WTI. FA_BRN_2 denotes forecast average between HAR-BRN and MIDAS-HAR-BRN weighted by the inverse of the mean squared forecast error of the previous forecast. FA_WTI_2 denotes forecast average between HAR-WTI and MIDAS-HAR-WTI weighted by the inverse of the mean squared forecast error of the previous forecast. Bold face numbers denote that the forecast average outperforms all other models according to the Model Confidence Set (MCS).

Table A3. Forecast average measures. The Mean Squared Forecasting Error (MSFE) evaluation function for 1-, 3-, 6-, 9-, 12- month ahead forecasting horizons. Volatility Measure: Monthly Realized Volatility, $RV_t^{(M)}$. Forecasting period: 2nd Food Crisis (2010-2012).

Months-ahead	FA_1	FA_2	FA_3	FA_4
		SOY		
1	0.2086	0.2242	0.2163	0.2218
3	1.3395	1.4503	1.3041	1.3795
6	1.6254	1.7137	2.7140	2.8767
9	1.5894	1.9007	3.1647	3.1720
12	1.5909	1.4998	3.0828	3.1272
		CORN		
1	0.1674	0.1714	0.1683	0.1801
3	0.5408	0.4949	0.5249	0.4896
6	0.6659	0.6920	0.8316	0.8880
9	0.5354	0.5507	0.6113	0.6744
12	0.5335	0.5352	0.5852	0.5919
		SUGAR		
1	0.2522	0.2773	0.2416	0.2731
3	0.5898	0.6234	0.5957	0.6251
6	0.8047	0.7477	0.6271	**0.5819**
9	0.8405	0.7984	0.6818	0.6886
12	0.9834	0.9784	0.9409	0.8995
		RICE		
1	0.2646	0.3155	0.2824	0.3758
3	0.9815	0.9450	0.9390	0.9596
6	1.1983	1.6525	1.1676	1.1197
9	1.2491	1.6002	1.3579	1.3700
12	1.5169	1.7618	2.0595	2.0481
		WHEAT		
1	0.2822	0.3017	0.2793	0.2969
3	0.5359	0.5277	0.5324	0.5262
6	0.5646	0.5750	0.6731	0.6540
9	0.5236	0.5272	0.5534	0.5417
12	0.5995	0.6077	0.6390	0.6424

Note: FA_BRN_1 denotes the simple forecast average between HAR-BRN and MIDAS-HAR-BRN. FA_WTI_1 denotes the simple forecast average between HAR-WTI and MIDAS-HAR-WTI. FA_BRN_2 denotes forecast average between HAR-BRN and MIDAS-HAR-BRN weighted by the inverse of the mean squared forecast error of the previous forecast. FA_WTI_2 denotes forecast average between HAR-WTI and MIDAS-HAR-WTI weighted by the inverse of the mean squared forecast error of the previous forecast. Bold face numbers denote that the forecast average outperforms all other models according to the Model Confidence Set (MCS).

Table A4. Forecast average measures. The Mean Squared Forecasting Error (MSFE) evaluation function for 1-, 3-, 6-, 9-, 12- month ahead forecasting horizons. Volatility Measure: Monthly Realized Volatility, $RV_t^{(M)}$. Forecasting period: Oil price collapse (2014-2016).

Months-ahead	FA_1	FA_2	FA_3	FA_4
		SOY		
1	0.2906	0.2590	0.3023	0.2622
3	1.0454	1.0801	1.0412	1.0823
6	1.2649	1.2101	1.4336	1.3932
9	1.0594	1.0363	1.4564	1.4078
12	0.9133	0.8689	0.8537	0.8601
		CORN		
1	0.4348	0.4035	0.3949	0.4291
3	1.3657	1.3112	1.3356	1.3228
6	1.1763	1.2216	1.2570	1.2705
9	0.9391	0.8984	1.1021	1.1362
12	1.4487	1.5999	1.9534	2.0619
		SUGAR		
1	0.4951	0.4591	0.5362	0.4892
3	0.7565	0.9124	0.7776	0.9007
6	0.8027	0.6947	1.0075	0.9622
9	0.9643	0.9942	1.5565	1.4900
12	1.0176	0.9660	1.6319	1.5751
		RICE		
1	0.5453	0.5600	0.5360	0.5480
3	1.6367	1.6409	1.6331	1.6540
6	1.2751	1.2692	1.6681	1.7140
9	1.0526	1.1580	1.7333	1.7910
12	1.1673	1.0851	1.5142	1.5877
		WHEAT		
1	0.6177	0.6125	0.6174	0.6121
3	1.2206	1.1206	1.1666	1.0982
6	1.3994	1.3562	1.4474	1.4501
9	1.4500	1.5645	2.0213	1.9584
12	1.3648	1.4533	1.8855	1.8770

Note: FA_BRN_1 denotes the simple forecast average between HAR-BRN and MIDAS-HAR-BRN. FA_WTI_1 denotes the simple forecast average between HAR-WTI and MIDAS-HAR-WTI. FA_BRN_2 denotes forecast average between HAR-BRN and MIDAS-HAR-BRN weighted by the inverse of the mean squared forecast error of the previous forecast. FA_WTI_2 denotes forecast average between HAR-WTI and MIDAS-HAR-WTI weighted by the inverse of the mean squared forecast error of the previous forecast. Bold face numbers denote that the forecast average outperforms all other models according to the Model Confidence Set (MCS).

Table A5. The Mean Squared Forecasting Error (MSFE) evaluation function for 1-, 3-, 6-, 9-, 12- month ahead forecasting horizons. Volatility Measure: Monthly Price Range; $PR_t^{(M)}$. Forecasting period: Jan 2000 – March 2017.

Months-ahead	RW	AR(p)	HAR	HAR-WTI	HAR-BRN	MIDAS-HAR-WTI	MIDAS-HAR-BRN
				SOY			
1	164.9	**0.6398***	**0.5894***	**0.6101***	**0.6095***	**0.5973***	**0.5713***
3	166.5	**0.9285**	**0.8000***	**0.8378***	**0.8318***	**0.8024***	**0.7694***
6	169.6	**0.9900**	**0.8290***	**0.8567***	**0.8496***	**0.8667**	**0.8768**
9	172.5	1.0000	**0.8510***	**0.9038**	**0.8875**	**0.8516***	**0.8725***
12	176.1	1.0006	**0.8887***	**0.9710**	**0.9472**	**0.8864***	**0.8325***
				CORN			
1	215.8	**0.7447**	**0.6738***	**0.6835***	**0.6872***	**0.6997***	**0.6951***
3	217.8	**0.9408**	**0.7893***	**0.8090***	**0.8035***	**0.8108***	**0.7562***
6	221.2	**0.9964**	**0.8142***	**0.8413**	**0.8291***	**0.8404**	**0.8395***
9	223.7	1.0013	**0.8002***	**0.8118***	**0.8006***	**0.7881***	**0.7962***
12	228.4	1.0013	**0.8170***	**0.8139***	**0.8034***	**0.8341**	**0.8249**
				SUGAR			
1	155.8	**0.6836***	**0.6380***	**0.6418***	**0.6508***	**0.6534***	**0.6605***
3	154.5	**0.8254**	**0.7650***	**0.7780***	**0.7845***	**0.7599***	**0.8304**
6	154.4	**0.9141**	**0.8316***	**0.8400***	**0.8407***	**0.8426***	**0.8543***
9	152.5	**0.9731**	**0.9115***	**0.9154***	**0.9102***	**0.8492***	**0.9633**
12	148.0	**0.9914**	**0.9514***	**0.9473***	**0.9358***	**0.9500***	**0.9419***
				RICE			
1	184.6	**0.7324**	**0.6961***	**0.6880***	**0.6999***	**0.7015***	**0.6999***
3	187.2	**0.8864**	**0.8510***	**0.8691***	**0.8574***	**0.8226***	**0.8729***
6	190.8	**0.9388***	**0.9193***	**0.9397***	**0.9429**	**0.9471**	1.0026
9	180.4	**0.9406***	**0.9396***	**0.9712***	**0.9739***	**0.9800**	**0.9784**
12	181.1	**0.9721***	**0.9807***	1.0160	1.0160	1.0105	**0.9475***
				WHEAT			
1	168.5	**0.6967***	**0.6641***	**0.6724***	**0.6766***	**0.6831***	**0.6712***
3	170.6	**0.8668**	**0.7327***	**0.7497***	**0.7444***	**0.7644***	**0.7356***
6	174.0	**0.9388**	**0.7540***	**0.7672***	**0.7563***	**0.7764***	**0.7891***
9	177.7	**0.9795**	**0.7980***	**0.8087***	**0.7980***	**0.7698***	**0.8402**
12	181.4	**0.9941**	**0.8512***	**0.8583***	**0.8506***	**0.8771**	**0.8528***

Note: WTI = WTI crude oil price volatility, BRN = Brent crude oil price volatility. The RW column shows the actual MSFE. All other columns show the MSFE ratios, for each forecasting model, that have been normalized relative to the monthly RW forecast. The order of the AR models for Soy and Corn is 1, for Sugar and Wheat is 2, whereas for Rice is 4, based on the Bayesian Information Criterion. Bold face numbers denote that the forecast outperforms the RW. * denotes that the model is included in the set of the best models according to the Model Confidence Set (MCS).

Table A6. The Mean Absolute Forecasting Error (MAFE) evaluation function for 1-, 3-, 6-, 9-, 12- month ahead forecasting horizons. Volatility Measure: Monthly Price Range; $PR_t^{(M)}$. Forecasting period: Jan 2000 – March 2017.

Months-ahead	RW	AR(p)	HAR	HAR-WTI	HAR-BRN	MIDAS-HAR-WTI	MIDAS-HAR-BRN
				SOY			
1	8.28	**0.8056***	**0.7874***	**0.7983***	**0.8007***	**0.8068***	**0.7971***
3	8.31	**0.9567**	**0.9266***	**0.9362***	**0.9471**	**0.9483**	**0.9206***
6	8.40	**0.9976**	**0.9381***	**0.9571***	**0.9583***	**0.9714**	**0.9714**
9	8.46	1.0000	**0.9480***	**0.9764**	**0.9811**	**0.9492***	**0.9681***
12	8.58	**0.9988**	**0.9697***	1.0210	1.0186	**0.9848**	**0.9231***
				CORN			
1	9.76	**0.8596***	**0.8279***	**0.8412***	**0.8432***	**0.8494***	**0.8361***
3	9.81	**0.9664**	**0.9072***	**0.9307**	**0.9307**	**0.9246***	**0.9011***
6	9.88	**0.9970**	**0.9089***	**0.9160***	**0.9170***	**0.9028***	**0.9281***
9	9.92	1.0010	**0.9063***	**0.9042***	**0.9073***	**0.9103***	**0.9073***
12	10.08	**0.9990**	**0.9216***	**0.9028***	**0.9077***	**0.9296***	**0.9266***
				SUGAR			
1	9.31	**0.8160***	**0.7916***	**0.8067***	**0.8088***	**0.8185***	**0.8281**
3	9.25	**0.8801***	**0.8649***	**0.8768***	**0.8843***	**0.8822***	**0.9373***
6	9.25	**0.9512**	**0.9276***	**0.9308***	**0.9265***	**0.9578**	**0.9362***
9	9.23	**0.9858**	**0.9653***	**0.9664***	**0.9599***	**0.9480***	**0.9859**
12	9.08	**0.9981**	**0.9802***	**0.9714***	**0.9626***	**0.9725***	**0.9548***
				RICE			
1	9.18	**0.8299***	**0.8039***	**0.7974***	**0.8061***	**0.8246***	**0.8072***
3	9.29	**0.9391***	**0.9247***	**0.9279***	**0.9225***	**0.9386***	**0.9440**
6	9.41	**0.9871***	**0.9692***	**0.9809***	**0.9745***	1.0085	1.0159
9	9.15	**0.9991**	**0.9770***	**0.9934**	**0.9891***	1.0120	**0.9967**
12	9.14	**1.0001**	1.0022	1.0230	1.0219	**0.9967***	**0.9847***
				WHEAT			
1	8.96	**0.8945**	**0.8426***	**0.8460***	**0.8516***	**0.8549***	**0.8571***
3	9.04	**0.9512**	**0.8982***	**0.9060***	**0.8993***	**0.9237***	**0.9126***
6	9.15	**0.9873**	**0.9246***	**0.9246***	**0.9126***	**0.9530**	**0.9574**
9	9.26	**0.9981**	**0.9374***	**0.9363***	**0.9276***	**0.9201***	**0.9644**
12	9.37	**0.9973**	**0.9626***	**0.9626***	**0.9552***	**0.9968**	**0.9787**

Note: WTI = WTI crude oil price volatility, BRN = Brent crude oil price volatility. The RW column shows the actual MAFE. All other columns show the MAFE ratios, for each forecasting model, that have been normalized relative to the monthly RW forecast. The order of the AR models for Soy and Corn is 1, for Sugar and Wheat is 2, whereas for Rice is 4, based on the Bayesian Information Criterion. Bold face numbers denote that the forecast outperforms the RW. * denotes that the model is included in the set of the best models according to the Model Confidence Set (MCS).

Table A7. The Mean Squared Forecasting Error (MSFE) evaluation function for 1-, 3-, 6-, 9-, 12- month ahead forecasting horizons. Volatility Measure: Monthly Realized Range; $RR_t^{(M)}$. Forecasting period: Jan 2000 – March 2017.

Months-ahead	RW	AR(p)	HAR	HAR-WTI	HAR-BRN	MIDAS-HAR-WTI	MIDAS-HAR-BRN
				SOY			
1	85.1	**0.3325***	**0.3067***	**0.3231***	**0.3184***	**0.3243***	**0.3114***
3	86.4	**0.6574***	**0.5498***	**0.5880***	**0.5799***	**0.6088***	**0.5822***
6	88.3	**0.8732**	**0.6750***	**0.7180***	**0.7135***	**0.7644***	**0.7180***
9	90.3	**0.9424**	**0.7165***	**0.7663***	**0.7730***	**0.7486***	**0.7841***
12	92.7	**0.9752**	**0.7843***	**0.8382***	**0.8522**	**0.8662**	**0.8166***
				CORN			
1	123.8	**0.3207***	**0.2722***	**0.2851***	**0.2827***	**0.2892***	**0.2722***
3	125.4	**0.6364**	**0.4306***	**0.4514***	**0.4434***	**0.4665***	**0.4290***
6	128.1	**0.8704**	**0.4965***	**0.5144***	**0.5090***	**0.5144***	**0.5105***
9	130.4	**0.9363**	**0.4816***	**0.4847***	**0.4847***	**0.4425***	**0.5199***
12	134.0	**0.9716**	**0.5321***	**0.5328***	**0.5358***	**0.5015***	**0.5358***
				SUGAR			
1	115.6	**0.4230***	**0.3832***	**0.3901***	**0.3884***	**0.3867***	**0.3910***
3	116.2	**0.7177**	**0.5740***	**0.5981***	**0.5895***	**0.5912***	**0.5921***
6	118.0	**0.8763**	**0.6483***	**0.6729***	**0.6619***	**0.6466***	**0.6737***
9	115.9	**0.9560**	**0.7455***	**0.7619***	**0.7386***	**0.7567***	**0.7092***
12	117.5	**0.9813**	**0.8170***	**0.8077***	**0.7719***	**0.7455***	**0.7319***
				RICE			
1	83.3	**0.4128***	**0.4418***	**0.4406***	**0.4442***	**0.4394***	**0.4286***
3	83.8	**0.5849***	**0.5871***	**0.6241***	**0.6062***	**0.5752***	**0.5979***
6	85.8	**0.7105**	**0.6620***	**0.7401**	**0.7168**	**0.6667***	**0.7063***
9	85.8	**0.8574**	**0.8112***	**0.8916**	**0.8636**	**0.8497***	**0.8427***
12	87.5	**0.9136***	**0.8560***	**0.9406**	**0.9131***	**0.9246**	**0.8789***
				WHEAT			
1	126.2	**0.3938***	**0.3201***	**0.3249***	**0.3217***	**0.3526***	**0.3249***
3	128.0	**0.7164**	**0.4445***	**0.4484***	**0.4453***	**0.4422***	**0.4211***
6	131.4	**0.9110**	**0.5076***	**0.5068***	**0.5061***	**0.5046***	**0.5076***
9	134.6	**0.9688**	**0.5676***	**0.5691***	**0.5698***	**0.5743***	**0.6248***
12	138.3	**0.9913**	**0.6905***	**0.6898***	**0.6949***	**0.7332**	**0.7166***

Note: WTI = WTI crude oil price volatility, BRN = Brent crude oil price volatility. The RW column shows the actual MSFE. All other columns show the MSFE ratios, for each forecasting model, that have been normalized relative to the monthly RW forecast. The order of the AR models for Soy, Corn and Sugar is 1, whereas for Rice and Wheat is 2, based on the Bayesian Information Criterion. Bold face numbers denote that the forecast outperforms the RW. * denotes that the model is included in the set of the best models according to the Model Confidence Set (MCS).

Table A8. The Mean Absolute Forecasting Error (MAFE) evaluation function for 1-, 3-, 6-, 9-, 12- month ahead forecasting horizons. Volatility Measure: Monthly Realized Range; $RR_t^{(M)}$. Forecasting period: Jan 2000 – March 2017.

Months-ahead	RW	AR(p)	HAR	HAR-WTI	HAR-BRN	MIDAS-HAR-WTI	MIDAS-HAR-BRN
				SOY			
1	6.18	**0.5971***	**0.5922***	**0.6019***	**0.5987***	**0.6052***	**0.6019***
3	6.25	**0.8064***	**0.7904***	**0.8032***	**0.8080***	**0.7952***	**0.7984***
6	6.32	**0.9351**	**0.8544***	**0.8766***	**0.8797***	**0.9035**	**0.8813***
9	6.39	**0.9687**	**0.8545***	**0.8967***	**0.9014***	**0.8936***	**0.9061***
12	6.51	**0.9800**	**0.8771***	**0.9155***	**0.9217**	**0.9263**	**0.8894***
				CORN			
1	8.18	**0.5685***	**0.5342***	**0.5440***	**0.5428***	**0.5538***	**0.5440***
3	8.27	**0.8041**	**0.6892***	**0.7146***	**0.7074***	**0.7146***	**0.6868***
6	8.36	**0.9378**	**0.7201***	**0.7344***	**0.7368***	**0.7261***	**0.7249***
9	8.42	**0.9644**	**0.6888***	**0.6865***	**0.6936***	**0.6449***	**0.7078***
12	8.59	**0.9802**	**0.7183***	**0.7229***	**0.7311***	**0.6950***	**0.7229***
				SUGAR			
1	7.95	**0.6365***	**0.5950***	**0.6038***	**0.6025***	**0.6088***	**0.6038***
3	7.94	**0.8300**	**0.7481***	**0.7657***	**0.7620***	**0.7758***	**0.7670***
6	7.99	**0.9299**	**0.8198***	**0.8373***	**0.8260***	**0.8235***	**0.8373***
9	7.96	**0.9749**	**0.8907***	**0.8945***	**0.8794***	**0.8957***	**0.8593***
12	8.00	**0.9875**	**0.9338***	**0.9375***	**0.9175***	**0.9038***	**0.9088***
				RICE			
1	6.51	**0.7311**	**0.6897***	**0.6928***	**0.6959***	**0.6928***	**0.6774***
3	6.53	**0.8291**	**0.7734***	**0.8132**	**0.8086**	**0.7657***	**0.7871***
6	6.62	**0.9417**	**0.8006***	**0.8550**	**0.8535**	**0.8218***	**0.8414***
9	6.59	**0.9739**	**0.8801***	**0.9256**	**0.9135***	**0.9272**	**0.9181***
12	6.68	**0.9889**	**0.8862***	**0.9251***	**0.9087***	**0.9341**	**0.9222***
				WHEAT			
1	7.78	**0.6056***	**0.5566***	**0.5604***	**0.5591***	**0.5823***	**0.5527***
3	7.88	**0.7810**	**0.6459***	**0.6383***	**0.6434***	**0.6472***	**0.6244***
6	8.00	**0.8911**	**0.7163***	**0.7088***	**0.7150***	**0.7150***	**0.7138***
9	8.12	**0.9472**	**0.7648***	**0.7586***	**0.7722***	**0.7623***	**0.7931***
12	8.28	**0.9608**	**0.8200***	**0.8249***	**0.8297***	**0.8466***	**0.8285***

Note: WTI = WTI crude oil price volatility, BRN = Brent crude oil price volatility. The RW column shows the actual MAFE. All other columns show the MAFE ratios, for each forecasting model, that have been normalized relative to the monthly RW forecast. The order of the AR models for Soy, Corn and Sugar is 1, whereas for Rice and Wheat is 2, based on the Bayesian Information Criterion. Bold face numbers denote that the forecast outperforms the RW. * denotes that the model is included in the set of the best models according to the Model Confidence Set (MCS).

Table A9. Directional accuracy for 1-, 3-, 6-, 9-, 12- month ahead forecasting horizons. Volatility Measure: Monthly Price Range; $PR_t^{(M)}$. Forecasting period: Jan 2000 – March 2017.

Months-ahead	RW	AR(p)	HAR	HAR-WTI	HAR-BRN	MIDAS-HAR-WTI	MIDAS-HAR-BRN
				SOY			
1	0.6893	0.8981	0.8981	0.8981	0.8883	0.8932	0.8786
3	0.6912	0.6765	0.7108	**0.7157**	0.6961	0.7108	**0.7206**
6	0.7413	0.7264	0.7463	0.7463	0.7463	0.7463	**0.7512**
9	0.6919	0.6919	0.7020	**0.7121**	**0.7121**	**0.7273**	**0.7374**
12	0.6513	0.6410	0.6821	0.6513	0.6615	0.6667	0.6769
				CORN			
1	0.6699	0.8447	0.8738	0.8544	0.8544	0.8447	0.8592
3	0.6814	0.6765	0.7402	0.6912	0.7010	0.7255	0.7059
6	0.7164	0.7214	0.7761	0.7313	0.7512	0.7463	0.7264
9	0.6919	0.6970	0.7273	0.7121	0.7071	**0.7424**	**0.7475**
12	0.6923	0.6872	0.6923	**0.6974**	**0.6974**	**0.7026**	0.6923
				SUGAR			
1	0.6650	0.8058	0.7816	0.7913	0.7816	0.7864	0.7864
3	0.6961	0.7157	0.7402	0.7157	0.7255	0.7255	0.7402
6	0.6766	0.6766	0.6667	0.6468	**0.6816**	0.6517	0.6617
9	0.7677	0.7677	0.8030	**0.8081**	0.8030	**0.8081**	**0.8081**
12	0.6821	0.7128	0.7128	**0.7333**	**0.7282**	**0.7282**	**0.7333**
				RICE			
1	0.6990	0.8932	0.8981	**0.9078**	0.8835	0.8981	**0.9029**
3	0.6961	0.7353	0.7353	0.7255	0.7010	0.7059	0.7304
6	0.6766	0.7214	0.7413	0.7214	0.7114	0.7214	0.7164
9	0.7071	0.7071	0.7071	**0.7424**	0.7071	0.7020	0.6768
12	0.7333	0.7333	0.7231	**0.7436**	**0.7436**	**0.7385**	0.7282
				WHEAT			
1	0.7184	0.8058	0.7524	0.7670	0.7864	0.7670	0.7282
3	0.6912	0.6912	0.7157	0.7157	**0.7206**	**0.7255**	0.7059
6	0.6866	0.6716	0.6816	0.6766	0.6716	0.6766	0.6816
9	0.6667	0.6667	0.6768	0.6768	0.6616	**0.6970**	**0.6919**
12	0.6564	0.6564	0.6513	0.6256	0.6256	0.6154	0.6462

Note: WTI = WTI crude oil price volatility, BRN = Brent crude oil price volatility. Bold face indicates improvement in directional accuracy relative to the benchmark models (RW, AR(p) or HAR). The order of the AR models for Soy and Corn is 1, for Sugar and Wheat is 2, whereas for Rice is 4, based on the Bayesian Information Criterion.

Table A10. Directional accuracy for 1-, 3-, 6-, 9-, 12- month ahead forecasting horizons. Volatility Measure: Monthly Realized Range; $RR_t^{(M)}$. Forecasting period: Jan 2000 – March 2017.

Months-ahead	RW	AR(p)	HAR	HAR-WTI	HAR-BRN	MIDAS-HAR-WTI	MIDAS-HAR-BRN
				SOY			
1	0.5874	0.8592	0.8544	**0.8641**	**0.8738**	0.8447	0.8350
3	0.6373	0.6618	0.6422	0.6324	0.6422	0.6127	0.6225
6	0.6169	0.6269	0.6816	0.6617	**0.6915**	0.6617	0.6219
9	0.6667	0.6717	0.6919	0.6768	0.6616	0.6515	0.6364
12	0.6256	0.6308	0.6615	0.6256	0.6051	0.6154	0.6513
				CORN			
1	0.5922	0.8495	0.8447	0.8204	0.8495	0.8398	0.8252
3	0.5882	0.6176	0.6765	**0.6961**	**0.6863**	0.6618	0.6667
6	0.6468	0.6517	0.7463	0.7164	0.7463	0.7214	0.7264
9	0.6212	0.6162	0.7273	0.7172	0.7121	**0.7626**	0.7222
12	0.6410	0.6410	0.6359	0.6205	0.6359	**0.6564**	0.6051
				SUGAR			
1	0.5825	0.8350	0.8738	**0.8932**	**0.8786**	0.8447	0.8398
3	0.6422	0.6667	0.6912	0.6863	0.6716	**0.6961**	**0.7108**
6	0.6318	0.6368	0.6965	**0.7164**	**0.7065**	0.6716	0.6866
9	0.6970	0.7020	0.6818	**0.7071**	**0.7222**	0.6970	**0.7121**
12	0.6872	0.6923	0.6821	**0.7026**	**0.7077**	0.6821	**0.7231**
				RICE			
1	0.6214	0.8981	0.8835	0.8981	0.8981	0.8932	0.8689
3	0.6127	0.7353	0.7696	0.7549	0.7598	**0.8039**	0.7696
6	0.6020	0.6219	0.6368	0.6020	0.6119	0.6219	0.5920
9	0.6768	0.6869	0.7778	0.7071	0.7121	0.7778	0.7677
12	0.6769	0.6769	0.6667	0.6769	**0.6872**	**0.7026**	0.6718
				WHEAT			
1	0.5922	0.8495	0.8350	0.8252	0.8447	0.8350	0.8252
3	0.5784	0.6225	0.6471	**0.6667**	0.6373	**0.6667**	**0.6520**
6	0.6070	0.6269	0.7313	0.7065	0.7214	**0.7463**	0.7214
9	0.6313	0.6263	0.6616	0.6465	0.6465	0.6465	0.6414
12	0.6103	0.6103	0.6103	**0.6256**	0.6000	0.5795	**0.6154**

Note: WTI = WTI crude oil price volatility, BRN = Brent crude oil price volatility. Bold face indicates improvement in directional accuracy relative to the benchmark models (RW, AR(p) or HAR). The order of the AR models for Soy, Corn and Sugar is 1, whereas for Rice and Wheat is 2, based on the Bayesian Information Criterion.

Table A11. The Mean Squared Forecasting Error (MSFE) evaluation function for 1-, 3-, 6-, 9-, 12- month ahead forecasting horizons. Volatility Measure: Monthly Price Range; $PR_t^{(M)}$. Forecasting period: 1st Food Crisis (2007-2009).

Months-ahead	RW	AR(p)	HAR	HAR-WTI	HAR-BRN	MIDAS-HAR-WTI	MIDAS-HAR-BRN
				SOY			
1	307.8759	**0.2548***	**0.1341***	**0.1642***	**0.1738***	**0.1368***	**0.1568***
3	311.0233	**0.7969**	**0.4952***	**0.5681**	**0.5310***	**0.5422***	**0.5663**
6	315.1073	**0.9634**	**0.6044***	**0.6553***	**0.6162***	**0.7922**	**0.7344***
9	318.7726	**0.9959**	**0.6872***	**0.7352***	**0.7029***	**0.7039***	**0.7537***
12	321.8291	1.0021	**0.7811***	**0.8448**	**0.8051***	**0.7259***	**0.7295***
				CORN			
1	641.4172	**0.3625***	**0.2435***	**0.2124***	**0.2158***	**0.2318***	**0.2498***
3	646.7001	**0.8964**	**0.6378***	**0.6463***	**0.6337***	**0.6754***	**0.6302***
6	652.5210	**0.9879**	**0.7255***	**0.7561***	**0.7351***	**0.7602***	**0.7427***
9	657.5189	1.0010	**0.7684***	**0.7923***	**0.7751***	**0.7949***	**0.7973***
12	661.9364	1.0018	**0.7966***	**0.8067***	**0.7933***	**0.7535***	**0.7832***
				SUGAR			
1	215.7638	**0.3856***	**0.3912***	**0.3625***	**0.3862***	**0.4327**	**0.4052***
3	218.0761	**0.9347**	**0.8443***	**0.8920***	**0.9314**	**0.8738***	**0.8983***
6	219.5691	**0.9859**	**0.9771***	1.0541	1.0763	**0.9971**	1.0509
9	220.5991	**0.9870***	1.0027	1.0745	1.0938	**0.9836***	1.0424
12	221.1037	**0.9885***	1.0192	1.0924	1.1020	1.0661	1.1148
				RICE			
1	394.1671	**0.3564***	**0.3210***	**0.2567***	**0.2608***	**0.2597***	**0.3057***
3	398.0422	**0.8920**	**0.7667***	**0.7598***	**0.7125***	**0.7058***	**0.7327***
6	401.6413	**0.9883**	**0.9531***	**0.9864**	**0.9515***	**0.9418***	1.0484
9	403.8994	**0.9973***	1.0416	1.0800	1.0316	1.0706	1.0054
12	404.5361	1.0001	1.1247	1.1669	1.1108	1.1228	1.0645
				WHEAT			
1	569.5917	**0.7248**	**0.4076***	**0.4027***	**0.3962***	**0.4106***	**0.3592***
3	574.6782	**0.9827**	**0.5253***	**0.5529***	**0.5380***	**0.5693***	**0.5410***
6	581.1326	**0.9908**	**0.6305***	**0.6535***	**0.6372***	**0.6128***	**0.6466***
9	587.1412	**0.9906**	**0.6739***	**0.6825***	**0.6710***	**0.5973***	**0.7396**
12	593.7450	**0.9910**	**0.8162***	**0.8351***	**0.8163***	**0.8486**	**0.8198***

Note: WTI = WTI crude oil price volatility, BRN = Brent crude oil price volatility. The RW column shows the actual MSFE. All other columns show the MSFE ratios, for each forecasting model, that have been normalized relative to the monthly RW forecast. The order of the AR models for Soy and Corn is 1, for Sugar and Wheat is 2, whereas for Rice is 4, based on the Bayesian Information Criterion. Bold face numbers denote that the forecast outperforms the RW. * denotes that the model is included in the set of the best models according to the Model Confidence Set (MCS).

Table A12. The Mean Absolute Forecasting Error (MAFE) evaluation function for 1-, 3-, 6-, 9-, 12-month ahead forecasting horizons. Volatility Measure: Monthly Price Range; $PR_t^{(M)}$. Forecasting period: 1st Food Crisis (2007-2009).

Months-ahead	RW	AR(p)	HAR	HAR-WTI	HAR-BRN	MIDAS-HAR-WTI	MIDAS-HAR-BRN
				SOY			
1	14.3849	**0.4920***	**0.3385***	**0.3897***	**0.3937***	**0.3368***	**0.3570***
3	14.4688	**0.8656**	**0.6549***	**0.7147***	**0.6856***	**0.7131***	**0.7453**
6	14.5951	**0.9761**	**0.7499***	**0.8028***	**0.7712***	**0.8969**	**0.8641**
9	14.7148	**0.9970**	**0.8086***	**0.8434***	**0.8254***	**0.8291***	**0.8635***
12	14.8153	1.0019	**0.8591***	**0.9030**	**0.8798**	**0.8559***	**0.8299***
				CORN			
1	18.8599	**0.5843***	**0.4551***	**0.4441***	**0.4323***	**0.4211***	**0.4356***
3	18.9544	**0.9366**	**0.7840***	**0.8244***	**0.7940***	**0.8313**	**0.7958***
6	19.0814	**0.9947**	**0.8215***	**0.8394***	**0.8269***	**0.8581***	**0.8382***
9	19.1879	**0.9998**	**0.8340***	**0.8549***	**0.8369***	**0.8487***	**0.8519***
12	19.2947	1.0013	**0.8592***	**0.8717**	**0.8580***	**0.8443***	**0.8607***
				SUGAR			
1	10.8396	**0.5943***	**0.6110***	**0.6358***	**0.6557***	**0.6572***	**0.6293***
3	10.9028	**0.9535***	**0.9184***	**0.9571***	1.0090	**0.9779**	1.0144
6	10.9359	**0.9861**	**0.9656***	1.0316	1.0475	**0.9779**	1.0271
9	10.9658	**0.9880***	**0.9954***	1.0566	1.0761	1.0391	1.0447
12	10.9778	**0.9879***	**0.9952***	1.0547	1.0607	1.0115	1.0161
				RICE			
1	15.1502	**0.5685***	**0.5110***	**0.4453***	**0.4384***	**0.4468***	**0.4984***
3	15.2369	**0.9286**	**0.8192***	**0.8305***	**0.7931***	**0.8353***	**0.8517**
6	15.3417	**0.9911**	**0.9430***	**0.9639**	**0.9414***	**0.9530***	**0.9864**
9	15.4185	**0.9971**	**0.9878***	1.0036	**0.9819***	1.0068	**0.9646***
12	15.4726	**0.9993***	1.0601	1.0777	1.0542	1.0317	1.0045
				WHEAT			
1	19.3052	**0.8395**	**0.5853***	**0.5975***	**0.5826***	**0.5931***	**0.5666***
3	19.4149	**0.9868**	**0.6989***	**0.7197***	**0.7088***	**0.7442**	**0.7304***
6	19.5589	**0.9907**	**0.7598***	**0.7851***	**0.7685***	**0.7550***	**0.7718***
9	19.7040	**0.9909**	**0.7768***	**0.7929***	**0.7778***	**0.7335***	**0.8445**
12	19.8400	**0.9910**	**0.8581***	**0.8841**	**0.8631***	**0.8782***	**0.8544***

Note: WTI = WTI crude oil price volatility, BRN = Brent crude oil price volatility. The RW column shows the actual MAFE. All other columns show the MAFE ratios, for each forecasting model, that have been normalized relative to the monthly RW forecast. The order of the AR models for Soy and Corn is 1, for Sugar and Wheat is 2, whereas for Rice is 4, based on the Bayesian Information Criterion. Bold face numbers denote that the forecast outperforms the RW. * denotes that the model is included in the set of the best models according to the Model Confidence Set (MCS).

Table A13. The Mean Squared Forecasting Error (MSFE) evaluation function for 1-, 3-, 6-, 9-, 12- month ahead forecasting horizons. Volatility Measure: Monthly Realized Range; $RR_t^{(M)}$. Forecasting period: 1st Food Crisis (2007-2009).

Months-ahead	RW	AR(p)	HAR	HAR-WTI	HAR-BRN	MIDAS-HAR-WTI	MIDAS-HAR-BRN
			SOY				
1	302.9379	**0.0832***	**0.0582***	**0.0654***	**0.0751***	**0.0610***	**0.0593***
3	306.1570	**0.5072**	**0.3735***	**0.4152***	**0.4074***	**0.4262***	**0.3896***
6	310.4160	**0.7931**	**0.5339***	**0.6094***	**0.5927***	**0.6951**	**0.6510**
9	314.2463	**0.9295**	**0.6318***	**0.7016***	**0.6781***	**0.7112***	**0.7438***
12	317.2987	**0.9835**	**0.7065***	**0.7661***	**0.7444***	**0.7860**	**0.6717***
			CORN				
1	395.1188	**0.1009***	**0.0452***	**0.0498***	**0.0545***	**0.0522***	**0.0480***
3	399.4645	**0.4927***	**0.2305***	**0.2261***	**0.2185***	**0.2736***	**0.2211***
6	405.6371	**0.8197**	**0.3645***	**0.3881***	**0.3741***	**0.4017***	**0.3875***
9	411.2174	**0.9444**	**0.3870***	**0.3954***	**0.3838***	**0.3537***	**0.4593***
12	416.3806	**0.9877**	**0.5522**	**0.4264***	**0.4119***	**0.3295***	**0.3895***
			SUGAR				
1	216.0686	**0.1439***	**0.1208***	**0.1095***	**0.1147***	**0.1227***	**0.1141***
3	218.6752	**0.6678**	**0.5291***	**0.5660***	**0.5814***	**0.5569***	**0.5435***
6	221.5799	**0.9137**	**0.7221***	**0.8120***	**0.8276**	**0.6950***	**0.7872***
9	224.0076	**0.9745**	**0.7943***	**0.8627**	**0.8599**	**0.7755***	**0.7422***
12	225.9439	**0.9925**	**0.8671***	**0.8891**	**0.8677***	**0.8635***	**0.7954***
			RICE				
1	281.1942	**0.1582***	**0.1323***	**0.1071***	**0.1048***	**0.1176***	**0.1004***
3	284.0688	**0.6528**	**0.3902***	**0.4017***	**0.3841***	**0.3641***	**0.3897***
6	287.5526	**0.9136**	**0.6278***	**0.7112**	**0.6572***	**0.5882***	**0.6351***
9	290.2009	**0.9803**	**0.7880***	**0.8501**	**0.7876***	**0.7710***	**0.7917***
12	291.8690	**1.0000**	**0.9506***	1.0357	**0.9785***	**0.9410***	**0.9121***
			WHEAT				
1	560.3674	**0.1685***	**0.1108***	**0.1080***	**0.1082***	**0.1238***	**0.1159***
3	566.3112	**0.6745**	**0.3438***	**0.3493***	**0.3419***	**0.3552***	**0.3132***
6	573.9298	**0.9027**	**0.4227***	**0.4259***	**0.4182***	**0.4055***	**0.4111***
9	581.4297	**0.9679**	**0.4497***	**0.4738***	**0.4516***	**0.4426***	**0.5380***
12	588.6527	**0.9879**	**0.6082***	**0.6596***	**0.6164***	**0.6299***	**0.6260***

Note: WTI = WTI crude oil price volatility, BRN = Brent crude oil price volatility. The RW column shows the actual MSFE. All other columns show the MSFE ratios, for each forecasting model, that have been normalized relative to the monthly RW forecast. The order of the AR models for Soy, Corn and Sugar is 1, whereas for Rice and Wheat is 2, based on the Bayesian Information Criterion. Bold face numbers denote that the forecast outperforms the RW. * denotes that the model is included in the set of the best models according to the Model Confidence Set (MCS).

Table A14. The Mean Absolute Forecasting Error (MAFE) evaluation function for 1-, 3-, 6-, 9-, 12-month ahead forecasting horizons. Volatility Measure: Monthly Realized Range; $RR_t^{(M)}$. Forecasting period: 1st Food Crisis (2007-2009).

Months-ahead	RW	AR(p)	HAR	HAR-WTI	HAR-BRN	MIDAS-HAR-WTI	MIDAS-HAR-BRN
			SOY				
1	14.6792	**0.2811***	**0.2088***	**0.2317***	**0.2473***	**0.2223***	**0.2178***
3	14.7666	**0.6221**	**0.5447***	**0.5880***	**0.5852***	**0.6093**	**0.5649***
6	14.8933	**0.8503**	**0.6889***	**0.7488***	**0.7321***	**0.8069**	**0.7907**
9	15.0089	**0.9459**	**0.7251***	**0.7848***	**0.7653***	**0.7937***	**0.8094**
12	15.1069	**0.9870**	**0.7506***	**0.8090***	**0.7908***	**0.8022***	**0.7116***
			CORN				
1	17.9252	**0.3146***	**0.1830***	**0.1888***	**0.1905***	**0.1913***	**0.1860***
3	18.0314	**0.6642**	**0.4367***	**0.4285***	**0.4276***	**0.4840***	**0.4389***
6	18.1946	**0.8788**	**0.5412***	**0.5626***	**0.5606***	**0.5671***	**0.5638***
9	18.3514	**0.9634**	**0.5058***	**0.5337***	**0.5171***	**0.5097***	**0.5948***
12	18.4982	**0.9920**	**0.6906**	**0.5654***	**0.5504***	**0.4746***	**0.5231***
			SUGAR				
1	12.3213	**0.3677***	**0.3124***	**0.3071***	**0.3214***	**0.3292***	**0.2961***
3	12.4028	**0.7970**	**0.6846***	**0.7335**	**0.7552**	**0.7327**	**0.7376**
6	12.4974	**0.9439**	**0.8564***	**0.9354**	**0.9449**	**0.8363***	**0.9138**
9	12.5835	**0.9795**	**0.8770***	**0.9592**	**0.9560**	**0.8778***	**0.8533***
12	12.6704	**0.9917**	**0.8791***	**0.9527**	**0.9422**	**0.8789***	**0.8476***
			RICE				
1	13.1535	**0.3814***	**0.3068***	**0.3033***	**0.2990***	**0.3024***	**0.2863***
3	13.2239	**0.7564**	**0.5510***	**0.5873***	**0.5598***	**0.5322***	**0.5695***
6	13.3186	**0.9381**	**0.7744***	**0.8370**	**0.8031***	**0.7345***	**0.7757***
9	13.3911	**0.9775**	**0.8540***	**0.8961**	**0.8553***	**0.8598***	**0.8625***
12	13.4387	**0.9899**	**0.9615***	**0.9936**	**0.9645***	**0.9508***	**0.9329***
			WHEAT				
1	20.6266	**0.3944***	**0.2541***	**0.2501***	**0.2474***	**0.2693***	**0.2648***
3	20.7493	**0.7531**	**0.4785***	**0.4793***	**0.4732***	**0.4851***	**0.4424***
6	20.9338	**0.9258**	**0.5711***	**0.5774***	**0.5667***	**0.5672***	**0.5593***
9	21.1103	**0.9763**	**0.6058***	**0.6337***	**0.6065***	**0.6053***	**0.6759***
12	21.2725	**0.9884**	**0.7156***	**0.7644***	**0.7209***	**0.7320***	**0.7181***

Note: WTI = WTI crude oil price volatility, BRN = Brent crude oil price volatility. The RW column shows the actual MAFE. All other columns show the MAFE ratios, for each forecasting model, that have been normalized relative to the monthly RW forecast. The order of the AR models for Soy, Corn and Sugar is 1, whereas for Rice and Wheat is 2, based on the Bayesian Information Criterion. Bold face numbers denote that the forecast outperforms the RW. * denotes that the model is included in the set of the best models according to the Model Confidence Set (MCS).

Table A15. Directional accuracy for 1-, 3-, 6-, 9-, 12- month ahead forecasting horizons. Volatility Measure: Monthly Price Range; $PR_t^{(M)}$. Forecasting period: 1st Food Crisis (2007-2009).

Months-ahead	RW	AR(p)	HAR	HAR-WTI	HAR-BRN	MIDAS-HAR-WTI	MIDAS-HAR-BRN
				SOY			
1	0.5600	0.8000	0.9200	0.9200	0.9200	0.9200	0.8800
3	0.4400	0.4800	0.5200	0.5200	0.5200	**0.5600**	**0.6400**
6	0.5200	0.5200	0.6800	0.6400	0.6800	0.6000	0.5600
9	0.4000	0.3600	0.5600	0.4800	0.5200	0.5200	0.5200
12	0.4000	0.3600	0.5200	0.4000	0.4800	0.4800	**0.5600**
				CORN			
1	0.5600	0.8000	0.9200	0.8800	0.8800	0.9200	0.9200
3	0.6000	0.6400	0.8000	0.7200	0.7600	0.7200	0.7600
6	0.6000	0.6000	0.8000	0.7600	0.8000	0.8000	0.8000
9	0.5200	0.5200	0.7200	0.6800	**0.7600**	0.7200	0.6800
12	0.6000	0.6000	0.6000	0.6000	0.6000	0.6000	**0.6400**
				SUGAR			
1	0.6000	0.7600	0.7600	**0.8000**	0.7600	0.7600	**0.8000**
3	0.8000	0.8000	0.8400	0.8000	0.7600	0.7200	0.7200
6	0.6400	0.6400	0.5600	0.5200	0.5600	0.5600	0.6000
9	0.6800	0.6800	0.6400	0.6800	0.6800	**0.7600**	0.6800
12	0.7200	0.7200	0.7200	0.7200	0.7200	0.7200	0.7200
				RICE			
1	0.6400	0.7600	0.8800	**0.9200**	0.8800	0.8400	0.8000
3	0.7600	0.7600	0.7200	0.6800	0.7200	0.7200	0.6800
6	0.7200	0.7200	0.8000	0.8000	0.8000	0.8000	0.7600
9	0.6400	0.6400	0.6400	0.6400	0.6400	0.6400	0.6400
12	0.7600	0.7600	0.7200	0.7600	0.7200	0.7200	0.7600
				WHEAT			
1	0.6400	0.7600	0.7600	**0.8400**	**0.8400**	**0.8400**	**0.8000**
3	0.6400	0.6400	0.8000	0.7600	0.7600	0.7600	0.8000
6	0.5600	0.6000	0.6000	0.5600	0.6000	0.5600	0.5200
9	0.4800	0.4800	0.6000	0.6000	0.5200	0.6400	0.6000
12	0.4400	0.4400	0.5200	0.5200	0.5200	0.5200	0.5200

Note: WTI = WTI crude oil price volatility, BRN = Brent crude oil price volatility. Bold face indicates improvement in directional accuracy relative to the benchmark models (RW, AR(p) or HAR). The order of the AR models for Soy and Corn is 1, for Sugar and Wheat is 2, whereas for Rice is 4, based on the Bayesian Information Criterion.

Table A16. Directional accuracy for 1-, 3-, 6-, 9-, 12- month ahead forecasting horizons. Volatility Measure: Monthly Realized Range; $RR_t^{(M)}$. Forecasting period: 1st Food Crisis (2007-2009).

Months-ahead	RW	AR(p)	HAR	HAR-WTI	HAR-BRN	MIDAS-HAR-WTI	MIDAS-HAR-BRN
				SOY			
1	0.5200	0.7600	0.8400	0.7600	0.8000	0.7600	0.8000
3	0.4800	0.5600	0.4800	0.4400	0.4800	0.4000	0.4400
6	0.3200	0.3600	0.4000	0.3600	0.4000	0.3200	0.2800
9	0.4400	0.4400	0.5600	0.5200	0.5200	0.4400	0.4800
12	0.3200	0.3200	0.4400	0.4400	0.4000	0.3600	0.5200
				CORN			
1	0.5200	0.6800	0.7600	0.7200	0.7600	**0.8000**	**0.8000**
3	0.4800	0.5200	0.6400	0.6400	0.5600	0.4800	0.6000
6	0.4000	0.4000	0.6000	0.5600	0.5600	0.4800	0.4800
9	0.4800	0.4800	0.6400	0.6000	**0.6800**	0.6400	0.6000
12	0.3600	0.3600	0.4000	0.4000	0.4800	**0.6000**	0.4400
				SUGAR			
1	0.5600	0.7600	0.8800	**0.9600**	**0.9600**	0.8400	**0.9200**
3	0.7600	0.8000	0.6800	0.6800	0.6400	0.7600	0.6400
6	0.7600	0.8000	0.8400	0.7200	0.6400	0.8400	0.8000
9	0.7200	0.7200	0.7200	0.6800	0.6800	0.7200	0.7200
12	0.6000	0.6000	0.6800	0.6800	**0.7200**	0.6400	**0.7200**
				RICE			
1	0.4800	0.7600	0.7200	0.6800	0.6800	0.7600	0.7600
3	0.6800	0.7200	0.8000	0.8000	0.8000	0.8000	0.7200
6	0.5600	0.5600	0.5600	0.5600	**0.6000**	0.5600	0.4800
9	0.6400	0.6400	0.6000	0.4800	0.4800	0.6400	0.5600
12	0.7200	0.7200	0.7200	0.6400	0.6800	0.6800	0.6800
				WHEAT			
1	0.5200	0.8000	0.8000	0.8000	0.8000	0.8000	0.8000
3	0.4800	0.4800	0.7600	0.7200	0.7200	0.7200	0.7200
6	0.4800	0.4800	0.6800	0.6000	0.6800	0.6000	0.6400
9	0.4000	0.4000	0.4000	0.4000	0.4000	0.4800	0.4000
12	0.3200	0.3200	0.4000	0.4000	0.4000	0.4000	0.4000

Note: WTI = WTI crude oil price volatility, BRN = Brent crude oil price volatility. Bold face indicates improvement in directional accuracy relative to the benchmark models (RW, AR(p) or HAR). The order of the AR models for Soy, Corn and Sugar is 1, whereas for Rice and Wheat is 2, based on the Bayesian Information Criterion.

Table A17. The Mean Squared Forecasting Error (MSFE) evaluation function for 1-, 3-, 6-, 9-, 12- month ahead forecasting horizons. Volatility Measure: Monthly Price Range; $PR_t^{(M)}$. Forecasting period: 2nd Food Crisis (2010-2012).

Months-ahead	RW	AR(p)	HAR	HAR-WTI	HAR-BRN	MIDAS-HAR-WTI	MIDAS-HAR-BRN
				SOY			
1	44.6642	**0.1648***	**0.2778***	**0.3132***	**0.3031***	**0.2970***	**0.3146***
3	45.1307	**0.9525***	1.2995	1.4249	1.4623	1.1198	1.1279
6	45.1790	1.0364	1.6468	1.8790	1.9601	1.5741	1.7753
9	44.9614	1.0230	1.6345	1.9926	2.0933	1.7966	1.9055
12	44.8095	1.0058	1.3159	1.8602	1.8485	1.1096	1.2986
				CORN			
1	163.3885	**0.2698***	**0.2706***	**0.2764***	**0.2624***	**0.3095***	**0.2873***
3	164.7547	**0.9110**	**0.7994***	**0.8422**	**0.8139***	**0.8216**	**0.7238***
6	165.6785	**0.9980**	**0.9135***	**0.9119***	**0.9007***	**0.8692***	**0.9917**
9	166.2834	1.0023	**0.8415**	**0.8271***	**0.8050***	**0.7561***	**0.8796**
12	167.4844	1.0050	**0.8076***	**0.7908***	**0.7614***	**0.8304**	**0.7516***
				SUGAR			
1	262.4001	**0.3487***	**0.2567***	**0.2792***	**0.2874***	**0.2757***	**0.2551***
3	265.0368	**0.8930**	**0.5891***	**0.6078***	**0.6421**	**0.6097***	**0.5964***
6	267.9442	**0.9758**	**0.7082***	**0.7372***	**0.7817**	**0.6618***	**0.7526**
9	270.9380	**0.9844**	**0.8152**	**0.8432**	**0.8824**	**0.6857***	**0.8884**
12	273.3100	**0.9861**	**0.9151***	**0.9354**	**0.9609**	**0.8849***	**0.8886***
				RICE			
1	110.6482	**0.3003***	**0.3033***	**0.3582***	**0.3448***	**0.3463***	**0.3330***
3	111.5965	**0.9087**	**0.7767***	**0.8561**	**0.8976**	**0.8108***	**0.8379***
6	112.4538	**0.9926**	**0.9246***	**0.9853**	**0.9826**	1.0109	1.0295
9	112.8238	**0.9969**	**0.9531***	1.0239	1.0173	**0.9348***	**0.9648***
12	113.2969	1.0000	1.0543	1.1131	1.1075	1.1919	1.0947
				WHEAT			
1	201.9052	**0.5710***	**0.5081***	**0.5201***	**0.4998***	**0.5150***	**0.5341***
3	203.7855	**0.9736**	**0.7520***	**0.7676***	**0.7554***	**0.7454***	**0.7550***
6	205.0665	**0.9913**	**0.8148***	**0.8349***	**0.8156***	**0.8347***	**0.8576**
9	206.2018	**0.9914**	**0.7794***	**0.8014**	**0.7781***	**0.7256***	**0.7921**
12	207.6606	**0.9911**	**0.7493***	**0.7623***	**0.7536***	**0.8032**	**0.7028***

Note: WTI = WTI crude oil price volatility, BRN = Brent crude oil price volatility. The RW column shows the actual MSFE. All other columns show the MSFE ratios, for each forecasting model, that have been normalized relative to the monthly RW forecast. The order of the AR models for Soy and Corn is 1, for Sugar and Wheat is 2, whereas for Rice is 4, based on the Bayesian Information Criterion. Bold face numbers denote that the forecast outperforms the RW. * denotes that the model is included in the set of the best models according to the Model Confidence Set (MCS).

Table A18. The Mean Absolute Forecasting Error (MAFE) evaluation function for 1-, 3-, 6-, 9-, 12-month ahead forecasting horizons. Volatility Measure: Monthly Price Range; $PR_t^{(M)}$. Forecasting period: 2nd Food Crisis (2010-2012).

Months-ahead	RW	AR(p)	HAR	HAR-WTI	HAR-BRN	MIDAS-HAR-WTI	MIDAS-HAR-BRN
				SOY			
1	5.5170	**0.3899***	**0.5267**	**0.5591**	**0.5558**	**0.5420**	**0.5648**
3	5.5460	**0.9741***	1.1514	1.2050	1.2164	1.0796	1.0872
6	5.5501	1.0211	1.2789	1.3663	1.3870	1.2735	1.3292
9	5.5349	1.0078	1.2234	1.3210	1.3332	1.2590	1.3388
12	5.5199	1.0006	1.1649	1.3441	1.3382	1.0498	1.1610
				CORN			
1	9.7750	**0.4953***	**0.4952***	**0.4995***	**0.4953***	**0.5192***	**0.5193***
3	9.8229	**0.9489**	**0.8774***	**0.9206**	**0.9058**	**0.8914**	**0.8462***
6	9.8499	1.0010	**0.9608**	**0.9675**	**0.9535**	**0.9158***	1.0253
9	9.8682	1.0029	**0.9541**	**0.9301**	**0.9258**	**0.8821***	**0.9994**
12	9.9003	1.0021	**0.9271***	**0.9003***	**0.8836***	**0.9321**	**0.9104***
				SUGAR			
1	12.3806	**0.5652***	**0.4722***	**0.4847***	**0.4970***	**0.4802***	**0.4803***
3	12.4485	**0.9309**	**0.7380***	**0.7527***	**0.7753**	**0.7663***	**0.7679***
6	12.5342	**0.9808**	**0.8687***	**0.8841**	**0.9049**	**0.8640***	**0.8821***
9	12.6122	**0.9857**	**0.9403***	**0.9446***	**0.9715**	**0.8233***	**0.9634**
12	12.6885	**0.9868**	1.0044	1.0063	1.0216	**0.9559***	**0.9365***
				RICE			
1	7.8768	**0.5171***	**0.5198***	**0.5687***	**0.5734***	**0.5613***	**0.5286***
3	7.9133	**0.9448**	**0.8678***	**0.9443**	1.0014	**0.9178**	**0.9160**
6	7.9494	**0.9968**	**0.9835***	1.0055	1.0188	1.0630	1.0681
9	7.9670	**0.9975**	**0.9952**	1.0213	1.0256	**0.9675***	1.0179
12	7.9868	**0.9988***	1.0486	1.0628	1.0623	1.0567	1.0506
				WHEAT			
1	10.6118	**0.7345***	**0.7196***	**0.7247***	**0.7059***	**0.7121***	**0.7431***
3	10.6690	**0.9781**	**0.9138***	**0.9283**	**0.9162***	**0.8804***	**0.8879***
6	10.7096	**0.9909***	1.0047	1.0274	1.0069	1.0188	1.0348
9	10.7394	**0.9912**	**0.9834**	1.0104	**0.9925**	**0.9238***	**0.9444***
12	10.7654	**0.9911**	**0.9240***	0.9180	**0.9137***	**0.9416***	**0.9004***

Note: WTI = WTI crude oil price volatility, BRN = Brent crude oil price volatility. The RW column shows the actual MAFE. All other columns show the MAFE ratios, for each forecasting model, that have been normalized relative to the monthly RW forecast. The order of the AR models for Soy and Corn is 1, for Sugar and Wheat is 2, whereas for Rice is 4, based on the Bayesian Information Criterion. Bold face numbers denote that the forecast outperforms the RW. * denotes that the model is included in the set of the best models according to the Model Confidence Set (MCS).

Table A19. The Mean Squared Forecasting Error (MSFE) evaluation function for 1-, 3-, 6-, 9-, 12- month ahead forecasting horizons. Volatility Measure: Monthly Realized Range; $RR_t^{(M)}$. Forecasting period: 2nd Food Crisis (2010-2012).

Months-ahead	RW	AR(p)	HAR	HAR-WTI	HAR-BRN	MIDAS-HAR-WTI	MIDAS-HAR-BRN
				SOY			
1	20.7780	**0.0501***	**0.1205***	**0.1219***	**0.1233***	**0.1574***	**0.1527***
3	20.9913	**0.7627***	1.0155	1.0267	1.0656	1.0616	1.1122
6	21.1388	1.0483	1.5486	1.5431	1.6825	1.6332	1.4853
9	21.2359	**0.9752***	1.6403	1.6119	1.8860	1.4609	1.7546
12	21.3914	**0.9711***	1.8433	1.9092	2.4176	2.2477	2.8585
				CORN			
1	115.7960	**0.0545***	**0.0594***	**0.0587***	**0.0558***	**0.0502***	**0.0589***
3	117.0610	**0.4775***	**0.3748***	**0.3948***	**0.3994***	**0.3714***	**0.3608***
6	118.6893	**0.7671**	**0.5269***	**0.5542***	**0.5819**	**0.5082***	**0.4972***
9	120.2932	**0.8410**	**0.4629***	**0.4319***	**0.4783***	**0.3959***	**0.5551**
12	122.2206	**0.9098**	**0.4570***	**0.4226***	**0.4974***	**0.3883***	**0.4379***
				SUGAR			
1	251.5367	**0.1068***	**0.0596***	**0.0677***	**0.0717***	**0.0754***	**0.0632***
3	254.2560	**0.5611**	**0.3372***	**0.3640***	**0.3605***	**0.3620***	**0.3764***
6	257.8190	**0.8255**	**0.4518***	**0.4851***	**0.4747***	**0.4259***	**0.4780***
9	261.6524	**0.9271**	**0.5621***	**0.5995***	**0.5773***	**0.6092***	**0.5305***
12	265.1334	**0.9752**	**0.7199**	**0.7424**	**0.6928**	**0.5476***	**0.5764***
				RICE			
1	83.3472	**0.5837**	**0.1150***	**0.1468***	**0.1798***	**0.1711***	**0.2096***
3	83.8201	**0.6868**	**0.5995**	**0.3307***	**0.4402***	**0.4202***	**0.3458***
6	85.8951	**0.7903**	**0.8775**	**0.5279***	**0.6711***	**0.6563***	**0.5307***
9	85.8082	**0.8685**	**0.9481**	**0.5851***	**0.7612***	**0.7527***	**0.6428***
12	87.5434	**0.9833**	**0.9896**	**0.7092***	**0.8606***	**0.8640**	**0.8956**
				WHEAT			
1	147.0142	**0.0925***	**0.1314***	**0.1402***	**0.1318***	**0.1305***	**0.1289***
3	148.5144	**0.5941**	**0.3808***	**0.3629***	**0.3757***	**0.3669***	**0.3960***
6	150.4761	**0.8481**	**0.4743***	**0.4400***	**0.4679***	**0.4857***	**0.5154***
9	152.3439	**0.9217**	**0.4484***	**0.4204***	**0.4500***	**0.3930***	**0.3986***
12	154.5133	**0.9594**	**0.4884***	**0.4422***	**0.5004**	**0.4972***	**0.4674***

Note: WTI = WTI crude oil price volatility, BRN = Brent crude oil price volatility. The RW column shows the actual MSFE. All other columns show the MSFE ratios, for each forecasting model, that have been normalized relative to the monthly RW forecast. The order of the AR models for Soy, Corn and Sugar is 1, whereas for Rice and Wheat is 2, based on the Bayesian Information Criterion. Bold face numbers denote that the forecast outperforms the RW. * denotes that the model is included in the set of the best models according to the Model Confidence Set (MCS).

Table A20. The Mean Absolute Forecasting Error (MAFE) evaluation function for 1-, 3-, 6-, 9-, 12-month ahead forecasting horizons. Volatility Measure: Monthly Realized Range; $RR_t^{(M)}$. Forecasting period: 2nd Food Crisis (2010-2012).

Months-ahead	RW	AR(p)	HAR	HAR-WTI	HAR-BRN	MIDAS-HAR-WTI	MIDAS-HAR-BRN
				SOY			
1	3.3533	**0.2144***	**0.3601***	**0.3530***	**0.3660***	**0.4046**	**0.4211**
3	3.3744	**0.8914***	1.0932	1.0933	1.1125	1.1209	1.1577
6	3.3885	1.0231	1.3623	1.3527	1.4008	1.3932	1.3408
9	3.3984	**0.9520***	1.3762	1.3664	1.4500	1.3117	1.3858
12	3.4219	**0.9644***	1.4811	1.5060	1.6405	1.5898	1.7155
				CORN			
1	9.0002	**0.2294***	**0.2415***	**0.2490***	**0.2384***	**0.2268***	**0.2435***
3	9.0549	**0.6461***	**0.6196***	**0.6236***	**0.6305***	**0.6118***	**0.6144***
6	9.1445	**0.8216**	**0.7311***	**0.7503***	**0.7684**	**0.7267***	**0.7170***
9	9.2371	**0.8907**	**0.6788**	**0.6655***	**0.6906**	**0.6102***	**0.6978**
12	9.3387	**0.9415**	**0.6444***	**0.6289***	**0.6873**	**0.6033***	**0.6283***
				SUGAR			
1	12.3376	**0.3120***	**0.2250***	**0.2292***	**0.2407***	**0.2640***	**0.2371***
3	12.4081	**0.7230**	**0.5656***	**0.5891***	**0.5813***	**0.5872***	**0.6170***
6	12.5079	**0.9058**	**0.6584***	**0.6884***	**0.6847***	**0.6455***	**0.6800***
9	12.6084	**0.9662**	**0.7717***	**0.7931***	**0.7674***	**0.8149**	**0.7578***
12	12.7016	**0.9841**	**0.9187**	**0.9204**	**0.8760***	**0.7686***	**0.8014***
				RICE			
1	6.1474	**0.3260***	**0.3410***	**0.3826***	**0.3717***	**0.4273***	**0.3844***
3	6.1860	**0.7440**	**0.5451***	**0.6360**	**0.6255**	**0.5737***	**0.5940***
6	6.2365	**0.9114**	**0.6187***	**0.7430**	**0.7319**	**0.6369***	**0.6939**
9	6.2856	**0.9671**	**0.6893***	**0.8176**	**0.8151**	**0.7467**	**0.6740***
12	6.3373	**0.9870**	**0.7631***	**0.8449**	**0.8455**	**0.8604**	**0.8602**
				WHEAT			
1	9.6425	**0.2910***	**0.3328***	**0.3372***	**0.3355***	**0.3305***	**0.3280***
3	9.7015	**0.7113**	**0.5920***	**0.5693***	**0.5919***	**0.5716***	**0.6162***
6	9.7911	**0.8768**	**0.6699***	**0.6346***	**0.6666***	**0.6696***	**0.6977***
9	9.8850	**0.9326**	**0.6572***	**0.6273***	**0.6653***	**0.6151***	**0.6027***
12	9.9882	**0.9674**	**0.7028***	**0.6572***	**0.7255**	**0.7050***	**0.6866***

Note: WTI = WTI crude oil price volatility, BRN = Brent crude oil price volatility. The RW column shows the actual MAFE. All other columns show the MAFE ratios, for each forecasting model, that have been normalized relative to the monthly RW forecast. The order of the AR models for Soy, Corn and Sugar is 1, whereas for Rice and Wheat is 2, based on the Bayesian Information Criterion. Bold face numbers denote that the forecast outperforms the RW. * denotes that the model is included in the set of the best models according to the Model Confidence Set (MCS).

Table A21. Directional accuracy for 1-, 3-, 6-, 9-, 12- month ahead forecasting horizons. Volatility Measure: Monthly Price Range; $PR_t^{(M)}$. Forecasting period: 2nd Food Crisis (2010-2012).

Months-ahead	RW	AR(*p*)	HAR	HAR-WTI	HAR-BRN	MIDAS-HAR-WTI	MIDAS-HAR-BRN
				SOY			
1	0.6944	0.9167	0.8611	0.8611	0.8056	0.8333	0.8611
3	0.8056	0.8333	0.7500	0.7222	0.6667	0.7222	0.7222
6	0.9167	0.9167	0.8056	0.7778	0.7500	0.8056	0.8056
9	0.6667	0.6667	0.6389	0.6667	0.6389	**0.6944**	0.6667
12	0.7222	0.7222	0.7222	0.6944	0.7222	0.7222	0.6944
				CORN			
1	0.6944	0.8056	0.8333	0.8056	0.8056	0.8333	0.8333
3	0.6667	0.6944	0.8056	0.7500	0.7778	0.8056	0.7500
6	0.6944	0.6944	0.7222	0.6667	0.6667	0.7222	0.6389
9	0.5833	0.5833	0.6667	0.6389	0.6389	**0.7222**	0.6111
12	0.6944	0.6944	0.7500	0.7222	0.7500	0.7500	0.7500
				SUGAR			
1	0.6389	0.8056	0.8056	**0.8611**	**0.8333**	0.7778	0.8056
3	0.6667	0.7222	0.7222	0.7222	0.7222	**0.7500**	**0.7500**
6	0.7222	0.7222	0.6667	0.6389	0.6667	0.6667	0.6389
9	0.6944	0.6944	0.6944	**0.7222**	**0.7222**	**0.7500**	0.6667
12	0.6389	0.6389	0.6111	0.6111	0.5833	0.6389	0.6111
				RICE			
1	0.7778	0.9444	0.9444	0.9722	0.9444	0.9167	0.9722
3	0.7222	0.7500	0.7222	0.5833	0.5278	0.6667	0.7222
6	0.7222	0.7500	0.7500	0.6944	0.7222	0.7500	0.7500
9	0.7222	0.7222	0.6389	**0.7500**	0.6944	0.6944	0.6111
12	0.8611	0.8611	0.7778	0.8333	0.8056	0.7778	0.7778
				WHEAT			
1	0.5833	0.7222	0.7222	0.6944	**0.7500**	0.6944	0.6667
3	0.7500	0.7500	0.7778	**0.8056**	**0.8056**	0.7778	0.7778
6	0.6944	0.6944	0.6111	0.6111	0.6111	0.6667	0.6111
9	0.7222	0.7222	0.6944	0.7222	0.6944	**0.7500**	**0.7500**
12	0.6944	0.6944	0.7222	0.6389	0.6111	0.6389	**0.7222**

Note: WTI = WTI crude oil price volatility, BRN = Brent crude oil price volatility. Bold face indicates improvement in directional accuracy relative to the benchmark models (RW, AR(*p*) or HAR). The order of the AR models for Soy and Corn is 1, for Sugar and Wheat is 2, whereas for Rice is 4, based on the Bayesian Information Criterion.

Table A22. Directional accuracy for 1-, 3-, 6-, 9-, 12- month ahead forecasting horizons. Volatility Measure: Monthly Realized Range; $RR_t^{(M)}$. Forecasting period: 2nd Food Crisis (2010-2012).

Months-ahead	RW	AR(p)	HAR	HAR-WTI	HAR-BRN	MIDAS-HAR-WTI	MIDAS-HAR-BRN
				SOY			
1	0.6667	0.9444	0.9444	0.9722	0.9444	0.9444	0.9444
3	0.8333	0.8333	0.6667	0.6944	0.6667	0.6389	0.6389
6	0.7500	0.7778	0.6944	0.7222	0.6944	0.6389	0.6667
9	0.7222	0.7500	0.7500	0.7500	0.6944	0.7500	0.6667
12	0.7778	0.8056	0.7222	0.7500	0.6667	0.7222	0.6389
				CORN			
1	0.5278	0.8333	0.8611	**0.8889**	**0.9167**	0.8611	0.8333
3	0.5278	0.6111	0.7500	**0.7778**	**0.7778**	0.7222	0.7500
6	0.5833	0.6111	0.7222	0.6944	**0.7500**	0.7222	0.7222
9	0.5278	0.5278	0.6944	0.6944	0.6667	**0.7500**	0.6944
12	0.6944	0.6944	0.7222	0.6944	0.6944	**0.7778**	0.6944
				SUGAR			
1	0.5556	0.8056	0.8889	0.8889	0.8611	0.8611	0.8889
3	0.6389	0.6389	0.7500	0.6944	0.6667	0.6944	0.7222
6	0.5833	0.6111	0.6667	**0.7222**	**0.6944**	0.6667	0.6667
9	0.7222	0.7500	0.6389	0.6667	0.6944	0.6111	0.6389
12	0.6389	0.6389	0.6389	0.6389	0.6389	**0.7500**	**0.7778**
				RICE			
1	0.5556	0.8889	0.8889	0.8889	0.8889	0.8333	0.8889
3	0.6111	0.7500	0.7500	0.7500	**0.7778**	**0.7778**	**0.7778**
6	0.6111	0.6667	0.8333	0.7222	0.7222	0.6667	0.6944
9	0.7500	0.7500	0.8889	0.7500	0.7778	0.8611	0.8889
12	0.7222	0.7222	0.7222	0.7222	0.6944	0.7222	**0.7500**
				WHEAT			
1	0.5000	0.8611	0.8333	0.8056	0.8333	0.8611	0.8333
3	0.6389	0.7500	0.6389	0.6944	0.6389	0.6667	0.6389
6	0.6389	0.6944	0.8333	0.8333	0.8056	**0.8611**	0.7500
9	0.5278	0.6667	0.6667	0.6667	0.6389	0.6389	0.6944
12	0.6667	0.6667	0.6389	**0.6944**	0.6111	0.5556	0.6389

Note: WTI = WTI crude oil price volatility, BRN = Brent crude oil price volatility. Bold face indicates improvement in directional accuracy relative to the benchmark models (RW, AR(p) or HAR). The order of the AR models for Soy, Corn and Sugar is 1, whereas for Rice and Wheat is 2, based on the Bayesian Information Criterion.

Table A23. The Mean Squared Forecasting Error (MSFE) evaluation function for 1-, 3-, 6-, 9-, 12- month ahead forecasting horizons. Volatility Measure: Monthly Price Range; $PR_t^{(M)}$. Forecasting period: Oil price collapse (2014-2016).

Months-ahead	RW	AR(p)	HAR	HAR-WTI	HAR-BRN	MIDAS-HAR-WTI	MIDAS-HAR-BRN
			SOY				
1	121.8969	**0.2195***	**0.3569***	**0.3666***	**0.3663***	**0.3651***	**0.3954***
3	122.8292	**0.9551***	1.0899	1.1448	1.1248	1.1723	1.3306
6	122.6115	1.0230	1.1381	1.2551	1.1881	1.3792	1.4104
9	122.0617	1.0153	1.0834	1.2146	1.1348	1.2931	1.3400
12	121.5293	**0.9986**	**0.8785**	**0.9939**	**0.8807**	**0.7265***	**0.8551***
			CORN				
1	47.4760	**0.2335***	**0.3940***	**0.4280***	**0.3990***	**0.4265***	**0.3631***
3	47.8947	**0.9925***	1.1381	1.2435	1.2020	1.2389	1.1800
6	47.8319	1.0172	1.2056	1.1793	1.1941	1.3150	1.3639
9	47.7050	**0.9969***	1.0662	**0.9628***	**0.9719***	1.3664	**0.9747***
12	47.8403	**0.9995***	1.2759	1.2135	1.2598	1.3172	1.4567
			SUGAR				
1	57.5135	**0.2090***	**0.4394***	**0.4983***	**0.4562***	**0.4449***	**0.5148**
3	58.1219	1.0432	1.0349	1.0390	1.0398	1.0285	1.0790
6	58.3557	**0.9789**	**0.8079***	**0.8053***	**0.7866***	**0.8089***	**0.7839***
9	58.8467	**0.9828**	**0.7975***	**0.8030***	**0.8030***	**0.8220***	**0.8703***
12	59.3987	**0.9847**	**0.7974***	**0.8003***	**0.7877***	**0.7868***	**0.8134***
			RICE				
1	36.4679	**0.2222***	**0.5486**	**0.5684**	**0.5669**	**0.5955**	**0.5791**
3	36.7066	1.0920	1.4782	1.5218	1.5492	1.4578	1.5037
6	36.6490	**0.9832***	1.1640	1.2443	1.3227	**0.9931***	1.0798
9	36.7804	**0.9962***	1.1412	1.1905	1.2668	1.2717	1.2262
12	36.9719	**0.9967***	1.0851	1.0551	1.1122	1.3148	1.1311
			WHEAT				
1	42.3858	**0.4449***	**0.6064***	**0.6164***	**0.5614***	**0.6564**	**0.6530**
3	42.7715	**0.9664**	1.0305	**0.9214***	**0.8888***	**0.9554**	1.0664
6	42.9733	1.0025	1.2998	1.1482	1.0724	1.5327	1.5360
9	43.0873	1.0013	1.4823	1.3449	1.2591	1.9740	2.0886
12	43.0174	1.0035	1.5903	1.5572	1.4710	1.6677	1.9983

Note: WTI = WTI crude oil price volatility, BRN = Brent crude oil price volatility. The RW column shows the actual MSFE. All other columns show the MSFE ratios, for each forecasting model, that have been normalized relative to the monthly RW forecast. The order of the AR models for Soy and Corn is 1, for Sugar and Wheat is 2, whereas for Rice is 4, based on the Bayesian Information Criterion. Bold face numbers denote that the forecast outperforms the RW. * denotes that the model is included in the set of the best models according to the Model Confidence Set (MCS).

Table A24. The Mean Absolute Forecasting Error (MAFE) evaluation function for 1-, 3-, 6-, 9-, 12-month ahead forecasting horizons. Volatility Measure: Monthly Price Range; $PR_t^{(M)}$. Forecasting period: Oil price collapse (2014-2016).

Months-ahead	RW	AR(p)	HAR	HAR-WTI	HAR-BRN	MIDAS-HAR-WTI	MIDAS-HAR-BRN
				SOY			
1	7.3925	**0.4279***	**0.5677***	**0.5458***	**0.5653***	**0.5723***	**0.5740***
3	7.4270	**0.9694***	1.0673	1.0701	1.0805	1.1410	1.3055
6	7.4277	1.0220	1.1463	1.1873	1.1654	1.3608	1.3691
9	7.3954	1.0082	1.1201	1.1699	1.1296	1.2327	1.2555
12	7.3833	**0.9958***	1.0191	1.0887	1.0411	**0.9793***	1.0201
				CORN			
1	5.6398	**0.4613***	**0.5773***	**0.6271**	**0.6027**	**0.5976***	**0.5662***
3	5.6656	**0.9653***	1.0019	1.0883	1.0764	1.0977	1.0837
6	5.6669	1.0017	1.0502	1.0536	1.0673	1.0968	1.0837
9	5.6767	**0.9906**	**0.9837**	**0.9348***	**0.9515***	1.0247	**0.9136***
12	5.7028	**0.9942***	1.1144	1.1127	1.1495	1.1747	1.1927
				SUGAR			
1	5.9479	**0.4581***	**0.6073***	**0.6628**	**0.6157**	**0.6450**	**0.6583**
3	5.9789	**0.9953**	**0.9250**	**0.9112***	**0.8887***	**0.9718**	**0.9038***
6	6.0011	**0.9810**	**0.8597**	**0.8279***	**0.7689***	**0.8452**	**0.8122***
9	6.0200	**0.9856**	**0.8407***	**0.8253***	**0.7815***	**0.8509***	**0.8634**
12	6.0694	**0.9877**	**0.8918**	**0.8563**	**0.8210***	**0.7987***	**0.8068***
				RICE			
1	4.9528	**0.4660***	**0.6721***	**0.6855**	**0.6859**	**0.7411**	**0.6845**
3	4.9714	1.0157	1.1456	1.1736	1.1869	1.1195	1.0787
6	4.9767	**0.9854***	**0.9758***	**0.9955**	1.0821	**0.9276***	**0.9460***
9	4.9933	**0.9957**	**0.9807***	1.0059	1.0451	1.0802	1.0534
12	5.0147	**0.9975***	1.0142	**0.9803***	1.0433	1.1334	1.0517
				WHEAT			
1	5.2991	**0.6534***	**0.7310***	**0.7512**	**0.7393***	**0.7953**	**0.8080**
3	5.3279	**0.9699**	1.0041	**0.9219***	**0.9274***	**0.9409***	**0.9943**
6	5.3431	1.0019	1.1250	1.0381	**0.9933**	1.2493	1.2396
9	5.3446	1.0005	1.1740	1.1029	1.0494	1.4170	1.4523
12	5.3409	1.0019	1.2760	1.2407	1.2037	1.2625	1.4231

Note: WTI = WTI crude oil price volatility, BRN = Brent crude oil price volatility. The RW column shows the actual MAFE. All other columns show the MAFE ratios, for each forecasting model, that have been normalized relative to the monthly RW forecast. The order of the AR models for Soy and Corn is 1, for Sugar and Wheat is 2, whereas for Rice is 4, based on the Bayesian Information Criterion. Bold face numbers denote that the forecast outperforms the RW. * denotes that the model is included in the set of the best models according to the Model Confidence Set (MCS).

Table A25. The Mean Squared Forecasting Error (MSFE) evaluation function for 1-, 3-, 6-, 9-, 12- month ahead forecasting horizons. Volatility Measure: Monthly Realized Range; $RR_t^{(M)}$. Forecasting period: Oil price collapse (2014-2016).

Months-ahead	RW	AR(p)	HAR	HAR-WTI	HAR-BRN	MIDAS-HAR-WTI	MIDAS-HAR-BRN
				SOY			
1	24.0730	**0.0488***	**0.1255***	**0.1321***	**0.1329***	**0.1190***	**0.1487***
3	24.3079	**0.7987***	**0.9224**	1.0511	1.0009	1.1602	1.0954
6	24.4169	1.0570	1.2170	1.4800	1.4110	1.5654	1.7685
9	24.3628	1.0610	1.2276	1.5220	1.4621	1.4717	1.4699
12	24.2985	1.0075	1.1405	1.4289	1.3571	1.2752	1.0790
				CORN			
1	21.3347	**0.0446***	**0.1531***	**0.1790***	**0.1720***	**0.1691***	**0.1768***
3	21.5230	**0.9960***	**0.9851***	1.1081	1.0346	1.2091	1.1695
6	21.5988	1.0795	1.0932	1.1210	1.0974	1.2324	1.1607
9	21.6168	1.0561	1.0289	1.0075	1.0055	1.0441	1.2185
12	21.6473	1.0550	1.3170	1.2589	1.2774	1.2800	1.2317
				SUGAR			
1	28.7057	**0.0690***	**0.1777***	**0.1541***	**0.1658***	**0.2197***	**0.2601**
3	28.9520	**0.9784***	**0.9947**	**0.9793***	**0.9624***	1.1161	1.1628
6	29.0191	**0.9376***	1.0227	1.0324	1.0151	**0.9787**	**0.9214***
9	29.2981	**0.9797***	1.3442	1.3903	1.3786	1.2972	1.1285
12	29.2826	**0.9715***	1.2994	1.4528	1.4719	1.8418	1.8181
				RICE			
1	24.8292	**0.1097***	**0.4881**	**0.4464**	**0.4505**	**0.4379**	**0.5178**
3	24.9686	**0.9210**	**0.8746***	1.1590	1.0407	**0.8701***	**0.8815***
6	25.1246	1.0054	1.2643	1.6543	1.5670	1.2686	1.1591
9	25.1423	1.0072	1.2149	1.6506	1.4876	1.5630	1.7313
12	25.1099	1.0094	1.3347	1.5497	1.3956	1.4472	1.3031
				WHEAT			
1	22.7409	**0.0724***	**0.2552**	**0.2372**	**0.2177**	**0.2847**	**0.2664**
3	22.9599	**0.6334***	**0.8882**	**0.7884***	**0.8182**	**0.8076***	**0.7862***
6	23.1637	**0.9481***	1.3792	1.2344	1.3012	1.2099	1.3439
9	23.2409	1.0126	1.6275	1.4059	1.5394	2.0060	2.2435
12	23.1996	1.0113	1.7743	1.5591	1.7003	1.9534	2.2151

Note: WTI = WTI crude oil price volatility, BRN = Brent crude oil price volatility. The RW column shows the actual MSFE. All other columns show the MSFE ratios, for each forecasting model, that have been normalized relative to the monthly RW forecast. The order of the AR models for Soy, Corn and Sugar is 1, whereas for Rice and Wheat is 2, based on the Bayesian Information Criterion. Bold face numbers denote that the forecast outperforms the RW. * denotes that the model is included in the set of the best models according to the Model Confidence Set (MCS).

Table A26. The Mean Absolute Forecasting Error (MAFE) evaluation function for 1-, 3-, 6-, 9-, 12-month ahead forecasting horizons. Volatility Measure: Monthly Realized Range; $RR_t^{(M)}$. Forecasting period: Oil price collapse (2014-2016).

Months-ahead	RW	AR(p)	HAR	HAR-WTI	HAR-BRN	MIDAS-HAR-WTI	MIDAS-HAR-BRN
				SOY			
1	3.8820	**0.2112***	**0.3454***	**0.3493***	**0.3447***	**0.3616***	**0.3720***
3	3.9025	**0.9150***	**0.9944**	1.0627	1.0210	1.1414	1.0985
6	3.9131	1.0493	1.1291	1.2496	1.1929	1.2789	1.3729
9	3.9125	1.0224	1.1257	1.2797	1.2337	1.2868	1.2626
12	3.9090	1.0024	1.0749	1.2200	1.1966	1.1560	1.0726
				CORN			
1	3.4551	**0.2049***	**0.4236***	**0.4545**	**0.4356**	**0.4423**	**0.4773**
3	3.4745	1.0534	1.0784	1.1937	1.1528	1.2213	1.2011
6	3.4817	1.0462	1.1074	1.1528	1.1382	1.2053	1.1861
9	3.4813	1.0195	1.0326	1.0757	1.0505	**0.9962***	1.1887
12	3.4791	1.0393	1.2120	1.2187	1.2356	1.3214	1.2692
				SUGAR			
1	4.3146	**0.2561***	**0.3520***	**0.3267***	**0.3274***	**0.4060***	**0.4291***
3	4.3348	**0.9460**	**0.8894***	**0.8278***	**0.8084***	**0.8960***	**0.8962***
6	4.3520	**0.9603**	**0.9165**	**0.8462***	**0.8115***	**0.9070**	**0.8173***
9	4.3770	**0.9799***	1.0573	1.0512	1.0324	1.0397	**0.9603***
12	4.3881	**0.9623***	1.0630	1.1444	1.1454	1.3679	1.3191
				RICE			
1	3.8536	**0.3222***	**0.7121**	**0.6992**	**0.6983**	**0.6654**	**0.7373**
3	3.8640	**0.9886***	**0.9950***	1.1416	1.0873	**0.9862***	1.0043
6	3.8771	1.0426	1.1086	1.2969	1.2769	1.1444	1.1008
9	3.8879	1.0084	1.0679	1.1854	1.1451	1.2741	1.3504
12	3.8895	1.0257	1.1942	1.1659	1.1051	1.2465	1.1558
				WHEAT			
1	3.7516	**0.2637***	**0.5286**	**0.5249**	**0.4939***	**0.5543**	**0.5299**
3	3.7720	**0.8346***	1.0095	**0.9493**	**0.9588**	**0.9387**	**0.9269**
6	3.7820	1.0035	1.3130	1.2028	1.2645	1.1873	1.2728
9	3.7863	1.0424	1.4568	1.2719	1.3854	1.6141	1.7008
12	3.7724	1.0368	1.5132	1.3911	1.4651	1.5791	1.6458

Note: WTI = WTI crude oil price volatility, BRN = Brent crude oil price volatility. The RW column shows the actual MAFE. All other columns show the MAFE ratios, for each forecasting model, that have been normalized relative to the monthly RW forecast. The order of the AR models for Soy, Corn and Sugar is 1, whereas for Rice and Wheat is 2, based on the Bayesian Information Criterion. Bold face numbers denote that the forecast outperforms the RW. * denotes that the model is included in the set of the best models according to the Model Confidence Set (MCS).

Table A27. Directional accuracy for 1-, 3-, 6-, 9-, 12- month ahead forecasting horizons. Volatility Measure: Monthly Price Range; $PR_t^{(M)}$. Forecasting period: Oil price collapse (2014-2016).

Months-ahead	RW	AR(p)	HAR	HAR-WTI	HAR-BRN	MIDAS-HAR-WTI	MIDAS-HAR-BRN
				SOY			
1	0.7143	0.8571	0.8571	**0.9048**	**0.9048**	**0.9048**	**0.9048**
3	0.7619	0.7143	0.6667	0.7619	0.7143	0.6667	0.6190
6	0.8095	0.8095	0.6667	0.6667	0.6667	0.6190	0.6190
9	0.7143	0.7143	0.7143	0.6190	0.7143	0.7143	0.7143
12	0.7619	0.7619	0.7619	0.7143	0.6667	**0.8095**	0.7143
				CORN			
1	0.6190	0.9048	0.8571	0.8095	0.8571	0.8095	0.7619
3	0.7143	0.6667	0.6667	0.6667	0.6667	0.6667	**0.7619**
6	0.8095	0.8571	0.8095	0.7143	0.7619	0.7143	0.7619
9	0.6190	0.6667	0.6190	**0.7143**	0.6190	0.6667	0.6667
12	0.8095	0.7619	0.7619	0.7619	0.7143	0.8095	0.7143
				SUGAR			
1	0.7143	0.9048	0.8571	0.7143	0.7619	0.8095	0.8095
3	0.7619	0.8095	0.8095	0.8095	0.8095	**0.9048**	**0.8571**
6	0.7143	0.7143	0.7143	0.7143	0.7619	0.7143	**0.7619**
9	0.8095	0.8095	0.9048	0.9048	0.9048	0.9048	**0.9524**
12	0.7143	0.7143	0.7619	**0.8095**	**0.8095**	**0.8095**	**0.8095**
				RICE			
1	0.6667	0.9048	0.8571	0.8095	0.8571	0.8095	0.9048
3	0.8095	0.8095	0.7619	0.8095	0.8095	0.8095	0.7619
6	0.6667	0.7143	0.8095	0.7143	0.6667	0.6667	0.8095
9	0.9048	0.9048	0.9048	0.9048	0.8571	0.8571	0.8571
12	0.8095	0.8095	0.8095	0.8095	0.8095	**0.9524**	0.8095
				WHEAT			
1	0.7619	0.9524	0.7619	0.7619	0.7619	0.6667	0.5714
3	0.6190	0.6190	0.5238	0.5714	0.5714	0.5714	0.5714
6	0.7143	0.7143	0.7619	**0.8095**	**0.8095**	0.6667	0.7143
9	0.7619	0.7619	0.7619	0.7143	0.7619	0.6190	0.6190
12	0.9524	0.9524	0.8095	0.8095	0.8095	0.8095	0.7619

Note: WTI = WTI crude oil price volatility, BRN = Brent crude oil price volatility. Bold face indicates improvement in directional accuracy relative to the benchmark models (RW, AR(p) or HAR). The order of the AR models for Soy and Corn is 1, for Sugar and Wheat is 2, whereas for Rice is 4, based on the Bayesian Information Criterion.

Table A28. Directional accuracy for 1-, 3-, 6-, 9-, 12- month ahead forecasting horizons. Volatility Measure: Monthly Realized Range; $RR_t^{(M)}$. Forecasting period: Oil price collapse (2014-2016).

Months-ahead	RW	AR(p)	HAR	HAR-WTI	HAR-BRN	MIDAS-HAR-WTI	MIDAS-HAR-BRN
SOY							
1	0.5238	0.9524	0.8095	0.8571	0.8571	0.8571	0.6667
3	0.6667	0.7619	0.7143	0.5714	0.5714	0.4762	0.5714
6	0.7143	0.7143	0.7143	0.5714	0.6667	0.6190	0.5714
9	0.8095	0.8095	0.6190	0.5238	0.5238	0.4762	0.4762
12	0.7619	0.7619	0.6667	0.6190	0.6667	0.6667	0.7143
CORN							
1	0.6190	0.9048	0.8095	0.8095	0.8571	0.8095	0.7143
3	0.7143	0.7143	0.6190	0.6190	0.6667	0.6190	0.6190
6	0.6190	0.6667	0.7619	0.6667	0.7143	0.7143	0.7619
9	0.7619	0.7143	0.6190	0.6190	0.5714	0.8571	0.6190
12	0.8571	0.8571	0.7143	0.6667	0.7143	0.7143	0.6667
SUGAR							
1	0.6190	0.9048	0.8571	0.9048	**0.9524**	0.8571	0.8571
3	0.7143	0.8095	0.7143	0.7143	0.7619	0.8095	**0.8571**
6	0.6667	0.6667	0.6667	**0.8571**	**0.8571**	**0.7143**	**0.7143**
9	0.8571	0.8571	0.7619	0.8571	0.8571	0.8571	**0.9048**
12	0.8571	0.8571	0.7619	0.8095	0.7619	0.6190	0.7143
RICE							
1	0.6190	0.9048	0.8571	**0.9524**	**0.9524**	**0.9524**	0.9048
3	0.7143	0.8571	0.8095	0.7143	0.7619	0.8571	0.8571
6	0.6667	0.6190	0.5714	0.5238	0.5238	0.5714	0.6190
9	0.8571	0.8571	0.8571	0.7619	0.7143	0.8095	0.6667
12	0.8095	0.8095	0.7619	**0.8571**	0.9048	0.8095	0.8095
WHEAT							
1	0.5238	0.9524	0.7619	0.8095	0.7619	0.7619	0.7619
3	0.4762	0.6667	0.5714	0.6190	0.5714	0.5714	0.6667
6	0.7143	0.8095	0.6667	0.7143	0.6190	0.7619	0.6667
9	0.7143	0.7143	0.6190	0.7143	0.6667	0.5714	0.6190
12	0.8571	0.8571	0.6190	0.7143	0.6667	0.5714	0.6190

Note: WTI = WTI crude oil price volatility, BRN = Brent crude oil price volatility. Bold face indicates improvement in directional accuracy relative to the benchmark models (RW, AR(p) or HAR). The order of the AR models for Soy, Corn and Sugar is 1, whereas for Rice and Wheat is 2, based on the Bayesian Information Criterion.