Future volatility forecast in agricultural commodity markets

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Abstract

Recent changes in commodity markets suggest that risk management in agriculture has become even more important for both long and short hedgers. We found that over the last decades significant changes occurred in corn, soybean, and wheat term structure volatilities. We compare forecast performance of three methods to predict realized volatilities: implied forward volatility (IFV), historical volatility based on the SARIMA model (SARIMA-HV), and a naïve forecast. Our study covers the period from 2006 to 2016, and analyses three sub-periods: before, during, and after the 2008 crisis. Our results suggest that the IFV and the SARIMA-HV models perform equally well at predicting future volatility in the corn and wheat markets. However, the results for the IFV were unbiased and efficient in most of our analysis. The SARIMA-HV method outperformed all other methods in the soybean market, in most of the analyzed periods.

Keywords: *agricultural commodity options, implied forward volatility, term structure.*

1. Introduction

Hedgers and speculators who trade agricultural futures or options contracts need to determine their risk levels in order to guide production planning, investment levels, inventory positions, and portfolio composition. As a result of the seasonal biological characteristic of agricultural commodities, market participants expect to face higher price volatility during the growing season, when uncertainty due to weather conditions is also higher. Therefore, participants deal with different risk levels in different periods of the year, since the market conditions follow the growing and the harvest seasons very closely.

Pindyck (2001) highlights the importance of volatility for hedgers, since it drives the demand for price risk management tools (for example, futures and options contracts) and it is important to determine the levels of inventories in the cash market. For instance, producers and inventory holders who believe that prices of a certain commodity will be very volatile in the future can use derivatives to hedge their final selling prices. If they believe that the future cash price is likely to fall below a certain level, they can lock in their future selling price by either selling futures contracts or buying put options. Likewise, long hedgers who also expect highly volatile prices in the future can hedge their final purchase price by buying futures contracts or by buying call options on the underlying futures contract. Many other trading strategies combining futures and/or options contracts can also be created for market participants who have different expectations regarding future prices volatility (straddles, strangles, butterflies, bull/bear spreads, etc.).

According to Poon and Granger (2003), volatility is the most important variable in pricing derivative securities such as futures and options contracts. Therefore, market participants seek to forecast volatility over defined periods in order to price such derivative contracts.

For all the reasons previously mentioned, both long and short hedgers have interest in predicting future price variation, and may use various methods to forecast future volatility in agricultural commodity markets. Even though different studies have already investigated the performance of different methods to predict volatility, they have not covered recent years in order to evaluate whether their results can still be applied to current agricultural markets.

This type of comparison is important because most of the commodity markets have faced significant changes over the last 15 years. These changes, including a financial crisis and technology innovations, can change price patterns and the term structure of implied forward volatility. (Figures 1A, 2A and 3A in the Annex show the evolution of the realized volatility for corn, soybeans, and wheat futures prices from 1969 to 2016.)

Therefore, our research question is: which of the most-used methods in the empirical literature has superior performance predicting the realized volatility in grains and oilseed markets? We are also interested in investigating if the most recent changes in the agricultural and financial markets have changed the seasonal patterns of agricultural commodity volatilities.

Our main objective with this study is to compare different approaches to forecast future volatility in the agricultural commodities markets using historical volatility data. We investigate the corn, soybean, and wheat U.S. futures and options markets between 2006 and 2016. We closely follow the methodology introduced by Egelkraut, Garcia, and Sherrick (2007) to calculate the term structure volatility implied in the aforementioned commodities futures prices. We compare the predictive performance of the implied forward volatility (IFV) with a naïve forecast, and a SARIMA model to forecast the realized volatility for different periods within the crop year.

In addition, we also investigate the forecast performance for different models before, during, and after the 2008 crisis. The analysis of these sub-periods is important since the literature highlights unusual price movements of various commodity markets since 2006, especially during the financial crisis (Etienne et al., 2014). In addition to updating the important contribution presented by Egelkraut, Garcia, and Sherrick (2007), our study contributes to the literature in the area using SARIMA models to forecast seasonal patterns for select commodities. As far as we know, no other study in the area uses such a model, even though most of the authors who studied similar problems mentioned the seasonal effect.

2. Review of literature

Egelkraut and Garcia (2006) classify the various methods available in the literature into two groups: backward- and forward-looking. Backward-looking models make predictions based on historical past information. This type of model can be as simple as a naïve model that uses the last period realized volatility to forecast the one-step-ahead volatility, or more complex models such as those in the ARIMA family and stochastic volatility. On the other hand, forward-looking models estimate future values based on prices implied volatility, which is available in the options market. The option pricing models developed by Black and Scholes (1973), and by Black (1976) are the most popular models in the area and can be used to calculate the implied volatility when one can observe call or put options values (or options on futures, regarding the Black model).

Several studies have investigated which type of model has superior forecast performance. Most of the literature on the subject concludes that the implied forward volatility has a superior performance to forecast future volatilities. For instance, Egelkraut and Garcia (2006) investigated five agricultural commodities (corn, soybeans, soybean meal, wheat, and hogs) and found that the IFV dominated forecasts based on historical volatility information, between 1992 and 2001. Szakmary et al. (2002) also found that the IFV outperformed the historical volatility as a predictor for realized volatility in most of the 35 markets investigated. The performance of the FIV model was compared to the moving average and the GARCH model forecasts. The authors implemented different models to forecast the volatility of several futures options contracts, including indexes, interest rates, currencies, energy assets, metals, agricultural, and livestock contracts. The authors used datasets very similar to those used by Egelkraut and Garcia (2006), and by Egelkraut, Garcia, and Sherrick (2007) to investigate the agricultural commodities markets. This is probably the reason the two studies found similar results.

Berlova (2011) compared volatility forecast models to investigate their efficiency predicting volatility in the crude oil and in the natural gas markets. The author used a model-free FIV developed by Britten-Jones and Neuberger (2000), a model-based FIV estimated using the Black's (1976) model, a GARCH model, and a historical volatility (HV) model based on a 250-day moving average. The authors found that the FIV-type models outperformed the others.

Locke (2014) found strong volatility seasonal patterns in the corn, wheat, and soybeans markets between 1995 and 2012. Differently from the aforementioned studies, the author used intraday prices (tick prices) in his analysis. He compared the IV with the historical volatility calculated using a 30-day rolling window. He found that the IV forecasts outperformed the historical volatility predicting the future realized volatility in all markets in his analysis.

During the last decades, the study done by Martens and Zein (2004) seems to be the most relevant in the area to have found different results regarding the dominance of IV models over HV (and/or time series) models to forecast realized volatilities. The authors analyzed three classes of assets (equity, foreign exchange, and commodities) between 1993 and 2000 using high-frequency data and long-memory modeling. Since the authors considered the 24-hour period in their analysis, they calculated the realized volatility based on the intraday and the intra-night returns. They compared the forecasts obtained from the (high-frequency) Autoregressive Fractionally Integrated Moving Average (ARFIMA) and (daily) GARCH models to the IV forecasts for different assets and horizons. The first part of their findings confirm the results from previous researchers: the daily GARCH volatility forecasts have little or no information over that already contained in implied volatilities. However, they found that the ARFIMA outperformed the GARCH model, and that the first model contains information not already built in the options-implied volatilities.

3. Data and methods

Our analysis is similar to the approach presented in the literature by Egelkraut and Garcia (2006) and by Egelkraut, Garcia, and Sherrick (2007). However, our dataset covers a different period for futures and options prices on the corn, soybeans, and wheat futures contracts. In addition, we also compare the forecast results of a SARIMA model to predict the realized volatilities.

The methodology is divided into three different steps: i) we first build volatility intervals for which we further calculate the realized and the implied volatilities (IV), and estimate historical volatilities (HV); ii) we obtain volatilities forecasts using different methods; iii) at last, we use an econometric model to compare forecast performances for different methods, during different time periods.

3.1. Data

Our dataset consists of futures and standard options on futures prices for corn, soybeans, and wheat contracts traded at the CME Group, obtained at the websites Barchart (http://www.barchart.com/) and Quandl (http://www.quandl.com/).

We use daily settle futures prices from November 1969 to June 2016 to calculate historical volatilities. The dataset consists of 11,965 daily observations for corn and wheat, and 12,034 daily observations for soybeans.

The options on futures data extend from February 2006 to June 2016. We used all the options traded (non-zero volume) to calculate the implied volatility for each day representing a correspondent time interval. All in-, at-, and out-of-the-money options were used in our calculation. A total of 4,564 options on the corn and wheat futures contracts (2,606 calls and 1,958 puts for each commodity), and 5,155 options on the soybeans futures contract (2,918 calls and 2,237 puts) were used to calculate the implied volatilities.

3.2. Forecast intervals

We only use serial options in our analysis. For this reason, we calculate volatilities for intervals between two underlying futures contracts expiration months. Since corn and wheat futures contracts are traded for five expiration months (March, May, July, September, December) and soybeans futures are traded for seven months (January, March, May, July, August, September, November), we create forward intervals with different lengths in our analysis (either one, two or three months long). According to tables 1 and 2, the non-overlapping time intervals cover different production and marketing stages for the analyzed commodities, and are fixed across time (EGELKRAUT; GARCIA, 2006).

Table 1. Forecast intervals for corn and wheat[1] futures contracts

Intervals	Contract expiration	Characteristic
FEB-APR (p1)	May (K)	Storage
APR-JUN (p2)	July (N)	Planting and beginning of growth period
JUN-AUG (p3)	September (U)	Critical growth period
AUG-NOV (p4)	December (Z)	Harvest
NOV-FEB (p5)	March (H)	Harvest and storage

Table 2. Forecast intervals for soybean futures contracts

Intervals	Contract expiration	Characteristic
FEB-APR (p1)	May (K)	Storage
APR-JUN (p2)	July (N)	Planting and beginning of growth period
JUN-JUL (p3)	August (Q)	Critical growth period
JUL-AUG (p4)	September (U)	Growth period
AUG-OCT (p5)	November (X)	Harvest
OCT-DEC (p6)	January (F)	Harvest
DEC-FEB (p7)	March (H)	Storage

3.3. Volatility forecast methods

3.3.1. Realized volatility

We calculated realized volatilities for each time interval as the annualized standard deviations of log returns. We calculated returns (R_t) using futures prices underlying options with the longest maturity for each time interval, according to equation (1):

[1] We assume that the spring wheat planting occurs from April through May, and the harvest from August through September. The winter wheat planting season occurs between August and October, and the harvest from May through July.

(1) $$\sigma_{real,T_a-T_b} = \sqrt{252 * \left(\frac{\sum_{t=1}^{N}(R_t - \overline{R_t})^2}{N}\right)}$$

Futures prices were used to calculate 233 realized volatilities for corn and wheat, and 325 realized volatilities for soybeans, from 1969 to 2016.

3.3.2. Implied forward volatility

We followed the procedure presented by Egelkraut and Garcia (2006), and by Egelkraut, Garcia, and Sherrick (2007) to calculate implied forward volatilities. Both studies assume no-arbitrage conditions and follow Cox and Ross' (1976) model to calculate call and put values, according to equations (2) and (3):

(2) $$V_c(x) = b(T)\int_0^{\infty} \max(0, F_T - x)\, g(F_T) dF_T$$

(3) $$V_p(x) = b(T)\int_0^{\infty} \max(0, x - F_T)\, g(F_T) dF_T$$

Where $V_c(x)$ and $V_p(x)$ are the European call and put option premiums for a given strike price *x*, $b(T)$ is a continuous discount factor using the time to maturity *T* and a risk-free interest rate[2], F_T is the current futures price of the underlying contract, and $g(F_T)$ is the market expected probability density function of the underlying futures contract price at maturity. Equations (2) and (3) represent Black's (1976) option pricing model when we assume that $g(F_T)$ is the log normal distribution. These equations are part of the following objective function (4) that we use to obtain implied futures prices and volatilities for specific maturities.

(4) $$\min_{\varphi}\left[\begin{array}{l}\sum_{i=1}^{k}\left(\left(V_{c,i} - b(T)\int_{x_i}^{\infty} g(F_T|\varphi)(F_T - x_i) dF_T\right)^2\right) \\ +\sum_{j=1}^{l}\left(\left(V_{p,j} - b(T)\int_{0}^{x_j} g(F_T|\varphi)(x_j - F_T) dF_T\right)^2\right)\end{array}\right]$$

[2] We used the three-month T-Bill interest rates obtained at the Federal Reserve in our analysis.

The variables in equation (4) are the same presented in equations (2) and (3), and include the various observed calls ($V_{c,i}$) and puts ($V_{p,j}$) premiums for different strike prices (x_i and x_j) with the same maturity.

The approach using equation (4) minimizes the sum of the squared difference between the observed premiums and the model premiums, calculated using equations (3) and (4). Differently from the traditional Black-Scholes and Black options pricing models, this approach does not impose any restrictions on the futures prices distribution, and allows the use of all options traded on a given date, regardless of if they are in-, at- or out-of-the money (EGELKRAUT; GARCIA; SHERRICK, 2007).

The solutions obtained from equation (4) were used to calculate the implied forward volatilities (IFV) for different periods assuming that the volatilities are time-additive. For a specific day $t = 0$, we use options contracts maturing in T_a and T_b ($T_b > T_a$), and calculate the volatility for each time interval $\sigma_{iv,0-T_a}$ and $\sigma_{iv,0-T_b}$. The same procedure is used to calculate implied forward volatilities for consecutive periods. According to Egelkraut, Garcia, and Sherrick (2007), the IFV calculated in equation (5) "represents the market's expectation of the average volatility that will occur during this future interval".

(5)
$$\sigma_{ifv,T,a-T_b} = \sqrt{\frac{T_b {\sigma^2}_{iv,0-T_b} - T_a {\sigma^2}_{iv,0-T_a}}{T_b - T_a}}$$

The IFV for each period was calculated using the premiums for all options traded on the last Friday of the month, two months before the option expiration.

3.3.3. *Historical volatility*

The series of calculated realized volatilities (equation 1) was used to estimate historical volatilities. We assume that a rational trader uses all available information to estimate the future volatility and therefore, to price an option. Market participants are also assumed to know how weather conditions and other seasonal effects affect prices and volatilities along the crop year, and how some of these patterns repeat over the years[3]. For this reason, we use a SARIMA model to estimate future volatilities based on historical data. We assume that realized volatilities follow an autoregressive process and use the Box and Jenkins (1976) approach to forecast two and three-step ahead historical volatilities. Brooks (2014) considers this approach as a relatively simple form of the class of stochastic volatility specifications. According to Pankratz (1983), ARIMA models are particularly useful for forecasting series with seasonal variations.

The econometric specification that we use for the SARIMA (p, d, q)x(P, D, Q)s model considers that the s observations for each year in our analysis (s=5 for corn and wheat, and s=7 for soybeans) present a seasonal pattern described by the following equation (5):

$$\phi(B)\Phi(B^S)\Delta^d\Delta_S^D Y_t = \theta(B)\Theta(B^S)e_t \quad (5)$$

Where $\phi(B)$ and $\theta(B)$ represent the autoregressive (AR) and the moving average components of orders p and q, respectively. $\Phi(B^S)$ and $\Theta(B^S)$ similarly represent the seasonal-AR and the seasonal-MA components of orders P and Q. Δ^d and Δ_S^D are difference and seasonal-difference operators, and e_t is a white noise process.

We follow the standard identification procedure described by Box and Jenkins (1976) to estimate 51 two-step ahead volatility forecasts for corn and wheat, and 71 two- or three-step ahead forecasts for soybeans. All the data prior to February 2016 was used to forecast the initial volatility value for all three commodities. We then added the new realized volatility to the model and re-estimated a new SARIMA model to forecast the next future volatility. We used the rolling window procedure to complete our volatility forecasts for all three commodities between April 2006 and June 2016.

3.3.4. Naïve volatilities

A historical naïve volatility (NV) is calculated to serve as a comparative reference to the SARIMA model forecasts, as follows:

$$\sigma_{NAIVE_T} = \sigma_{Realized\ T-S} \quad (5)$$

[3] For instance, a visual inspection of Figures 1A, 2A and 3A may suggest the existence of seasonal volatility effects in all the three commodities.

Where the naïve volatility is the same realized volatility for the same time interval, in the previous year.

3.4. Forecast evaluation

The volatility forecast methods are evaluated according to their performance predicting the realized volatility. We first use equation (6) to estimate a linear regression model, and then perform various tests to identify the performance of each forecast method.

$$\sigma_{REALIZED_t} = \alpha_0 + \alpha_1 \sigma_{FORECAST_{i,t}} + \varepsilon_{i,t} \tag{6}$$

According to Christensen e Prabhala (1998), different hypothesis can be tested using equation (6):

i) We assume that a forecast volatility method (i = IFV, naïve-HV, or SARIMA-HV) contains information about the realized volatility, if the slope coefficient α_1 is statistically different from zero.

ii) The forecast volatility method "i" provides unbiased predictions of the realized volatility if the join hypothesis $\alpha_0 = 0$ and $\alpha_1 = 1$ cannot be rejected. We use the Wald test to verify this hypothesis.

iii) The forecast volatility method "i" is efficient when the residuals are white noise, and uncorrelated with any other variable included in the market information set. We use the Durbin-Watson test to verify this hypothesis.

Moreover, we test the residuals estimated from the additional regression (7) to compare the informational efficiencies of the IFV and the SARIMA-HV forecasts.

$$\sigma_{REALIZED_t} = \alpha_0 + \alpha_1 \sigma_{IFV_t} + \alpha_2 \sigma_{SARIMA-HV_t} + \varepsilon_t \tag{7}$$

Equation (7) is used to test if the presence of an additional variable in the model can contribute to increase the prediction performance of a certain forecast method. We use the t-statistics to test individual null hypotheses that α_1 and α_2 are equal to zero. When one of the slope coefficients is found to be different from zero when the other one is not, we can conclude that the method with a non-zero coefficient is efficient whereas the other is not.

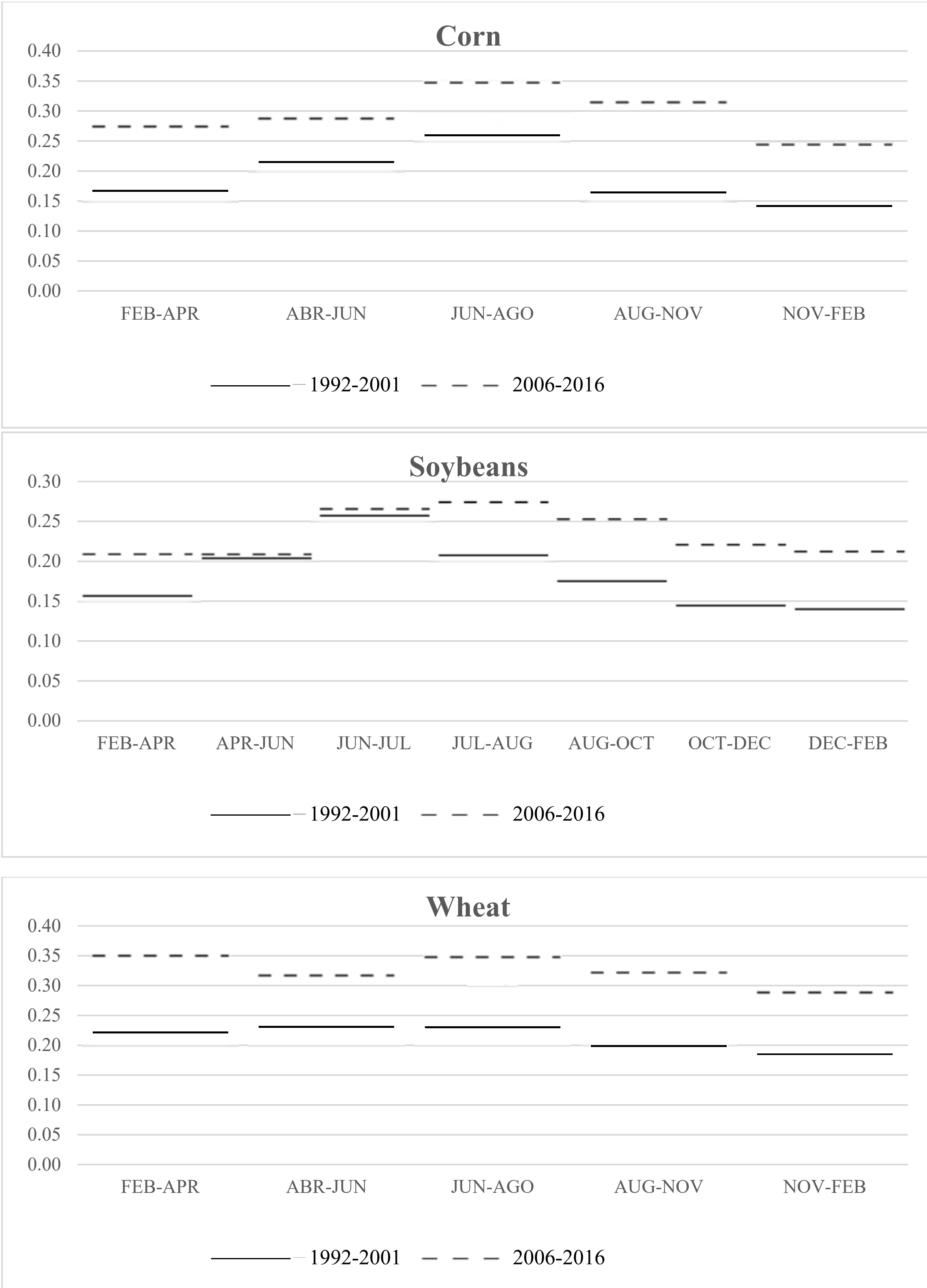
The accuracy of different forecast methods are evaluated using the mean absolute percentage errors (MAPE) and compared using the modified HLN test proposed by Diebold and Mariano (1995) – HLNDM, and suggested by Poon and Granger (2003)[4].

4. Results

During the first part of the analysis, realized volatilities for different time intervals for all commodities were calculated. Figure 1 presents the average volatilities calculated during the most recent period and the average volatilities calculated during the period between 1992 to 2001, which is the period previously studied by Egelkraut and Garcia (2006)[5]. A visual inspection of Figure 1 suggests that for most time intervals and commodities, the average volatilities still follow a defined pattern, increasing during the growing season and decreasing otherwise[6]. In addition, realized volatilities appears to have increased after the first period.

[4] Egelkraut, Garcia and Sherrick (2007) also used the same approach to compare different forecast methods.
[5] The comparison is based on the results found by Egelkraut and Garcia (2006), as this is the only study that covers a wide variety of agricultural commodities in the literature, and includes all three of the commodities investigated in our study.
[6] It is possible to observe two periods of high volatility for wheat. The first one corresponds to the growing season of the spring crop, while the second is related to the beginning of the planting season of the winter crop.

Figure 1. Annualized realized volatilities for different time intervals



We tested for the difference in the volatility means between the two periods using the t-test with unequal variances[7]. The results presented in Table 3 show that for corn and wheat, the null hypothesis that there is no difference in variance is rejected at the 5% significance level, for all time intervals. However, for soybeans the result is not the same, since the null hypothesis cannot be rejected for the time intervals between April to August, which represent the growing season for the commodity.

Table 3. Variance comparison using the t-test: 1992-2001 versus 2006-2016 (annualized values)

	1992-2001			2006-2016			t-test	
CORN	Mean	SD	n	Mean	SD	n	t-stat	p-value
Feb-Apr	0.1669	0.0471	10	0.2737	0.0632	11	4.4176	0.0000
Apr-Jun	0.2147	0.0583	10	0.2872	0.0640	11	2.7167	0.0079
Jun-Aug	0.2594	0.0676	10	0.3467	0.0657	10	2.9318	0.0171
Aug-Nov	0.1645	0.0322	10	0.3142	0.0978	10	4.5988	0.0005
Nov-Feb	0.1413	0.0318	10	0.2436	0.0966	10	3.1810	0.0036
SOYBEANS	Mean	SD	N	Mean	SD	n	t-stat	p-value
Feb-Apr	0.1578	0.0483	10	0.2093	0.0877	11	1.6847	0.0435
Apr-Jun	0.2046	0.0462	10	0.2091	0.0579	11	0.1968	0.4283
Jun-Jul	0.2582	0.0762	10	0.2665	0.0962	11	0.2189	0.3298
Jul-Aug	0.2087	0.0965	10	0.2750	0.1099	10	1.4353	0.2362
Aug-Oct	0.1761	0.0317	10	0.2535	0.0896	10	2.5757	0.0133
Oct-Dec	0.1456	0.0273	10	0.2215	0.0791	10	2.8714	0.0107
Dec-Feb	0.1409	0.0361	10	0.2132	0.0672	10	2.9975	0.0064
WHEAT	Mean	SD	n	Mean	SD	n	t-stat	p-value
Feb-Apr	0.2216	0.0469	10	0.3498	0.1143	11	3.4173	0.0010
Apr-Jun	0.2306	0.0567	10	0.3168	0.0887	11	2.6748	0.0048
Jun-Aug	0.2299	0.0465	10	0.3475	0.1085	10	3.1512	0.0076
Aug-Nov	0.1989	0.0269	10	0.3213	0.0988	10	3.7797	0.0011
Nov-Feb	0.1850	0.0182	10	0.2880	0.0836	10	3.8044	0.0010

[7] The null hypothesis for the t-test is that there is no difference in the sample means. The alternative hypothesis assumes that the realized volatility in the second period is larger than in the first period. Jarque-Bera tests were also conducted, and the null hypothesis that the volatility is normally distributed could not be reject for any time interval at the 1% significance level.

We continue our analysis using the calculated realized volatility to calculate the naïve volatilities and to estimate the historical volatilities using the SARIMA model. Moreover, we use the options data to calculate the implied forward volatilities. All volatility forecasts methods show significant seasonal patterns for all commodities. Figure 4A in the Annex illustrates the results found for the IFV forecasts using boxplots for all commodities.

Tables 1A through 4A present all the results for the forecast evaluation analysis. Table 1A presents the results for the whole period, while the other three tables show the results for three sub-periods: before, during, and after the 2008 crisis.

The analysis of the results presented in Table 1A show that most of the estimated slope coefficients are significantly different from zero in all regressions, indicating that the IFV, the naïve HV, and the SARIMA-HV contain information about the future realized volatility. Most of the forecast methods provided biased (except the SARIMA-HV for corn and soybeans, the IFV for wheat) and non-efficient predictors of the market volatility (except the IFV for corn and wheat).

A prior analysis of the results suggests that the naïve-HV was the poorest predictor of the realized volatility between 2006-2016. The coefficients of determination (R^2) and the slope parameters in the naïve-HV regressions have the smallest values among all regressions (with the exception of the R^2 for corn). The IFV, on the other hand, presents significant better outcomes. The results for all IFV regressions in Table 1A present the highest R^2 coefficients, and significant information predicting the realized volatility (high values for slope coefficients). Moreover, the IFV method seems to outperform the SARIMA-HV since the presence of historical forecasts does not improve the information already given by the implied volatility while predicting the realized values.

The analysis of the results for the three sub-periods have similar results regarding the naïve-HV forecast method. The results in Tables 2A, 3A and 4A show that the most basic method was outperformed by the other methods for all sub-periods, and commodities. Therefore, the volatility forecast based only in the past year information does not seem to be a good predictor for future volatilities.

The analysis for the first period (before the crisis) for corn shows that, even though the results using the IFV are unbiased, and the results using the SARIMA-HV contain less information about the market data, both models performed equally well predicting corn prices volatility. For the wheat market, all the methods resulted in biased and efficient results, and the IFV method seems to contain more information about the realized volatility than other forecasts. The SARIMA-HV outperformed all other forecast methods to predict soybean prices volatility during the first sub-period.

For the crisis period, we found similar results for corn and wheat. Most of the evaluated forecasts resulted in unbiased and efficient forecasts, and the results for both commodities were very poor during the crisis: the information content in the evaluated forecasts were very low, and as consequence, most of the models did not provide important contributions to predict the realized volatility (low R^2, and low and non-significant slope coefficients). No slope coefficients were statistically different from zero at the 5% significance level, for the corn and wheat analysis for the crisis period (Table 3A). The analysis for soybean prices volatilities, however, were different and the results for the IFV forecasts presented better outcomes than the other two methods.

The results for the last period for corn show that both the IFV and SARIMA-HV methods provide unbiased and efficient forecasts, and contain significant information about the realized volatility (slope coefficients close to one) - although the IFV method seems to have superior performance. The IFV also provided similar results predicting wheat and soybean prices volatilities. However, the performance for all models seems to be very poor after the crisis.

5. Conclusion

Our main findings suggest that volatility in the corn, soybean and wheat futures markets have increased over the last decades. Even though we found significant changes in the levels of risk, we also found that the seasonal patterns in all three markets are still present, and follow the critical events along the crop year for all analyzed commodities. Since market participants face higher risk levels in agricultural markets, we investigated how different forecast models perform predicting future realized volatilities.

We found that the implied forward volatility (IFV) and the historical volatility (HV) method based on SARIMA forecasts have similar predictive performance in the corn and wheat markets. Both methods seem to contain important information related to the realized volatilities, in those markets. The forecasts obtained with the FIV method seem to perform slightly better than other models since they were found to be unbiased and efficient predictors in most of the analyzed sub-periods. The historical volatility method based on the SARIMA model forecasts seems to be more appropriate to forecast future volatilities in the soybean market.

Other studies that evaluate different volatility forecast methods are still important to investigate price variation in the agricultural markets. Moreover, studies that investigate other contracts, such as the short-dated new crop options, could also help to understand how changes in volatility can affect hedgers' outcomes.

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Annex

Figure 1A. Realized volatility for corn futures from 1969 to 2016 (in cents/bushel)

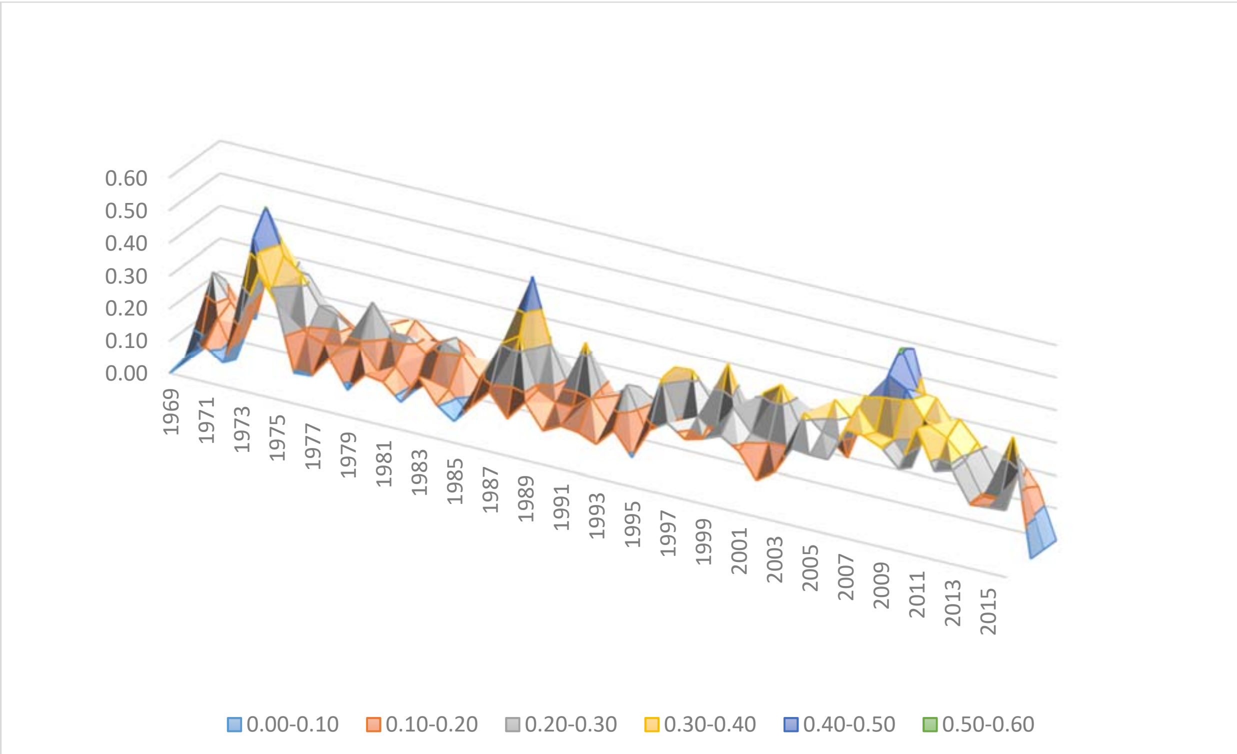

Figure 2A. Realized volatility for soybean futures from 1969 to 2016 (in cents/bushel)

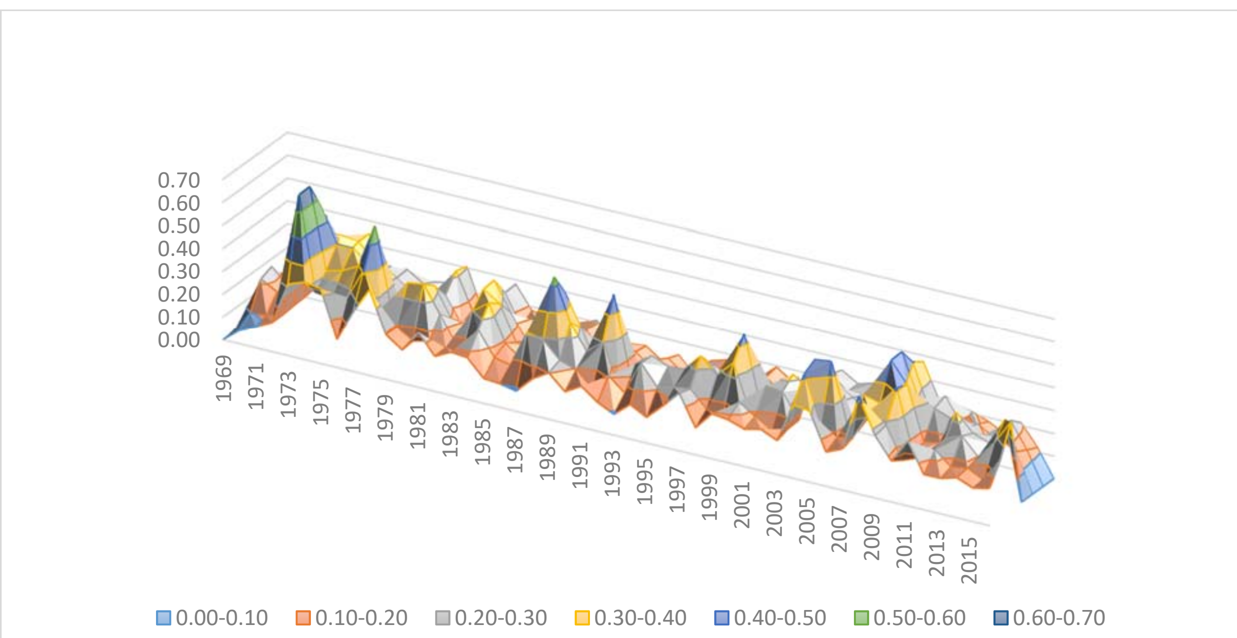

Figure 3A. Realized volatility for wheat from 1969 to 2016 (in cents/bushel)

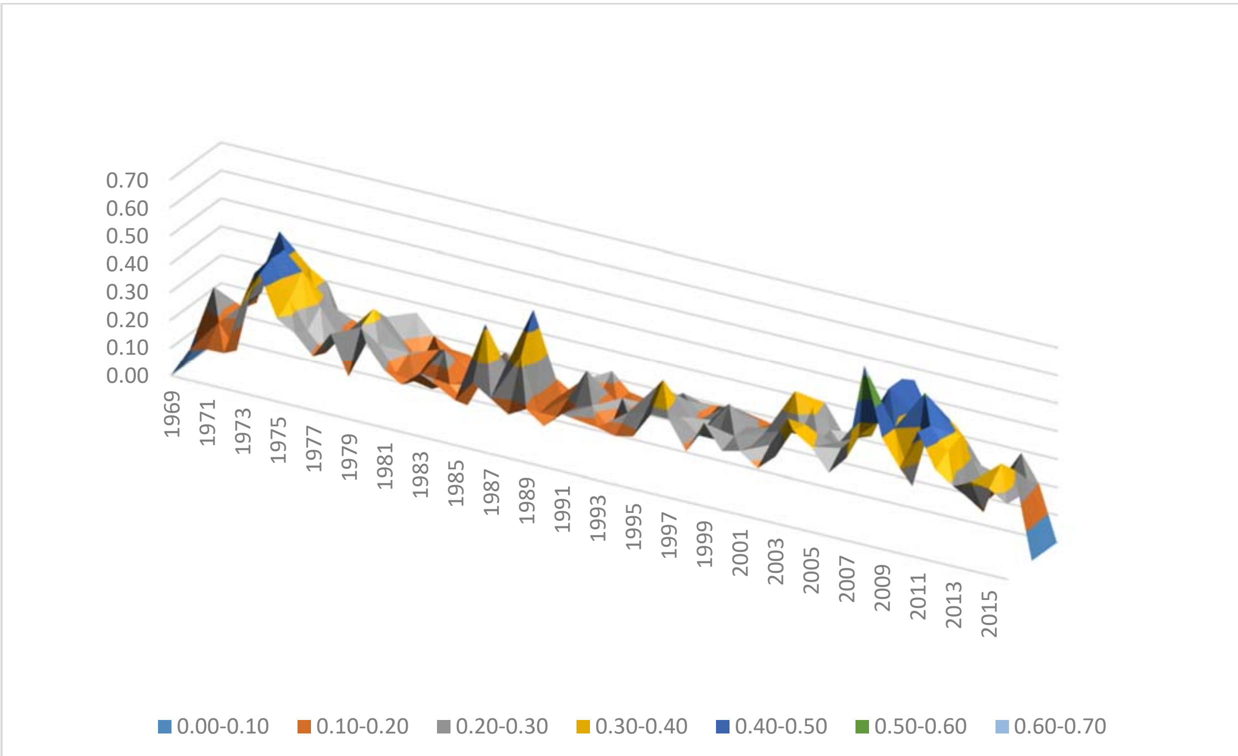

Figure 4A. Boxplots for implied forward volatilities (annualized) 2006-2016

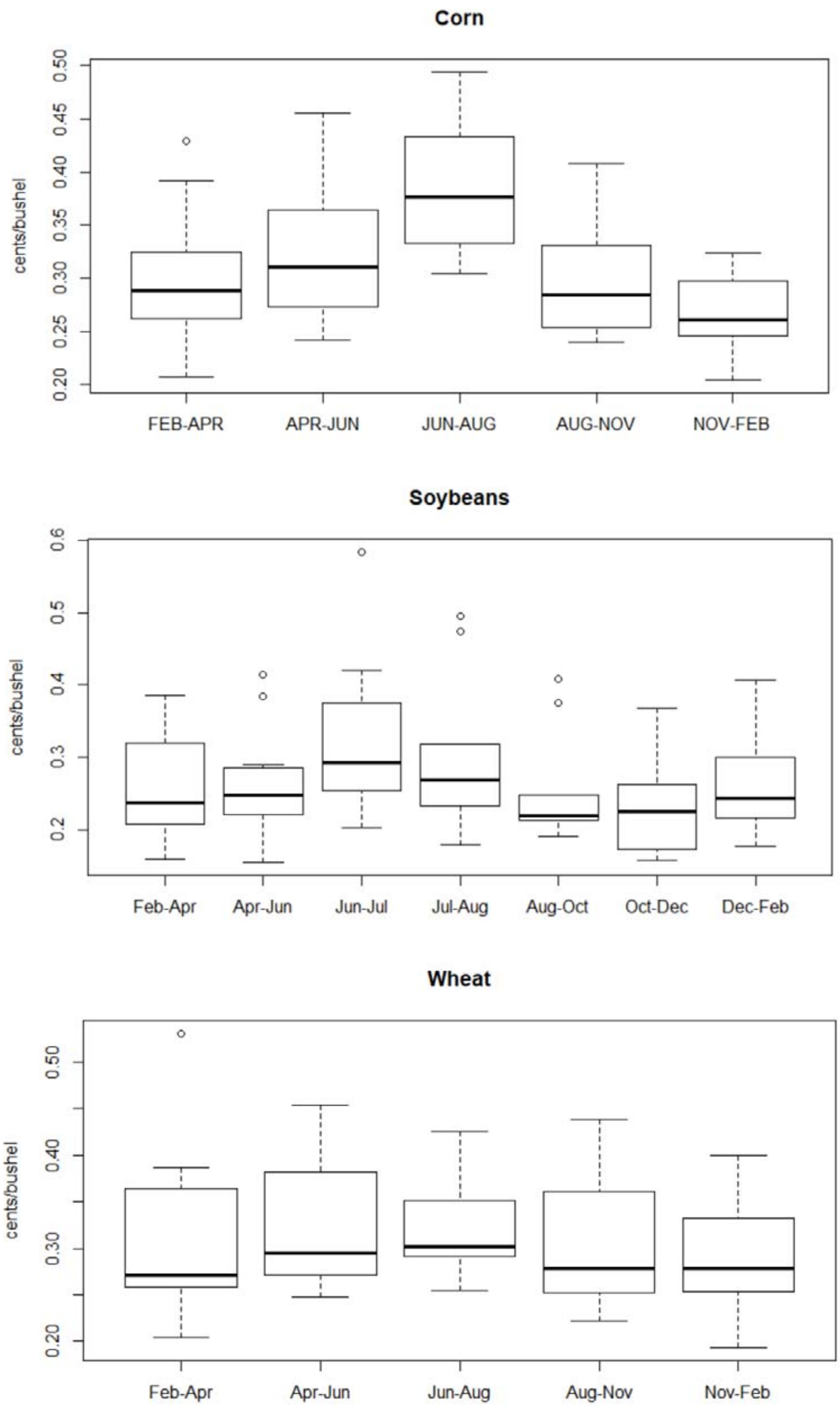

Table 1A: Summary of regressions: full period (2006 – 2016)

	CORN				***WHEAT***				***SOYBEANS***			
Variables/ Coefficients	IFV	HV-ARIMA	HV-NAIVE	IFV + HV-ARIMA	IFV	HV-ARIMA	HV-NAIVE	IFV + HV-ARIMA	IFV	HV-ARIMA	HV-NAIVE	IFV + HV-ARIMA
α_0	0.064 *	0.159 **	0.186 ***	0.121 **	0.094	0.156 ***	0.250 ***	0.060	0.072 ***	0.078 ***	0.200 ***	0.043
	[0.038]	[0.063]	[0.042]	[0.056]	[0.057]	[0.032]	[0.039]	[0.048]	[0.026]	[0.029]	[0.033]	[0.044]
σ_{IFV}	0.726 ***			0.918 ***	0.725 ***			0.539 ***	0.589 ***			0.535 ***
	[0.113]			[0.180]	[0.179]			[0.162]	[0.116]			[0.106]
$\hat{\sigma}_{ARIMA}$		0.480 **		-0.42		0.556 ***		0.303 ***		0.705 ***		0.196
		[0.190]		[0.267]		[0.081]		[0.094]		[0.138]		[0.189]
$\hat{\sigma}_{NAIVE}$			0.367 ***				0.236 ***				0.143	
			[0.108]				[0.086]				[0.133]	
R^2	0.38	0.08	0.13	0.41	0.336	0.201	0.058	0.389	0.384	0.137	0.021	0.392
# obs.	50	51	51	50	50	51	51	50	70	71	71	70
Wald test $\alpha_0 = 0, \alpha_1 = 1$	6.74	3.93	3598		1.48	15.01	43.15		9.87	4.00	20.88	
p-value	*0.003*	*0.026*	*0.000*		*0.237*	*0.000*	*0.000*		*0.000*	*0.023*	*0.000*	
Residualss												
Jarque-Bera	5.08	2.90	7.08	3.19	0.04	13.79	9.62	0.51	2.32	20.19	19.53	2.64
p-value	*0.08*	*0.23*	*0.03*	*0.20*	*0.98*	*0.001*	*0.01*	*0.78*	*0.314*	*0.000*	*0.000*	*0.266*
DW	1.62	1.00	1.04	1.71	1.62	1.24	1.09	1.63	1.18	0.97	0.71	1.22
MAPE	21.98	24.47	24.31		20.29	23.70	30.70		32.66	24.85	36.42	
HLN-DM (IFV and HV-ARIMA)	1.12				1.41				2.58			
p-value	*0.269*				*0.165*				*0.012*			
HLN-DM (HV-ARIMA and HV-NAIVE)		0.07				-2.32				3.25		
p-value		*0.948*				*0.024*				*0.002*		

*** significant at the 1% level.
** significant at the 5% level.
* significant at the 10% level.
Standard errors in brackets.

Table 2A: Summary of regressions: before the crisis

	CORN – p2.2006 - p3.2008				***WHEAT - p2.2006 - p3.2008***				***SOYBEANS - p2.2006 - p4.2008***			
Variables/ Coefficients	IFV	HV-ARIMA	HV-NAIVE	IFV + HV-ARIMA	IFV	HV-ARIMA	HV-NAIVE	IFV + HV-ARIMA	IFV	HV-ARIMA	HV-NAIVE	IFV + HV-ARIMA
α_0	0.156 *	0.126	0.313 ***	0.172	0.090	0.213 ***	0.134 *	0.124 ***	0.051	-0,044	0,251 ***	0,197
	[0.081]	[0.098]	[0.027]	[0.110]	[0.068]	[0.052]	[0.070]	[0.031]	[0.04]	[0,15]	[0,05]	[0,120]
σ_{IFV}	0.468 *			0.618	0.812 ***			0.357 *	0.618 ***			0,894 ***
	[0.231]			[0.920]	[0.235]			[0.161]	[0.13]			[0,236]
$\hat{\sigma}_{ARIMA}$		0.788 *		-0.257		0.517 ***		0.360 ***		1,392 **		-1,077
		[0.399]		[1.536]		[0.118]		[0.069]		[0,64]		[0,786]
$\hat{\sigma}_{NAIVE}$			0.018				0.847 **				0,003	
			[0.122]				[0.320]				[0,25]	
R^2	0.37	0.33	0.00	0.38	0.64	0.27	0.16	0.83	0.52	0,17	0,00	0,55
# obs.	11	12	12	11	11	12	12	11	16	17	17	16
Wald test $\alpha_0 = 0, \alpha_1 = 1$	3.46	13.72	70.60		8.47	9.08	12.07		12.20	2,03	11,98	
p-value	*0.076*	*0.001*	*0.000*		*0.009*	*0.006*	*0.002*		*0.001*	*0,166*	*0,001*	
Residuals												
Jarque-Bera	1.22	1.04	1.47	1.18	0.51	25.43	8.19	0.51	2.102	3,956	3,539	1,95
p-value	*0.54*	*0.59*	*0.48*	*0.55*	*0.77*	*0.000*	*0.017*	*0.78*	*0.35*	*0,14*	*0,17*	*0,377*
DW	1.861	1.931	1.44	1.90	2.01	1.69	1.93	2.63	2.04	1,43	0,78	1,99
MAPE	18.61	22.18	22.60						35.43	20,58	33,93	
HLN-DM (IFV and HV-ARIMA)	0.498				2.406				4.974			
p-value	*0.628*				*0.035*				*0.000*			
HLN-DM (HV-ARIMA and HV-NAIVE)		-0.11				-0.039				2.293		
p-value		*0.913*				*0.970*				*0.036*		

*** significant at the 1% level.
** significant at the 5% level.
* significant at the 10% level.
Standard errors in brackets.

Table 3A: Summary of regressions: during the crisis

	CORN – p4.2008 - p1.2011				***WHEAT – p4.2008 - p1.2011***				***SOYBEANS – p5.2008 - p1.2011***			
Variables/ Coefficients	IFV	HV-ARIMA	HV-NAIVE	IFV + HV-ARIMA	IFV	HV-ARIMA	HV-NAIVE	IFV + HV-ARIMA	IFV	HV-ARIMA	HV-NAIVE	IFV + HV-ARIMA
α_0	0.282 [0.161]	0.491 ** [0.214]	0.360 ** [0.120]	0.422 ** [0.189]	0.333 *** [0.096]	0.255 *** [0.069]	0.489 *** [0.068]	0.240 [0.146]	0.022 [0.10]	0,151 ** [0,06]	0,359 *** [0,10]	-0,024 [0,112]
σ_{IFV}	0.188 [0.393]			0.823 ** [0.343]	0.120 [0.261]			0.045 [0.316]	0.757 ** [0.27]			0,678 ** [0,279]
$\hat{\sigma}_{ARIMA}$		-0.449 [0.616]		-1.197 [0.844]		0.368 * [0.197]		0.361 * [0.189]		0,508 *** [0,13]		0,286 * [0,136]
$\hat{\sigma}_{NAIVE}$			-0.026 [0.283]				-0.269 [0.178]				- 0,240 [0,29]	
R²	0.02	0.05	0.00	0.22	0.01	0.117	0.086	0.119	0.34	0,13	0,06	0,38
# obs.	13	13	13	13	13	13	13	13	18	18	18	18
Wald test $\alpha_0 = 0, \alpha_1 = 1$	4.56	2.89	11.63		5.99	7.61	26.65		3.31	15,05	9,76	
p-value	*0.036*	*0.098*	*0.002*		*0.017*	*0.008*	*0.000*		*0.062*	*0,001*	*0,002*	
Residuals												
Jarque-Bera	0.86	0.57	0.77	0.77	0.20	0.252	0.708	0.19	0.420	1,097	1,05	0,382
p-value	*0.65*	*0.75*	*0.68*	*0.68*	*0.91*	*0.881*	*0.702*	*0.91*	*0.81*	*0,58*	*0,59*	*0,83*
DW	1.204	1.147	1.18	1.53	1.92	2.20	1.728	2.23	0.845	0,680	0,436	0,92
MAPE	24.12	23.61	25.74						39.81	28,63	56,90	
HLN-DM (IFV and HV-ARIMA)	0.09				0.886				1.45			
p-value	*0.925*				*0.393*				*0.167*			
HLN-DM (HV-ARIMA and HV-NAIVE)		0.37				1.670				3.09		
p-value		*0.714*				*0.121*				*0.007*		

*** significant at the 1% level.
** significant at the 5% level.
* significant at the 10% level.
Standard errors in brackets.

Table 4A: Summary of regressions: after the crisis

	CORN – p2.2011 - p2.2016				*WHEAT - p2.2011 - p2.2016*				*SOYBEANS - p2.2011 - p2.2016*			
Variables/ Coefficients	IFV	HV-ARIMA	HV-NAIVE	IFV + HV-ARIMA	IFV	HV-ARIMA	HV-NAIVE	IFV + HV-ARIMA	IFV	HV-ARIMA	HV-NAIVE	IFV + HV-ARIMA
α_0	0.001	-0.018	0.121 ***	0.003	-0.024	0.116 **	0.195 ***	-0.024	0.185 **	0,335 ***	0,178 ***	0,320 ***
	[0.044]	[0.076]	[0.033]	[0.189]	[0.097]	[0.048]	[0.05]	[0.099]	[0.07]	[0,08]	[0,04]	[0,09]
σ_{IFV}	0.903 ***			0.917 ***	1.101 ***			1.135 **	0.079			0,206
	[0.156]			[0.128]	[0.337]			[0.542]	[0.32]			[0,37]
$\hat{\sigma}_{ARIMA}$		0.968 ***		-0.021		0.563 ***		-0.032		-0,639		-0,782 *
		[0.262]		[0.292]		[0.172]		[0.248]		[0,38]		[0,43]
$\hat{\sigma}_{NAIVE}$			0.492 ***				0.289 *				0,116	
			[0.108]				[0.143]				[0,19]	
R^2	0.45	0.30	0.26	0.45	0.35	0.19	0.12	0.35	0.003	0,044	0,012	0,06
# obs.	26	26	26	26	26	26	26	26	36	36	36	36
Wald test $\alpha_0 = 0, \alpha_1 = 1$	5.18	3.14	12.94		0.10	3.24	12.53		4.69	13,93	12,72	
p-value//	*0.014*	*0.061*	*0.001*		*0.91*	*0.057*	*0.000*		*0.016*	*0,000*	*0,0001*	
Residuals												
Jarque-Bera	0.80	1.72	2.03	0.78	0.43	0.54	0.261	0.45	3.237	2,944	3,93	2,23
p-value	*0.67*	*0.42*	*0.36*	*0.68*	*0.80*	*0.76*	*0.878*	*0.80*	*0.198*	*0,229*	*0,14*	*0,33*
DW	1.919	1.579	1.518	1.92	1.38	0.97	0.847	1.40	1.312	1,363	1,35	1,372
MAPE	22.34	25.96	24.39						27.86	24,98	27,36	
HLN-DM (IFV and HV-ARIMA)	3.487				-0.911				0.605			
p-value	*0.002*				*0.371*				*0.549*			
HLN-DM (HV-ARIMA and HV-NAIVE)		-0.88				2.967				1.75		
p-value		*0.383*				*0.007*				*0.08*		

*** significant at the 1% level.
** significant at the 5% level.
* significant at the 10% level.
Standard errors in brackets.