Volatility Forecasting and Time-Varying Variance Risk Premiums in Grains Commodity Markets

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Abstract

In this paper we examine empirically the predictive power of model-free option implied variance and skewness in wheat, maize and soybeans derivative markets. We find that option-implied risk-neutral variance outperforms historical variance as a predictor of future realized variance for these three commodities. In addition, we find that risk-neutral option implied skewness significantly improves variance forecasting when added in the information variable set. Variance risk premia add significant predictive power when included as an additional factor for predicting future commodity returns.

Key words: Risk neutral variance and skewness, Variance Risk Premia, Agricultural Commodities, Maize, Wheat, Soybeans, Price and Variance forecasting

JEL classification: G10, G12, Q14

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1.Introduction

Unprecedented variability or volatility in world agricultural commodity prices creates much uncertainty and risks for all market participants, and makes both short and longer term planning very difficult. A major issue, therefore, is whether and how agricultural price volatility can be predicted. We assess some existing methods for predicting agricultural price volatility and examine their validity during a market upheaval, like the recent period, and discuss possible improvements.

All strategies to cope with these risks depend explicitly or implicitly on an assessment of the degree of future market uncertainty. Sudden changes in market fundamentals tend to upset existing risk management practices, and can be very costly for market participants. For instance if traders estimate that the future market price maybe much more uncertain or variable than in the past, they may try to hold more stocks. Such behavior in the aggregate may exacerbate price spikes, and is present in all cases of sudden market upheavals. Improved assessment of the degree of future market unpredictability may help.

There are two concepts of price volatility that have been discussed in the literature. The first is historic volatility which is an ex-post concept, and refers to observed variations of market prices from period to period. It is normally computed as the standard deviation of the logarithmic return of prices over a given period of time multiplied by the square root of the frequency of observations. However, the principal concern of market participants and policy makers alike is not large ex-post variations in past observed prices per se, but large shifts in the degree of unpredictability or uncertainty of future prices. This refers to the conditional probability distribution of prices, given current information. Such a concept cannot be readily and objectively quantified, as there are no corresponding market variables. It can only be inferred from observed market variables through some appropriate model. One relatively objective measure of unpredictability is “implied volatility”, which is a measure of the market estimate of the ex-ante or conditional variance of subsequent price, based on current observations of values of options on futures prices in organized exchanges, and using the Black-Scholes (1973) model for the computations.

Estimates based on the two concepts may point in different directions, depending on data and time period. For instance illustrations in Prakash (2011b) indicate that estimates over forty years of realized volatilities of cereals, based on observed spot prices in major international markets, such as the Gulf (as compiled by FAO), exhibit mild upward trends.

However, estimates of implied volatilities of some of the same cereal prices, as inferred from option prices on the Chicago Mercantile Exchange (CME), exhibit strong upward trends over the last twenty years, when such instruments have been traded. This suggests that for the post-1990 period, there maybe different determinants of the ex-post and the ex-ante volatilities of food commodities.

During the commodity and credit crisis of 2008, observed as well as implied volatility in food and agricultural prices increased dramatically, causing widespread concern about a major shift in global agricultural markets (Prakash, 2011a, Headey and Fan, 2010, Sarris, 2011, FAO, et. al, 2011). The concerns arose because basic agricultural food commodities such as wheat, maize and soybeans cover the basic nutrition needs of many countries, especially many Low Income Food Deficit Countries (LIFDC's). Any forecasting method of the future price variability of these commodities is important for market participants and policymakers. In order to forecast the volatility of grains prices, we use the model-free version of implied variance as predictor of future variance. Model-free implied variance can be computed by using only the observed prices of out-of-the-money grains options without assuming any specific stochastic process for the price path of the underlying commodities[2] (Jiang and Tian, 2005).

Our approach is most closely related to Wang, Fausti and Qasmi (2012) and Prokopczuk and Simen (2014). Wang, Fausti and Qasmi (2012) estimate model-free option implied variance in the maize market. They were the first to demonstrate that the model-free variance is a more effective estimator of future variance, compared to backward looking methods of estimating future variance (via the family of ARCH-GARCH models) or forward looking option implied volatility methods based on Black's (1976) model.[3] Prokopczuk and Simen (2014) also use the method of model-free variance and find significant negative variance risk premia in 21 commodity markets. Our contribution, building on the model-free approach, is twofold. First, we add model-free skewness as an additional explanatory variable for forecasting future realized variance and future commodity grain returns. The addition of model-free skewness is motivated by recent results in equity options markets which have shown that implied skewness contains useful

[2] Hence the term 'model-free".

[3]Previous studies in the commodity pricing literature that use Black's implied volatility to forecast future realized volatility are Simon, 2002, Giot, 2003 and Manfredo and Sanders, 2004.

information.[4] Second, we examine agricultural commodity variance risk premiums as predictors of agricultural commodity returns. To the best of our knowledge, this is the first study that examines the predictive power of variance risk premiums in the wheat, maize and soybeans commodities markets.[5]

We find that in the maize and wheat futures markets, model-free option implied variance is a more efficient predictor of future realized variance compared to historical (lagged) variance. In contrast, model-free implied variance has almost the same forecasting power with historical variance in the case of soybeans futures. Our predictive regressions show that model free option-implied skewness improves forecasting performance when added as an additional factor in soybeans predictive regressions, while it is not a statistically significant predictor of future variance in the case of maize and wheat. In all three markets examined, the risk-neutral skewness is not related to subsequent commodity returns. However, the inclusion of Variance Risk Premium (VRP), defined as the difference between realized variance and risk-neutral implied variance, adds important predictive power when used as an additional information variable for predicting future commodity returns.

The remainder of the paper is structured as follows. In the next Section we describe the methodology for computing model-free risk neutral variance and skewness. In Section 3 we describe the data employed in the analysis, in Section 4 we discuss the empirical results and the last Section summarizes the conclusions.

2. Methodology

Our objective is to assess methods to predict the actual or ex-post realized volatility (RV) of futures prices. We utilize as predictors the currently observed implied or ex-ante volatility and a number of other variables. Our measure of ex-ante volatility or

[4]For example, Rompolis and Tzavalis (2010) show that option implied skewness corrects for bias of option implied volatility to forecast realised volatility. Conrad, Dittmar and Ghysels (2013) find that risk-neutral skewness of individual stocks has a strong negative relation with subsequent returns and Chang, Christoffersen and Jacobs (2013) find an economically significant risk premium for equity systematic risk neutral skewness.

[5] Prokopczuk and Simen (2014) examine if the variance risk premium of gold can forecast the future return of grain commodities. Kang and Pan (2013) examine if crude oil's variance risk premium can forecast future oil returns and Pokharel (2011) examine the predictive ability of the variance risk premium in the soybean market. Other studies show that the equity market variance risk premium is a robust predictor of future stock market returns (e.g, Bollerslev, Tauchen and Zhou (2009)), bond returns and credit spreads (e.g., Zhou (2010)).

unpredictability is an option implied future variance of prices. In practice the actual volatility observed over the period of trading the relevant option is not the same as the implied or expected volatility at the beginning of the trading period of an option. This is natural as there are unpredictable events that take place during the period of trading of the option. To account for this difference, option pricing models have been extended to include risk factors that investors cannot hedge. The idea is that the observed returns are governed by true probabilities that include such risk factors, but the options are priced with reference to “risk neutral” probabilities, that combine estimates of true probabilities with the market’s risk preferences[6].

To fix notation, the τ-period log-return of a commodity future is given by $R(t,\tau) = \ln[(F(t,\tau)/\ln(F(t)]$, where $F(t)$ is the price of the future contract at time t, that expires at some time in the future at or after $t+\tau$, and $F(t,\tau)$ is the price of the same future contract at time t+τ[7]. Given a particular density function $p(R)$ that describes the time series dynamics of log-returns, the (realized-real world variance) of the τ period return is equal to $\int R^2 p(R)dR - \left(\int Rp(R)dR\right)^2$. Alternatively, the (risk neutral) variance of the τ period return can be computed using information from the options market. In this case the variance of the τ period return is equal to $\int R^2 q(R)dR - \left(\int Rq(R)dR\right)^2$, where the function $q(R)$ is a density function that reflects market's expectations about future outcomes and attitudes towards risk. Note that the two density functions need not be the same. Breeden and Litzenberger (1978) show that the density function $q(R)$ is equivalent to the prices of Arrow-Debreu contingent claim securities and can be extracted from observed prices of European call and put options. In the option pricing literature, the density function $q(R)$ is also known as state price density, because it is related to Arrow-Debreu securities, or risk-neutral density. These are probabilities under the risk-neutral measure and not natural probabilities. The term risk-neutral density does not imply that investors are risk-neutral. The density function

[6] The risk neutral probability does not imply that investors are risk neutral. In fact, they are far from being risk neutral. Breeden and Litzenberger (1978) show that the risk neutral probability measure incorporates both the true market expectations and their respective risk premia (the premium demanded due to investors’ risk aversion).

[7] In the sequel the expiration time t+τ of the future contract will be considered to be the same as the expiration time of the underlying options. According to Hull (2009), "the expiration date of a futures option is usually on, or a few days before, the earliest delivery date of the underlying futures contract. For example, the CBOT Treasury Bond futures option expires on the latest Friday that precedes by at least five business days the end of the month before the futures delivery month". This fact holds for options on agricultural commodity futures, but for modeling purposes we assume that option contracts have the same expiration date with as their underlying commodity futures.

extracted from option prices is called risk-neutral because expected payoffs calculated under this density can be discounted using the risk-free rate since investor's risk-premia are embedded in the probabilities.

We estimate the model-free version of option implied variance and skewness using the method of Bakhsi, Kapadia and Madan (2003). Under the risk-neutral probability measure Q, the τ-period conditional variance and skewness of returns are given by the following formulas:[8]

$$VAR(t,\tau) = E_t^Q[(R(t,\tau) - E_t^Q(R(t,\tau)]^2 \tag{1}$$

$$SKEW(t,\tau) = \frac{E_t^Q\left(R(t,\tau) - E_t^Q\left(R(t,\tau)\right)\right)^3}{VAR(t,\tau)^{3/2}} \tag{2}$$

More analytically, the skewness and variance equations can be written as:

$$VAR(t,\tau) = E_t^Q[R(t,\tau)^2] - (E_t^Q[R(t,\tau)])^2 \tag{3}$$

$$SKEW(t,\tau) = \frac{E_t^Q\left[R(t,\tau)^3\right] - 3E_t^Q\left[R(t,\tau)\right]E_t^Q\left[R(t,\tau)^2\right] + 2E_t^Q\left[R(t,\tau)\right]^3}{VAR(t,\tau)^{3/2}} \tag{4}$$

Bakshi, Kapadia and Madan (2003) show that any payoff can be spanned and priced using option positions across different strike prices. We define the "*Quad*" and "*Cubic*" contracts as follows:

$$Quad(t,\tau) = e^{-r\tau}E_t^Q\left[R(t,\tau)^2\right] \tag{5}$$

$$Cubic(t,\tau) = e^{-r\tau}E_t^Q\left[R(t,\tau)^3\right] \tag{6}$$

[8]The probability measure Q reflects the market's expectations about future outcomes and attitudes towards risk. Breeden and Litzenberger (1978) show that the risk-neutral probabilities are equivalent to the prices of Arrow-Debreu contingent claim securities and can be extracted from observed prices of European call and put options. Therefore, the risk-neutral variance and skewness will reflect the market's expectation of the future variance and skewness as well as the market's variance and skewness risk premiums.

where r is the risk-free interest rate (3 month US-Treasury Bill) and τ represents the time to maturity for commodity futures contracts, which in our estimations is approximately equal to 2 months. Bakshi, Kapadia and Madan (2003) show that they payo

If we substitute "*Quad*" and "*Cubic*" expressions into the analytical equations of Variance *(VAR)* and Skewness *(SKEW)* in (3) and (4), we get the model free version of option implied variance *(MFIV)* and implied skewness *(MFIS)* given below:

$$MFIV(t,\tau) = e^{r\tau} Quad(t,\tau) - [E_t^Q(R(t,\tau))]^2 \tag{7}$$

$$MFIS(t,\tau) = \frac{e^{r\tau} Cubic(t,\tau) - 3E_t^Q(R(t,\tau))e^{r\tau} Quad(t,\tau) + 2[E_t^Q(R(t,\tau))]^3}{MFIV(t,\tau)^{3/2}} \tag{8}$$

Furthermore, Bakhsi, Kapadia and Madan (2003) show that under the risk-neutral pricing measure Q, the *Quad* and *Cubic* contracts are functions of a continuum of out-of-the-money European calls $C(t,\tau,K)$ and out-of-the-money European puts $P(t,\tau,K)$ in the form given below:

$$Quad(t,\tau) = \int_F^\infty \frac{2\left(1-\ln\left[\frac{K}{F}\right]\right)}{K^2} C\left(t,\tau,K\right) dK + \int_0^F \frac{2\left(1+\ln\left[\frac{F}{K}\right]\right)}{K^2} P\left(t,\tau,K\right) dK \tag{9}$$

$$Cubic(t,\tau) = \int_F^\infty \frac{6\ln\left(\frac{K}{F}\right) - 3\ln\left(\frac{K}{F}\right)^2}{K^2} C\left(t,\tau,K\right) dK - \int_0^F \frac{6\ln\left(\frac{F}{K}\right) + 3\ln\left(\frac{F}{K}\right)^2}{K^2} P\left(t,\tau,K\right) dK \tag{10}$$

where is the strike price of the futures options contract, F is the price of the underlying futures contract, t is the trading date and τ is the time to expiration of the option contract which by definition coincides with the expiration date of the underlying futures contract.

In addition, Bakhsi, Kapadia and Madan (2003) prove that the expected risk-neutral first moment $E_t^Q\left[R(t,\tau)\right]$ in the $MFIV$ and $MFIS$ formulas, can be approximated by the following expression:

$$E^Q\left[R(t,\tau)\right] = e^{r\tau} - 1 - \frac{e^{r\tau}}{2} Quad(t,\tau) - \frac{e^{r\tau}}{6} Cubic(t,\tau) \quad (11)$$

The variance risk premium represents the compensation demanded by investors for bearing variance risk and is defined as the difference between ex-post realized variance and the risk-neutral expected value of the realized variance. More specifically, following Carr and Wu (2009) and Christoffersen, Kang and Pan (2010), we define the τ-period variance risk premium as the difference between the realized variance (RV) and the Q–measure expected variance, using the following formula:

$$VRP(t,\tau) = RV(t,\tau) - E_t^Q(RV(t,\tau)) = RV(t,\tau) - MFIV(t,\tau) \quad (12)$$

In our empirical applications framework, $RV(t,\tau)$ is the realized 2-month variance of commodity futures prices for the time interval [t,τ], and $E_t^Q(RV(t,\tau))$ is the ex-ante 2-month model-free implied variance $MFIV(t,\tau)$ which is computed from options traded at time t and expired at time τ. Thus, $MFIV(t,\tau)$ is computed from out-of-the-money put and call options with two months to expiration (τ-t=60 days).

3. Data and variables utilized

3.1. Futures and Options Data

We obtained daily options and futures data for maize, wheat and soybeans from the Chicago Board of Trade (CBOT). The data covers the period from January 1990 to December 2011. We first match for each day and each maturity, the maturity of the option with the maturity of the corresponding future contract in order to construct the correct mapping between options and underlying contracts.

Formulas (9) and (10) require a continuum of option prices. These must be inferred from the discrete number of observable option prices. The following procedure for this is followed. First, in order to avoid measurement errors, we eliminate observed options with moneyness level less than 80% $(K/F < 0.8)$ and options with moneyness level greater than 120% $(K/F > 1.2)$.[9] Then we first estimate implied volatilities via the Black (1976) model for the observed traded options. Then, following Jian gand Tian (2005) and Chang,

[9]Moneyness level is defined as K/F, where K is the strike price of the option contract and F is the price of the underlying futures contract.

Christoffersen, Jacobs and Vainberg (2009), we use a cubic spline in order to interpolate-extrapolate the implied volatilities estimated via the Black (1976) formula for various moneyness levels. We construct a fine grid of 1001 moneyness levels by interpolating-extrapolating our selected (with moneyness band [0.8 1.2]) moneyness levels. By this method we create a fine grid of 1001 moneyness levels with a band ranging between 50% and 300%. We then create a grid of 1001 implied volatilities each one corresponding to one of the 1001 moneyness levels[10]. In order to get econometrically reliable information from the grid of 1001 pairs of values for moneyness levels and implied volatilities, we do not make any interpolation – extrapolation, thus we do not compute model free variance and skewness when the number of traded options for a given trading day and a given maturity date is less than four[11].

Using Black's (1976) formula, we convert these 1001 implied volatilities into option prices. We choose out-of-the-money put options with moneyness level smaller than 100% $(K/F<1)$, and out-of-the-money call options with moneyness level larger than 100% $(K/F>1)$. We use numerical trapezoidal integration to compute the *Quad* and *Cubic* contracts in (9) and (10). We then use the prices of *Quad* and *Cubic* contracts in order to compute $MFIV$ and $MFIS$ in (7) and (8) for each trading day and each maturity.

We split the period January 1990- December 2011 into fixed non-overlapping successive 2-month periods[12]. For each 2 month period, we construct the fixed 2-month horizon $MFIV$ and $MFIS$ time series using the prices of the first trading day within the period. Finally we define the 2-month horizon model-free implied variance and model free implied skewness for each 60 day period using the following linear interpolation:

$$MFIV_{60} = \left(T_1 MFIV_1 \frac{T_2 - T_{60}}{T_2 - T_1} + T_2 MFIV_2 \frac{T_{60} - T_1}{T_2 - T_1} \right) \times \frac{T_{365}}{T_{60}} \tag{13}$$

where $MFIV_1$ is the model free implied variance with maturity closest to but less than 60 days, and $MFIV_2$ is the model free implied variance with maturity closest to but larger than

[10] We avoid the inclusion of deep out-of-the-money options (these options are less liquidly traded and because of this they lead to biased implied-volatility estimates), since we choose [0.8 1.2] as our original moneyness band. Afterwards we extrapolate this band in order to get a reliable (representative) set of 1001 moneyness-implied volatility pairs based on our original moneyness band.

[11] The phenomenon of having less than four options for a given trading date and a given maturity occurs only for 4 days in our whole data sample and as a result it does not have a significant impact on the construction of model free option implied moments.

[12] The results remain largely unchanged if we use overlapping monthly periods (namely January-February, as well as February-March, instead of January February, and then March-April)

60 days[13]. T_1 and T_2 are days to expiration for $MFIV_1$ and $MFIV_2$ with $T_1 < 60$ and $T_2 > 60$.[14] T_{365} and T_{60} are equal to 365 and 60 respectively, representing the number of days in the relevant time intervals. We follow the same interpolation method for the construction of the model-free implied skewness.

The realized variance is calculated using daily closing prices of the nearby futures contract to get the best possible approximation of a fixed maturity of 60 days. If the nearby contract has less than 60 days to expiration, we replace it with the next contract which always has more than 60 days to expiration[15]. We compute two–month realized variance on commodity futures using non-overlapping two-month estimation windows. For example, the realized variance of the January 1990-February 1990 period is the variance of daily returns of the these two months multiplied by 252 in order to be annualized.

3.2. Commodity Variables

In the empirical analysis we use several commodity specific variables: hedging pressure, basis and inventories.

The hedging pressure is defined as the difference between the number of short and the number of long hedge positions in the futures markets relative to the total number of hedge positions by large (commercial) traders. Following Christoffersen, Kang and Pan (2010), we compute hedging pressure in wheat, corn and soybeans futures markets using the following formula:

$$HedgingPressure_t = \frac{(\#\, of short\ hedgepositions)_t - (\#\, of long\ hedgepositions)_t}{(\#\, of total\ hedgepositions)_t}$$

Weekly data for the number of short and long hedge positions for wheat, maize and soybeans futures were obtained from the U.S. Commodity Futures Trading Commission.

[13]When, for example, for a given trading day we get a model free implied variance which has been computed by using OTM options which expire after 50 days and the next deferred model free implied variance has been computed by using OTM options which expire after 65 days, we linearly interpolate these two MFIVs using equation (13) mentioned above. After constructing the daily time series of $MFIV_{60}$ and $MFIS_{60}$, we choose the beginning of each 2-month period $MFIV_{60}$ and $MFIS_{60}$ prices in order to construct the 2-month time series.
[14]When time to maturity is equal to 60 days, we already have the 60 day model free implied variance, thus we do not need to use the interpolation method described in equation (13).
[15]For example, when at the beginning of a given 2-month period the nearest futures contract has 75 days to expiration, we keep it only for 15 days and then we change it with the next deferred contract which by definition will have more than 60 days to expiration. By replacing the commodity futures contracts inside the 2-month period, we get the best possible approximation of 2-month horizon realized variance.

We compute 2-month hedging pressure using the number of short and long hedge positions of the first week of the first month of each 2-month period.

The basis is defined as the percentage difference between futures price and the spot price at the beginning of each 2-month period. In order to calculate the basis, we obtain monthly data for commodity spot prices from CME group. We convert the units of spot prices ($/metric ton) into the same unit of futures prices (cents/bushel) and we calculate the basis for the beginning month for each 2-month period as follows:

$$Basis = \frac{F_{t,T} - S_t}{S_t} \tag{14}$$

where $F_{t,T}$ is the futures price at the first trading day of each two-month period(represented by t) for the future contract that expires at date T (hence $T-t$ denotes time to maturity). For computing the fixed 2-month basis, we choose the nearest futures contract with maturity always more than 60 days $(T-t \geq 60)$. S_t is the corresponding monthly commodity spot price at the beginning month of each 2-month period.

Concerning stocks, we obtained quarterly inventory data for maize, wheat and soybeans from the National Agricultural Statistics Service of US. From the quarterly data we construct monthly inventory data using a polynomial interpolation. We use the natural logarithm of the interpolated monthly inventory levels at the beginning month of each 2-month period. Motivated by the empirical findings of Du, Yu and Hayes (2011), who find volatility spillover effects from crude oil to maize and wheat markets, we also include the volatility of crude oil prices as an additional volatility predictor in the grains sector.

The daily data for crude oil prices were downloaded from Federal Reserve Bank of Saint Louis.

We compute the two-month futures commodities return according to a *rolling strategy* and a *held to maturity strategy*. In the rolling strategy we compute two-month returns of the nearby contract, when the contract expires at or after 60 days from the day t. When the maturity of the futures contract is less than 60 days, the futures contract is replaced by the next futures contract. The formula for computing 2-month futures returns of a rolling futures position is given below:

$$R^{roll}_{t,t+60} = \frac{F(t+60, T_2) - F(t, T_1)}{F(t, T_1)} \tag{15}$$

$F(t,T_1)$ is the price of the nearest futures contract at the beginning of the 2-month period, which has maturity date T_1 and expiration greater than 60 days $(T_1 - t \geq 60)$. In complete accordance with the selection of $F(t,T_1)$, $F(t+60,T_2)$ is the price of the nearest futures contract at the end of the 2-month period with expiration greater than 60 days $(T_2 - (t+60) \geq 60))$. By this means we compute the 2-month returns on a rolling long position in agricultural commodity futures with constant 2-month maturity.[16]

We also compute the return of a futures contract (with 2-month maturity) for an investor who buys the contract at the start of the 2-month period and keeps it until maturity (held to maturity strategy). This type of return almost coincides with the 'realized futures premium' described in Fama and French (1987), since near maturity, futures price converges to spot price.

The commodity futures return on a long futures position that is held till maturity is the following:

$$R_{t,t+60}^{mat} = \frac{F(t+60,T) - F(t,T)}{F(t,T)} \qquad (16)$$

where $F(t,T)$ is the price of the futures contract at the beginning of the 2-month period with maturity nearest to (but always more than) 60 days $(T - t \geq 60)$ and $F(t+60,T)$ is the price of the same futures contract at the end of the 2-month period, which in many cases converges to the corresponding spot price at the given date.[17]

3.3. Macroeconomic Data

[16]When computing the returns on a rolling position what we actually compute is the 2-month percentage change in commodity futures with (approximately) 2 months for maturity. By this we mean that in many cases the futures contracts $F(t,T_1)$, $F(t+60,T_2)$ which are used at the beginning and at the end of the period have different maturities ($T_1 \neq T_2$). Thus, in the return computation method described in equation (15), we do not take into consideration the necessary close of the initial position $F(t+\Delta t,T_1)$ and the synchronous opening of the position $F(t+\Delta t,T_2)$ which takes place during the 2-month period ($1<\Delta t<60$). This does not change our results-conclusions, since they remain unaltered when we add in formula (15) the extra gains-losses of the closing-opening of the positions occurring during the 2-month period.

[17]When for example, at the beginning of the 2-month period the nearest futures contract has 65 days to expiration, then, at the end of the 2-month period this contract will have 5 days to expiration. Thus, the return of the *held till maturity strategy* will in many cases coincide with the realized futures premium, since the prices of the futures contracts with only few days to expiration are always converging to the corresponding spot prices. We have to state here that in many of our 2-month periods we were able to find futures contracts with approximately 2-month maturity, thus, it is fair to say that our *held to maturity strategy* almost coincides (or numerically converges) with what Fama and French (1987) call realized futures premium.

In the empirical analysis we use as macroeconomic factors monthly data for the Consumer Price Index (CPI), Industrial Production Index (IPI), money supply M2 and the NBER recession index. For each macroeconomic factor (besides NBER) we compute the 2-month percentage changes. We also use the 3-month Treasury-Bill as the best approximation of a 2-month T-Bill. We were not able to find time series data for US Treasury-Bills with maturity shorter than 2 months, in order to construct an interpolated 2-month Treasury bill.[18] The data on CPI, Industrial Production Index, M2 money supply and NBER recession index were obtained from the Federal Reserve Bank of Saint Louis and cover the period from January 1990 through December 2011. The NBER recession index is a dummy variable which takes the value 1 whenever the US economy enters into a recessionary period and 0 otherwise. Three month US Treasury-Bill data were downloaded from DataStream and also cover the same time period. For exchange rate we use a weighted average of the foreign exchange value of US currency against a subset of index currencies outside US which are the Euro area, Canada, Japan, UK, Switzerland, Australia and Sweden. We obtain daily exchange rate data from Federal Reserve Bank of Saint Louis.

4. Empirical results

4.1 Descriptive statistics

Each observation of our sample refers to a 2 month non-overlapping period starting in January 1990 and ending in December 2011. The various statistics for each observation are computed from daily prices within each 2 month period as described earlier. Table 1 reports the descriptive statistics for the realized variance (RV), model free implied variance (MFIV), model free implied skewness (MFIS) and the variance risk premium (VRP). For maize and soybeans the average MFIV is higher than the average historical realized variance (RV). The average variance risk premium is negative in both markets and statistically significant at the 5% level (t-stat = -2.10 for maize and t-stat = -2.58 for soybeans). The negative VRP can be interpreted as the cost of insurance against variance risk. The soybeans market has the most negative variance risk premium. The variance risk

[18]The Treasury-Bill data we use have a constant 3-month maturity irrespective of the day.

premium of wheat is positive but is not statistically significant (t-stat = 1.04). The average implied skewness is negative for maize and positive for wheat and soybeans. [19]

[Insert Table 1 Here]

Figure 1 depicts the time series data of 2-month model free implied variance versus 2-month realized variance for maize, wheat and soybeans futures, respectively. At the beginning of 2008, realized as well as model free implied variance increased significantly. This happened because the fundamentals of the markets (production, carryover stocks, demand, etc.) pointed to a current as well as subsequent shortage, and created considerable uncertainty in the commodity markets. Figure 2 plots model-free implied variances and spot prices. For all three commodities the relationship between spot prices and *MFIV* is positive. This is consistent with the notion that extraordinarily high prices such as those that occurred during the recent commodity boom, tend to reflect, apart from current fundamentals, a high degree of uncertainty by market participants of the future market fundamentals, hence leading them to short-run risk management strategies that emphasize security in the form of speculatively high stocks. The additional demand for such stocks, tends to boost current prices. In addition, the dearth of adequate stocks during the 2007-2009 period made the market react strongly to every bit of news concerning future supplies and demands, thus increasing volatility.

[Insert Figure 1 Here]
[Insert Figure 2 Here]

Figure 3 plots the evolution of the variance risk premiums. We observe that the variance risk premiums are time-varying and, as indicated in table 1, negative on average. In other words, the RV is on average smaller than the MFIV. Our results are in line with the results of Wang, Fausti and Qasmi (2012) who report negative and statistically significant VRP for the corn (maize) market. The persistence of the negativity of VRP has been extensively shown for equity and energy markets (Bakshi and Kapadia, 2003; Doran and Ronn, 2008).

[19]The estimates of the variance risk premiums are somehow different from those found in Prokopczuk and Simen (2014) (-0.023 for corn, -0.008 for soybeans and -0.007 for wheat). The difference in the estimates is probably due to the different methods for calculating the realized variance. Prokopczuk and Simen (2014) calculate the realised variance using a constant maturity futures time series by linear interpolation of futures contracts maturing at T1 and T2 that are closest to and cover 60 days. In our paper we use the raw futures data without interpolation.

The higher MFIV compared to RV which we report shows that risk averse agricultural commodity investors, just like equity investors, are willing to pay a (variance risk) premium in order to hedge future variance risk. In other words, this illustrates that the MFIV of agricultural markets incorporates both economic uncertainty and risk aversion components.

[Insert Figure 3 Here]

We also examine seasonal patterns in variance risk premiums. To this end, we use the full data sample and calculate average premiums for each month during the year. The average overlapping monthly premiums having a 2-month horizon are plotted in Figure 4.[20] There does not seem to be a marked seasonal pattern for the VRPs. For wheat and maize the month with the highest value of the VRP seems to be October, while for soybeans it appears to be July.

[Insert Figure 4 Here]

We also examine the seasonal patterns of monthly realized variance. In complete accordance with the VRP computations, we again compute the average realized variance of futures prices for each month during the year. Figure 5 shows the average realized variance for each calendar month. From figure 5 we observe that for maize and soybeans July is the month with the highest price variability during the year, while for wheat is October. July tends to be the most important month for determining corn and soybeans yields. This is because critical stages of crop development (e.g., pollination) typically occur during July (source: United States Department of Agriculture). During that time period, volatility increases because of the new information arriving to the markets about the upcoming crops. We find that all the average monthly realized variances shown in figure 5 are statistically significant at 1% level, a fact which further strengthens the existence of seasonal patterns in the volatility path of maize, wheat and soybeans prices.[21]

[20]For each month we compute the overlapping VRPs with 2-month horizon using equation (12). Since we have 22 years of observations, we then have 22 VRP prices to be averaged for each calendar month.

[21]We also come to similar conclusions when we compute the average 2-month realized variance for each 2-month period during the year, since the July-August time interval is the one with the highest levels of realized variance for maize and soybeans markets. The average 2-month realized variances are also statistically significant at the 1% level. Since the realized variance is calculated using short-term futures contracts, the seasonality patterns may also depend on contract specific factors.

[Insert Figure 5 Here]

Figure 6 plots the time evolution of the option-implied skewness. We observe that until 2002, implied skewness had been largely negative in all three markets. In the post 2002 period, implied skewness turned positive. This means that after 2002 option writers started to assign higher risk neutral probabilities to the event of commodity price increases, probably due to the low interest rate environment and the monetary easing deployed by the Fed during that period[22].

[Insert Figure 6 Here]

Figure 7 plots the maize, wheat and soybeans basis. Maize and wheat basis were negative on average during the 1990-2011 period. The negative basis implies increased convenience yield for holding physical inventory of wheat and maize. This cannot hold over a whole year, it rather holds normally towards the end of the season. We also observe similar patterns in maize and wheat basis variation. Fama and French (1988) and Bailey and Chan (1993) analyze the existence of common risk factors driving commodity futures basis. On the other hand, soybeans basis is not persistently negative and changes signs randomly and quite often. Since soybeans is an internationally traded commodity the convenience yield for holding soybeans is insignificant because of the small probability of a stock-out of inventories. Another economic interpretation of the insignificance of soybeans convenience yield is the fact that soybeans storage is considerably less important in relation to production in the United States than are corn or wheat storage. Thus, we conclude that soybeans basis is probably driven by common (macroeconomic) risk factors instead of idiosyncratic (market-specific) ones.

[Insert Figure 7 Here]

[22]Frankel (2008) and Frankel and Rose (2010) find that the lax monetary policy deployed by the Fed during the last decade was the primary factor of the rise of agricultural and mineral prices. We additionally show that option-implied expectations about these prices were also upwardly revised from 2002 onwards.

4.2 Variance forecasting

We explore a variety of determinants of future commodity price RV. We use model free implied variance and historical variance as the predictors of future variance, supplemented by skewness, hedging pressure, changes in industrial production, money supply M2 and the 3-month US Treasury-Bill. Our baseline regression is given by:

$$\begin{aligned} RV_{t,t+1} &= b_0 + b_1 * IV_t + b_2 * RV_t + b_3 * IS_t + b_4 * HP_t + b_5 * Inv_t \\ &+ b_6 * IP_t + b_7 * T_t + b_8 * M_t + b_9 * NBER_t + e_{t,t+1} \end{aligned} \tag{17}$$

where $RV_{t,t+1}$ is the 2-month ahead realized variance, RV_t is the historical two-month realized variance over the two months period before the considered time, IV_t is the model free implied variance at the beginning of the 2-month period, IS_t is the model free implied skewness at the beginning of the 2-month period, HP_t is the hedging pressure at the beginning of the 2-month period, Inv_t is the logarithm of the national inventory level at the beginning of the two-month period, IP_t is the historical two-month percentage change in Industrial Production Index, M_t is the historical two-month percentage change in money supply M2, T_t is the 3-month Treasury-Bill and NBER is the US recession index from National Bureau of Economic Research. The sample period for the regressions is January 1990 to December 2011.

Table 2 summarizes the results of predictive regressions with respect to the future variance of maize, wheat and soybeans futures prices, respectively.

[Insert Table 2 Here]

We find statistically significant coefficients for both historical and implied variance. Implied variance has more predictive power compared to lagged variance in the case of wheat and maize futures[23]. Our results concerning wheat and maize are in line with those of Simon (2002) and Wang Fausti and Qasmi (2012), since we find that historical variance only marginally improves the forecasting performance when added as an additional regressor to implied variance. In addition, our results contradict those of Simon (2002)

[23] The adjusted R^2 of the wheat predictive regression increases from 46.6% to 68.0% and the adjusted R^2 of the maize predictive regression increases from 34.0% to 50.2%. We show these results in tables a and b of our Appendix.

concerning variance forecasting of soybeans futures prices. We find that implied variance has nearly the same forecasting power as historical variance in the case of soybeans. [24] Option-implied skewness is a statistically significant predictor of the future variance of soybeans futures. However, option-implied skewness does not have any predictive power when used as predictor of future variance of maize and wheat futures prices. When we use option-implied skewness as an additional factor to our initial univariate predictive regressions, the adjusted R^2 increases from 28.6% to 41.5% for the case of soybeans[25]. In Section 4.1 we found that the soybeans market has a substantial negative variance risk premium and therefore the inclusion of risk neutral skewness corrects for the biases in the predictive regressions following Rompolis and Tzavalis (2010). For all commodities considered, macroeconomic factors are insignificant and do not improve the forecasting performance for price variance. Inventories is a significant determinant of future price variance only for maize. This is somewhat unexpected as low inventories are normally correlated with high prices, and hence high variability, and vice versa for high inventories. The explanation maybe that the inventory figures we use pertain only to the US, and not the world. All three commodities considered are widely traded internationally. The US is the largest global exporter of maize (49 percent of total world exports, 24 percent of global ending stocks), and thus US inventories are more likely to affect international prices. On the other hand for wheat and soybeans, the US, while a significant world trader, accounts for a smaller world market share compared to maize (for wheat the US accounts for 21 percent of global exports and 13 percent of ending stocks).

4.3 Variance forecasting during the crisis

We noted above that during the recent commodity crisis both the realized and the implied variance increased, indicating greater ex-ante uncertainty during that period, as expected. The question arises as to whether our predictors of the realized variance perform equally well during the crisis. For this reason we redid the above regressions by introducing for each relevant explanatory variable an additional variable, which was the original variable multiplied by a dummy, which is equal to 1 during the crisis period (2006-11) and zero

[24]The adjusted R-squared is 29.8% when including historical variance in our univariate predictive model and the adjusted R-squared becomes 28.6% when including implied variance. We show these results in the table c of our Appendix. We also find that in the soybeans market Black's implied variance has better forecasting performance than model-free implied variance. This results are available from the authors upon the request.

[25] We show this result in table c of our Appendix.

otherwise. The new variables are indicated by their name with a suffix '…cris'. If the crisis changed the predictability of price variation, then the sign and significance of these new variables should indicate how. Table 3 summarizes the results of the new set of regressions for maize, wheat and soybeans. From table 3 we observe that the forecasting power of historical variance increases significantly in maize and soybeans, while it does not change for wheat. For both maize and soybeans, the total regression coefficient for RV during the crisis (which is the sum of the coefficients of the variables before and after the crisis) becomes positive, suggesting that increased RV during the crisis fed on itself. The coefficient of the model-free implied variance for maize becomes much smaller during the crisis and in the case of maize and soybeans it turns to negative. Additionally, the implied variance coefficient during the crisis is not statistically significant when forecasting variance of wheat and soybeans futures. Our results contradict those of Du, Yu and Hayes (2011), since we do not find any volatility spillover effects from crude oil to maize and wheat markets. On the other hand, from table 3 we observe a tighter interconnection between the variance of crude oil prices and soybeans prices when entering into the crisis period. While the crude oil variance coefficient is insignificant in the pre-crisis period, we observe that it becomes negative and statistically significant when forecasting soybeans variance during the crisis.[26]

[Insert table 3 Here]

4.4 Forecasting agricultural futures returns

We now examine whether option implied information is useful in predicting future commodity returns. First, we use predictive regressions with the basis and VRP as predictors of future variance. We also include skewness, historical returns, hedging pressure, the level of stocks, changes in industrial production, money supply M2, 3-month US Treasury-Bill and the NBER recession index. Our baseline regression is given by:

$$\begin{aligned} R_{t,t+1} &= b_0 + b_1 * B_t + b_2 * VRP_t + b_3 * IS_t + b_4 * R_t + b_5 * HP_t \\ &+ b_6 * INV_t + b_7 * RV_t + b_8 * IP_t + b_9 * T_t + b_{10} * M_t + b_{11} * NBER_t + \varepsilon_{t,t+1} \end{aligned} \tag{18}$$

[26]We come to similar conclusions when instead of using the dummy variable approach presented in this section, we split the data sample into two subsamples, namely the pre-crisis period (before 2006) and the post crisis period (after 2006), and estimate the same regression coefficients presented in section 4.3.

where $R_{t,t+1}$ is the 2-month percentage change in commodity futures prices of a constant 2-month maturity, B_t is the 2-month basis, VRP_t is the variance risk premium, IS_t is the implied skewness, HP_t is the hedging pressure, INV_t is the logarithm of inventory levels, RV_t is historical two-month realized variance (one time period before), IP_t is the historical two-month percentage change in Industrial Production Index, R_t is the historical 2-month percentage change in commodity futures prices, T_t is the 3-month US Treasury-Bill, M_t is the 2-month percentage change in money supply and $NBER_t$ is the US recession index from National Bureau of Economic Research.

Table 4 reports the results when returns are computed as 2-month returns of a rolling futures position (see equation 15).We see that commodity futures basis has the highest predictive power in the case of maize and soybeans futures returns.

Following Christoffersen, Kang and Pan (2010), we use the variance risk premium as an additional variable for predicting agricultural futures returns. We find a statistically significant negative relationship between VRP and 2-month ahead commodity futures returns, while the implied skewness coefficients are not statistically significant. The inclusion of VRP significantly increases predictability of maize and soybeans futures returns, respectively[27]. In our analysis we find that hedging pressure is a robust predictor of wheat and maize futures returns. However, none of the macro factors is statistically significant.

[Insert Table 4 Here]

When we repeat the same analysis with commodity returns computed according to the held to maturity strategy (see equation 16), we find similar results.

The time-series regressions show that the variance risk premium is a robust predictor of future returns. The results confirm the conjecture of Wang, Fausti and Qasmi (2012) that the model-free approach produces a superior VRP estimate for gauging and managing agricultural price risk. To understand better the economic underpinnings of this result we regress the variance risk premiums of the three commodities against macroeconomic variables and commodity specific factors. Table 5 reports the results. The variance risk

[27] For instance, when we include VRP, besides the basis, in our variable set, the regression R^2 values increase from 30.7% to 37.0% for maize returns and from 26.0% to 33.4% for soybeans returns respectively. We show these results in tables d, f of our Appendix.

premium of maize and soybean is significantly related to inflation and the coefficient estimate has a negative sign. Since inflation is positively associated with commodity prices (see Gordon and Rowenhorst, 2004) and commodity prices are also positively related to volatility, the negative coefficient implies that when commodity option markets observe a higher level of inflation they anticipate an increase in future variance of commodity prices and demand a higher (more negative) risk premium for bearing variance risk. Soybean variance risk premium is negatively related to M2 growth and positively related to interest rates while the wheat variance risk premium is positively related to M2 growth and negatively related to interest rates. These results suggest that inflationary expectations, whether proxied by actual recent inflation or faster M2 growth are associated with more market uncertainty. The economic underpinnings behind these results lie in the contemporaneous linkages between the level of actual-expected inflation and agricultural commodity markets (Frankel and Hardouvelis, 1985; Gordon and Rowenhorst, 2004).

[Insert Table 5 Here]

We also find that maize inventory level has a negative effect on maize variance risk premium. This means that investors of maize option markets demand a higher variance risk premium when they observe that the physical market of maize is short of storage (low level of stocks). Wheat variance risk premium is positively related to hedging pressure. The variance risk premium of soybeans is not related to any of the commodity specific factors. This result suggests that it is mostly macroeconomic factors which determine time variation in soybeans variance risk premium. One possible reason for this is the more globalized nature of production and trade of soybeans compared to wheat and maize. These results do not change substantially when we include crisis variables as was done in the previous section.

4.5 Explaining market uncertainty in agricultural markets

We now examine empirically the determinants of uncertainty (as measured by MFIV) in agricultural commodity markets. Our baseline regression model is the following:

$$MFIV_t = b_0 + b_1 * INV_t + b_2 * RVmz_{t-1} + b_3 * RVwh_{t-1} + b_4 * RVso_{t-1} + b_5 * RVoil_{t-1} + b_6 * Tbill_{t-1} + b_7 * RVTbill_{t-1} + b_8 * RVexch_{t-1} + b_9 * IP_{t-1} + \varepsilon_t \qquad (19)$$

where $MFIV_t$ is implied variance for period t as observed in period t, INV_t is the logarithm of inventory level at period t, $RVmz_{t-1}$ is the realized variance of maize futures prices during the 2-month period just before t, $RVwh_{t-1}$ is the realized variance of wheat futures prices, $RVso_{t-1}$ is the realized variance of soybeans futures prices, $RVoil_{t-1}$ is the realized variance of crude oil prices,$Tbill_{t-1}$ is the 3-month Treasury-Bill, $RVtbill3_t$ is the 2-month realized variance of the US-Tbill, $RVexc_{t-1}$ is the realized variance of the exchange rate and IP_{t-1} is the 2-month percentage change in Industrial Production. All realized variances are computed for the 2 month period before t. The results are exhibited in table 6.

We find that the historical 2-month variances of maize and wheat prices are statistically important determinants of uncertainty in the respective markets. Moreover, we observe that wheat historical variance is an important predictor of soybeans and maize MFIV, a fact which reveals a systemic risk component in agricultural markets. We find a statistically significant negative relationship between wheat MFIV and wheat inventory level.

[Insert Table 6 Here]

On the other hand, the variance of the crude oil prices does not appear to affect uncertainty in agricultural markets. Lastly, from table 6 we observe that the variance of the exchange rate is positively related with maize MFIV, while the level of US-Tbill is negatively related with wheat MFIV, implying that the macroeconomic conditions affect the overall uncertainty of agricultural commodity markets. When we include crisis variables as previously, we find some different results concerning the crisis period. While the coefficient of the 2-month US-Treasury Bill variance is not a statistically significant determinant of uncertainty in agricultural markets during normal times, it becomes significant during the recent crisis period (2006-2011). We additionally show that an increase in interest rate volatility has a positive and statistically significant impact on uncertainty (MFIV) of wheat and soybeans markets during the recent crisis[28]. Nominal interest rate volatility is a measure of instability of the level of inflation expectations and thus it can be controlled by monetary authorities when they decide to deploy a commitment towards inflation targeting (see Bernanke and Mishkin, 1997). Since less interest rate

[28] Table g in the Appendix shows our regression results when we use dummy variables for the crisis period.

volatility results to less uncertainty in agricultural markets during a crisis period, then monetary policy is (cap)able of calming down these markets under extreme market conditions.

5. Conclusions

In this paper we examine empirically the information content of model free option-implied variance and skewness in wheat, maize and soybeans derivative markets. We find that, in maize and wheat futures markets, model-free option-implied variance is more efficient predictor of future realized variance than historical (lagged) variance. Our predictive regressions show that risk neutral option-implied skewness improves forecasting performance when added as an additional factor in soybeans predictive regressions, while it is not a statistically significant predictor of future variance in the case of wheat and maize. For all three markets examined, the risk-neutral skewness is not related to subsequent commodity returns. However, the inclusion of Variance Risk Premium (VRP), defined as the difference between realized variance and risk neutral option-implied variance, adds important predictive power when used as an additional information variable for predicting commodity returns. We additionally show that macroeconomic factors are not statistically significant predictors of future variance and returns of grains prices. On the other hand, macroeconomic (monetary) factors like the money supply and the US-TBill explain a large part of time-variation in Variance Risk Premia (VRP) and in market uncertainty in grains commodity markets. This leads us to the conclusion that a promising avenue for future research would be to examine the relationship between the stance of monetary policy and uncertainty in the grain commodity derivative markets.

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Table 1: Descriptive Statistics of Maize-Wheat-Soybeans CBOT prices

	RV	MFIV	MFIS	VRP
Maize				
Mean	0.06	0.07	-0.10	-0.005
Median	0.04	0.05	0.07	-0.008
Maximum	0.37	0.24	1.07	0.26
Minimum	0.004	0.02	-2.21	-0.08
Stand. Dev	0.06	0.04	0.63	0.04
Skewness	2.41	1.26	-1.21	2.92
Kurtosis	10.94	4.57	4.07	18.59
Wheat				
	RV	MFIV	MFIS	VRP
Mean	0.08	0.07	0.02	0.002
Median	0.06	0.06	0.09	-0.002
Maximum	0.32	0.35	0.82	0.16
Minimum	0.008	0.01	-2.31	-0.06
Stand. Dev	0.06	0.05	0.42	0.03
Skewness	1.89	2.12	-1.96	1.46
Kurtosis	6.96	9.10	10.14	7.47
Soybeans				
	RV	MFIV	MFIS	VRP
Mean	0.05	0.07	0.03	-0.02
Median	0.04	0.05	0.12	-0.01
Maximum	0.28	0.40	1.30	0.13
Minimum	0.003	0.01	-2.53	-0.37
Stand. Dev	0.05	0.06	0.62	0.05
Skewness	2.33	2.64	-1.43	-2.16
Kurtosis	9.15	12.49	6.26	18.17

Source: Computed by authors

Table 2: Predicting 2-month variance of grains futures prices

		Maize Variance	Wheat Variance	Soybeans Variance
Intercept	Coef.	0.167**	0.035	0.099
	t-stat	(2.031)	(0.465)	(1.553)
Realized Variance	Coef.	0.099	-0.071	0.268***
	t-stat	(0.978)	(-0.647)	(2.915)
Implied Variance	Coef.	0.832***	0.884***	0.242***
	t-stat	(4.386)	(8.861)	(2.908)
Implied Skewness	Coef.	0.003	-0.001	0.016**
	t-stat	(1.223)	(-0.114)	(2.454)
Hedging Pressure	Coef.	0.006	0.034**	-0.015
	t-stat	(0.295)	(2.087)	(-0.811)
Log (Inventories)	Coef.	-0.011**	-0.001	-0.006
	t-stat	(-2.236)	(-0.153)	(-1.316)
Production Index	Coef.	0.280	0.048	-0.512
	t-stat	(0.412)	(0.134)	(-1.206)
M2 growth	Coef.	-0.670	0.630	0.125
	t-stat	(-0.868)	(0.593)	(0.238)
US-Tbill3	Coef.	0.047	-0.479*	0.003
	t-stat	(0.232)	(-1.853)	(0.018)
NBER - Recession	Coef.	0.015	0.011	0.013
	t-stat	(1.691)	(0.793)	(0.946)
% R^2		54.2	70.6	46.3
% Adjusted R^2		50.8	68.4	42.3

The t-statistics reported in parentheses are corrected for autocorrelation and heteroscedasticity using the Newey – West (1987) estimator. *denotes significance at the 10% level, ** at the 5% level and *** at the 1% respectively.

Source: Computed by authors

Table 3: Predicting 2-month variance of agricultural prices during crisis

		maize	wheat	soybeans
Intercept	Coef.	0.187*	0.078	0.076
	t-stat	(1.653)	(0.862)	(1.101)
Realized Variance	Coef.	-0.045	-0.219***	0.004
	t-stat	(-0.483)	(-2.875)	(0.031)
Realized VarianceCris	Coef.	0.627*	0.153	0.491***
	t-stat	(1.897)	(0.985)	(3.384)
Implied Variance	Coef.	1.027**	0.757***	0.704***
	t-stat	(2.554)	(5.336)	(2.884)
Implied VarianceCris	Coef.	-0.682*	0.028	-0.374
	t-stat	(-1.689)	(0.168)	(-1.301)
Implied Skewness	Coef.	0.001	0.001	0.010
	t-stat	(0.198)	(0.113)	(1.457)
Implied SkewnessCris	Coef.	0.007	-0.001	0.027
	t-stat	(0.227)	(-0.027)	(1.054)
Hedging Pressure	Coef.	0.002	0.048**	-0.022
	t-stat	(0.100)	(2.691)	(-1.214)
Log Inventories	Coef.	-0.013**	-0.003	-0.004
	t-stat	(-1.9508)	(-0.524)	(-0.964)
Log Inventories Cris	Coef.	0.002	0.001	-0.002
	t-stat	(1.053)	(1.216)	(-1.177)
Crude oil variance	Coef.	0.007	-0.007	-0.011
	t-stat	(0.314)	(-0.549)	(-0.819)
Crude oil variance cris	Coef.	-0.075	-0.055	-0.050**
	t-stat	(-1.429)	(-1.446)	(-2.092)
Production Index	Coef.	0.280	-0.102	-0.610
	t-stat	(0.423)	(-0.269)	(-1.302)
M2 growth	Coef.	-0.601	1.071	0.424
	t-stat	(-0.816)	(1.370)	(0.896)
US-Treasury Bill	Coef.	0.005	-0.505**	-0.017
	t-stat	(0.037)	(-2.392)	(-0.084)
NBER recession	Coef.	-0.075	0.017	0.010
	t-stat	(-1.430)	(1.026)	(0.704)
% R^2		58.3	73.6	52.8
% R^2 adjusted		52.8	70.1	46.5

The t-statistics reported in parentheses are corrected for autocorrelation and heteroscedasticity using the Newey – West (1987) estimator. *denotes significance at the 10% level, ** at the 5% level and *** at the 1% respectively. Source: Computed by authors

Table 4: Predicting 2-month returns of grains futures (rolling contract)

		Maize Returns	Wheat Returns	Soybeans Returns
Intercept	Coef.	-0.016	-0.419	-0.298
	t-stat	(-0.110)	(-1.339)	(-1.533)
Basis	Coef.	-1.350***	-0.488***	-1.275***
	t-stat	(-7.153)	(-2.972)	(-6.808)
VRP	Coef.	-0.894**	-0.986***	-0.514***
	t-stat	(-2.089)	(-3.003)	(-3.132)
Implied Skewness	Coef.	-1.015	0.025	-0.002
	t-stat	(-1.178)	(1.066)	(-0.161)
Historical returns	Coef.	0.114	-0.015	-0.059
	t-stat	(1.124)	(-0.127)	(-0.666)
Hedging Pressure	Coef.	0.093	0.294***	-0.026
	t-stat	(1.632)	(5.843)	(-0.700)
Log (Inventories)	Coef.	-0.007	0.022	0.023*
	t-stat	(-0.741)	(1.022)	(1.860)
Realized variance	Coef.	0.196	0.535**	-0.115
	t-stat	(0.752)	(2.196)	(-0.517)
Production Index	Coef.	0.692	1.092	0.997
	t-stat	(0.593)	(0.927)	(0.892)
US-Tbill3	Coef.	-0.091	-0.286	0.037
	t-stat	(-0.192)	(-0.332)	(0.072)
M2-growth	Coef.	0.194	-0.509	-2.062
	t-stat	(0.101)	(-0.319)	(-1.544)
NBER - Recession	Coef.	-0.008	-0.018	0.001
	t-stat	(-0.254)	(-0.765)	(0.042)
% R^2		43.9	26.3	41.4
% Adjusted R^2		38.7	19.5	35.9

The t-statistics reported in parentheses are corrected for autocorrelation and heteroscedasticity using the Newey – West (1987) estimator. *denotes significance at the 10% level, ** at the 5% level and *** at the 1% respectively. Source: Computed by authors

Table 5: Regression of Agricultural Variance Risk Premia (VRP) on Economic Fundamentals

		Maize VRP	Wheat VRP	Soybeans VRP
Intercept	Coef.	0.177^{**}	-0.002	0.110
	t-stat	(2.651)	(-0.030)	(1.370)
Basis	Coef.	-0.153^{*}	-1.365	-0.091
	t-stat	(-1.944)	(-1.398)	(-0.888)
Hedging Pressure	Coef.	0.015	0.051^{***}	-0.005
	t-stat	(0.635)	(3.312)	(-0.252)
Log(Inventories)	Coef.	-0.012^{***}	0.001	-0.009
	t-stat	(-2.849)	(0.018)	(-1.536)
Inflation	Coef.	-3.268^{**}	-0.878	-3.070^{**}
	t-stat	(-2.307)	(-1.237)	(-2.538)
Industrial Production	Coef.	-0.291	-0.180	0.007
	t-stat	(-0.937)	(-0.696)	(0.017)
M2 growth	Coef.	-0.137	1.044^{**}	-1.640^{**}
	t-stat	(-0.198)	(2.574)	(-2.481)
US-Tbill3	Coef.	0.231^{*}	-0.270^{*}	0.758^{***}
	t-stat	(1.678)	(-1.827)	(3.122)
NBER Recession	Coef.	-0.005	-0.008	-0.014
	t-stat	(-0.487)	(-0.678)	(-1.048)
% R^2		18.2	9.6	17.5
% Adjusted R^2		12.8	3.7	12.0

The t-statistics reported in parentheses are corrected for autocorrelation and heteroscedasticity using the Newey – West (1987) estimator. *denotes significance at the 10% level, ** at the 5% level and *** at the 1% respectively.

Source: Computed by authors

Table 6: Forecasting uncertainty (MFIV) in agricultural commodity markets

		Maize MFIV	Wheat MFIV	Soybeans MFIV
Intercept	Coef.	0.027	0.218***	-0.017
	t-stat	(0.541)	(3.748)	(-0.233)
Log (Inventories)	Coef.	-0.0003	-0.013***	0.003
	t-stat	(-0.111)	(-3.214)	(0.653)
Maize RV	Coef.	0.272***	0.097	0.011
	t-stat	(4.437)	(1.441)	(0.163)
Wheat RV	Coef.	0.350***	0.567***	0.565***
	t-stat	(6.625)	(7.086)	(4.887)
Soybeans RV	Coef.	-0.016	-0.104	0.132
	t-stat	(-0.319)	(-1.181)	(0.903)
Crude Oil RV	Coef.	-0.003	-0.001	-0.018
	t-stat	(-0.421)	(-0.076)	(-1.055)
US-Tbill3	Coef.	-0.055	-0.297*	-0.277
	t-stat	(-0.382)	(-1.811)	(-1.302)
US-Tbill3 RV	Coef.	-2.729	9.889	1.780
	t-stat	(-1.029)	(1.176)	(0.264)
Exchange rate RV	Coef.	1.951**	0.953	1.025
	t-stat	(2.128)	(0.944)	(0.860)
Industrial Production	Coef.	-0.1379	-0.278	-0.863**
	t-stat	(-0.7532)	(-0.675)	(-2.088)
% R^2		71.4	73.9	57.8
% Adjusted R^2		69.3	72.0	53.9

The t-statistics reported in parentheses are corrected for autocorrelation and heteroscedasticity using the Newey – West (1987) estimator. *denotes significance at the 10% level, ** at the 5% level and *** at the 1% respectively.

Figure 1:2-month model free implied variance versus 2-month realized variance for maize, wheat and soybeans futures respectively for the period January 1990 to December 2011.

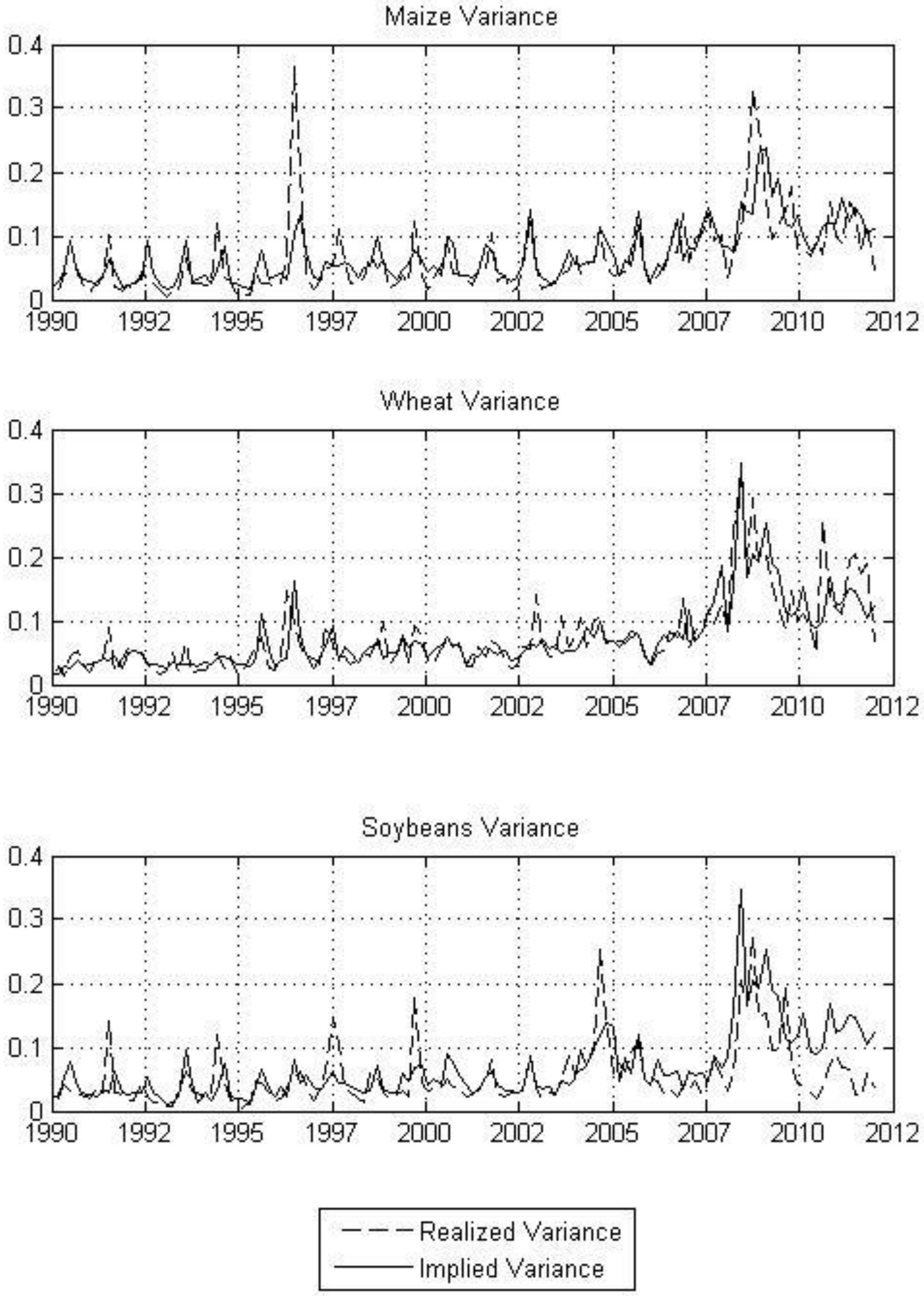
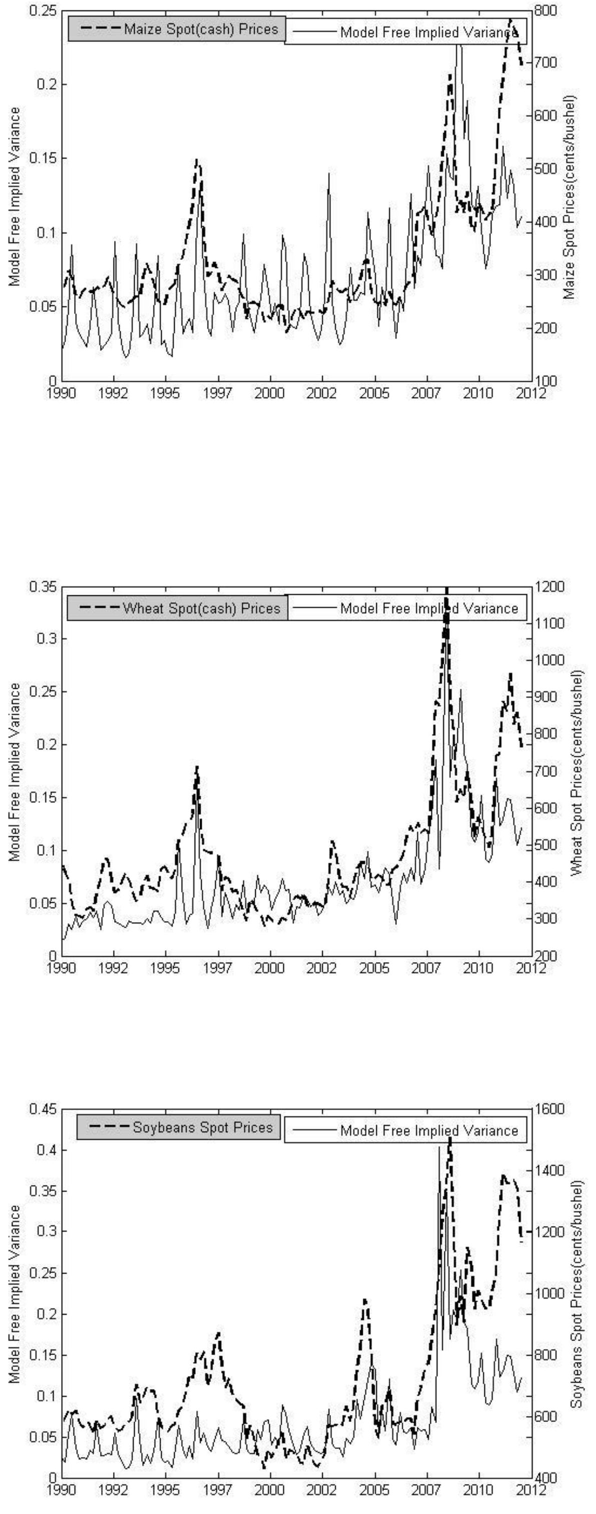


Figure 2: 2-month model free implied variance, and corresponding spot prices for maize, wheat and soybeans from January 1990 to December 2011.



Source : Computed by authors

Figure 3: 2-month variance risk premia (VRP) of maize, wheat and soybeans from January 1990 to December 2011.

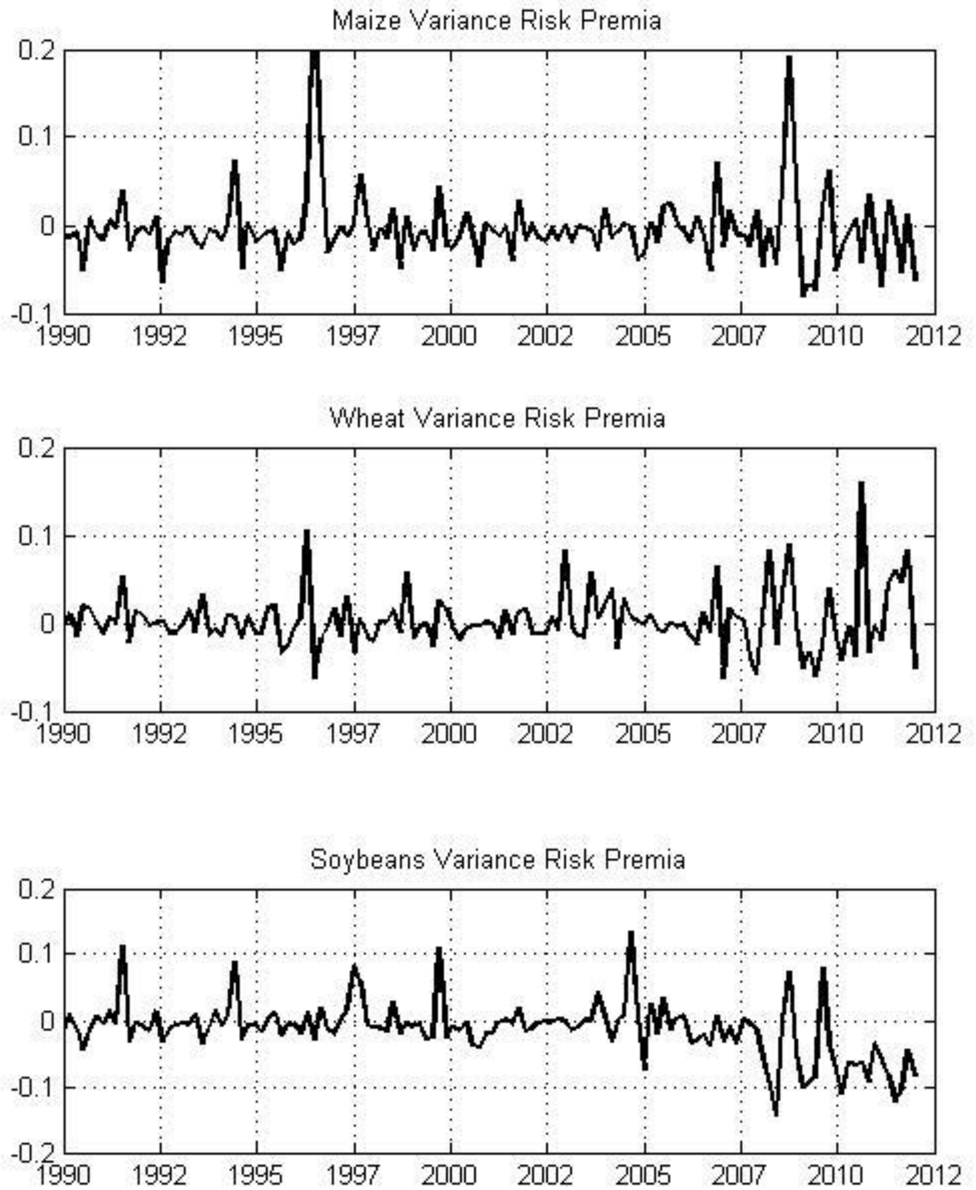


Figure 4: Average overlapping monthly variance risk premiums (with 2-month horizon) for the time period covering January 1990 till December 2011.

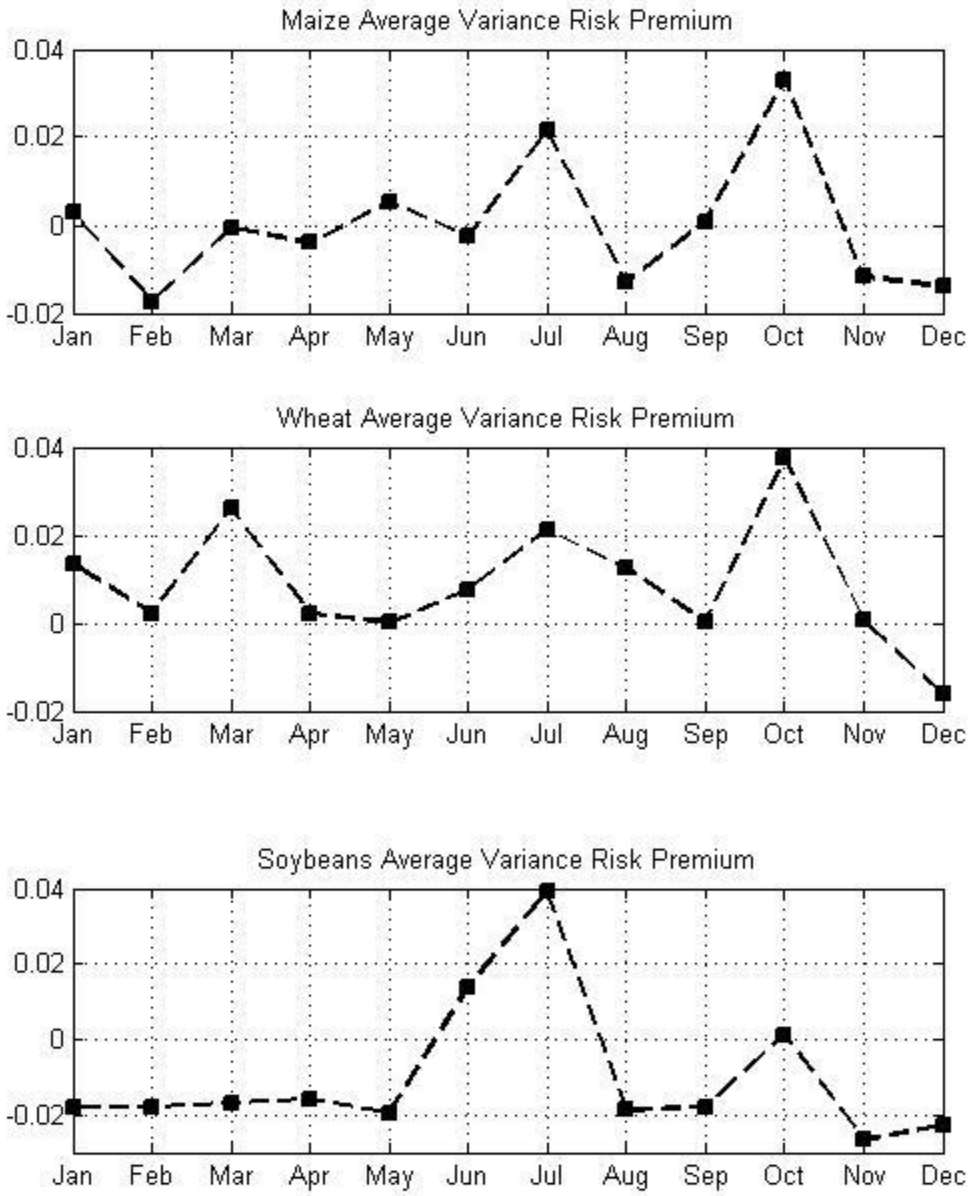
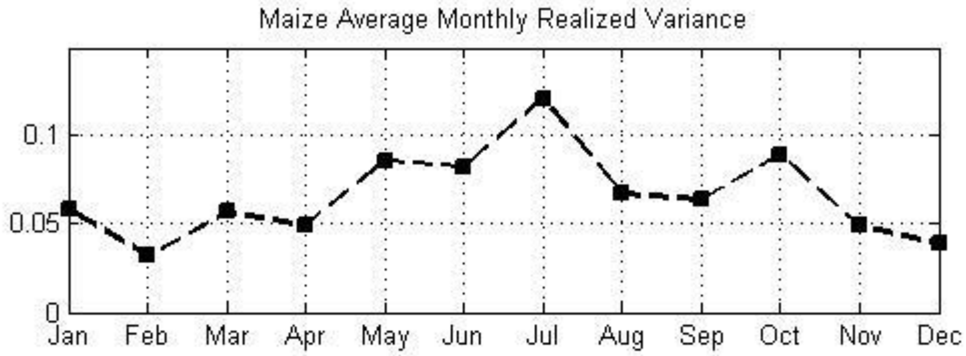
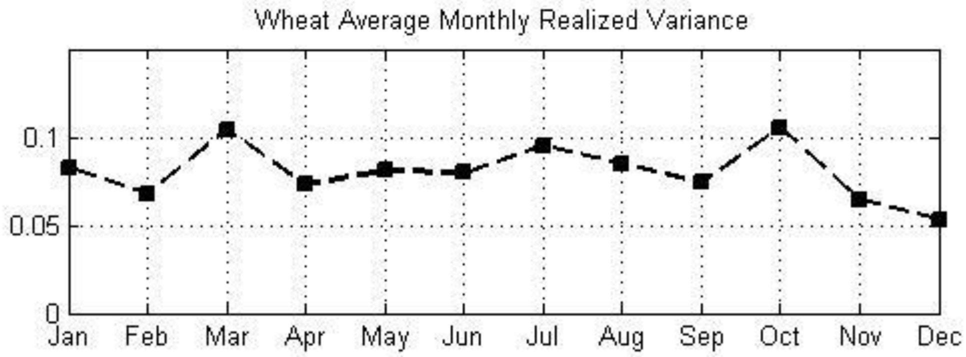


Figure 5: Average monthly realized variance of agricultural futures prices for the time period covering January 1990 till December 2011.





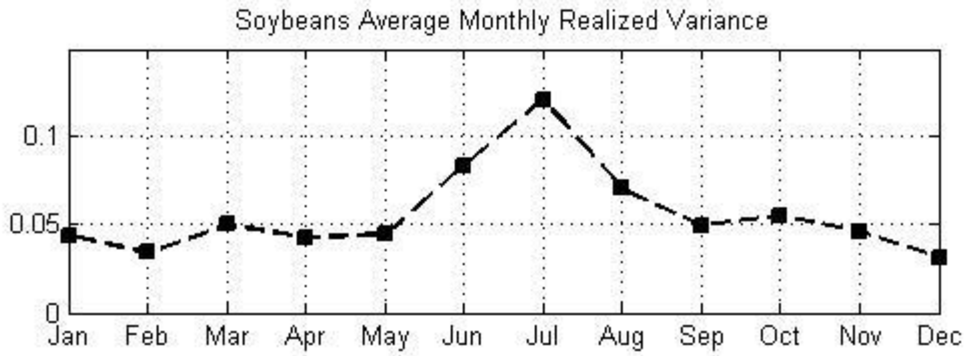


Figure 6: 2-month model-free option-implied skewness of maize, wheat and soybeans futures options from January 1990 to December 2011.

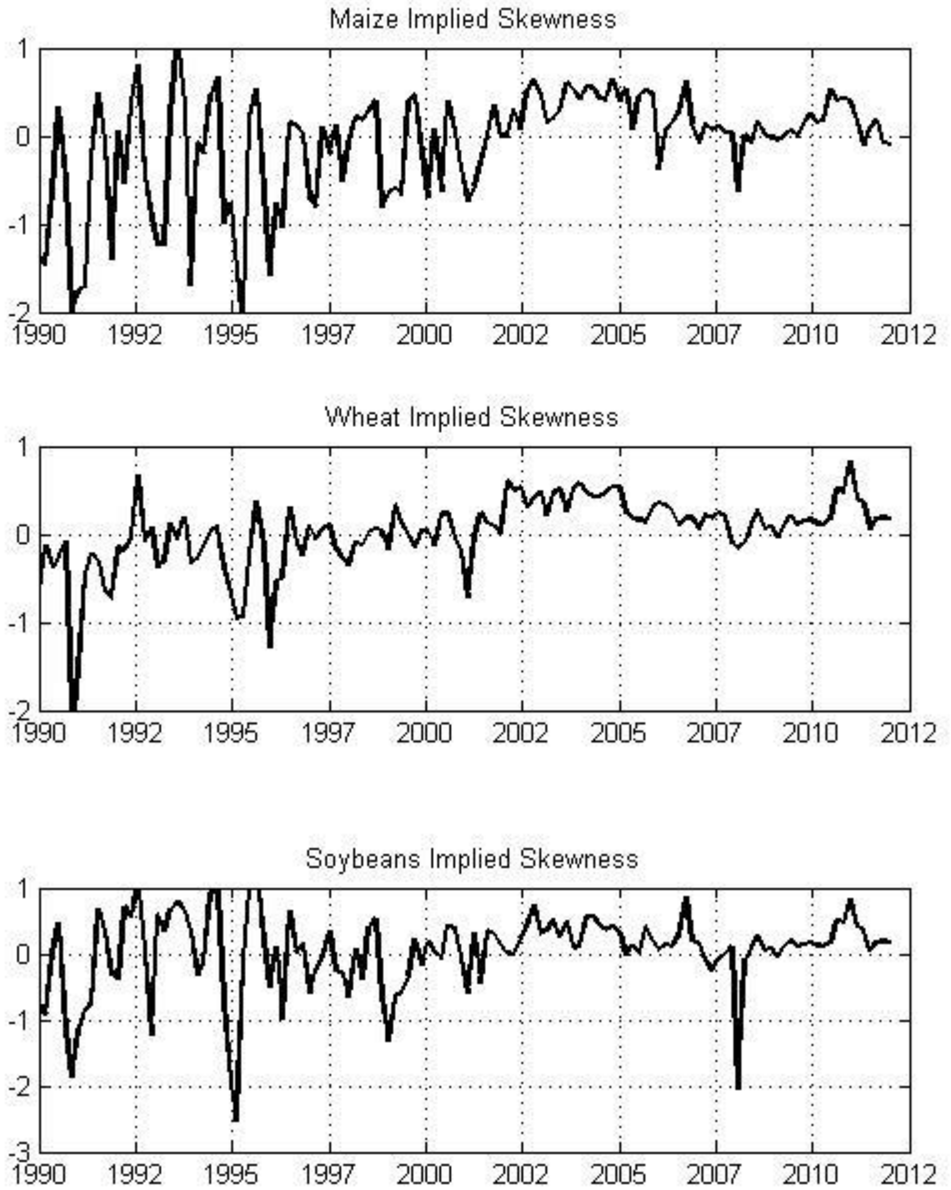
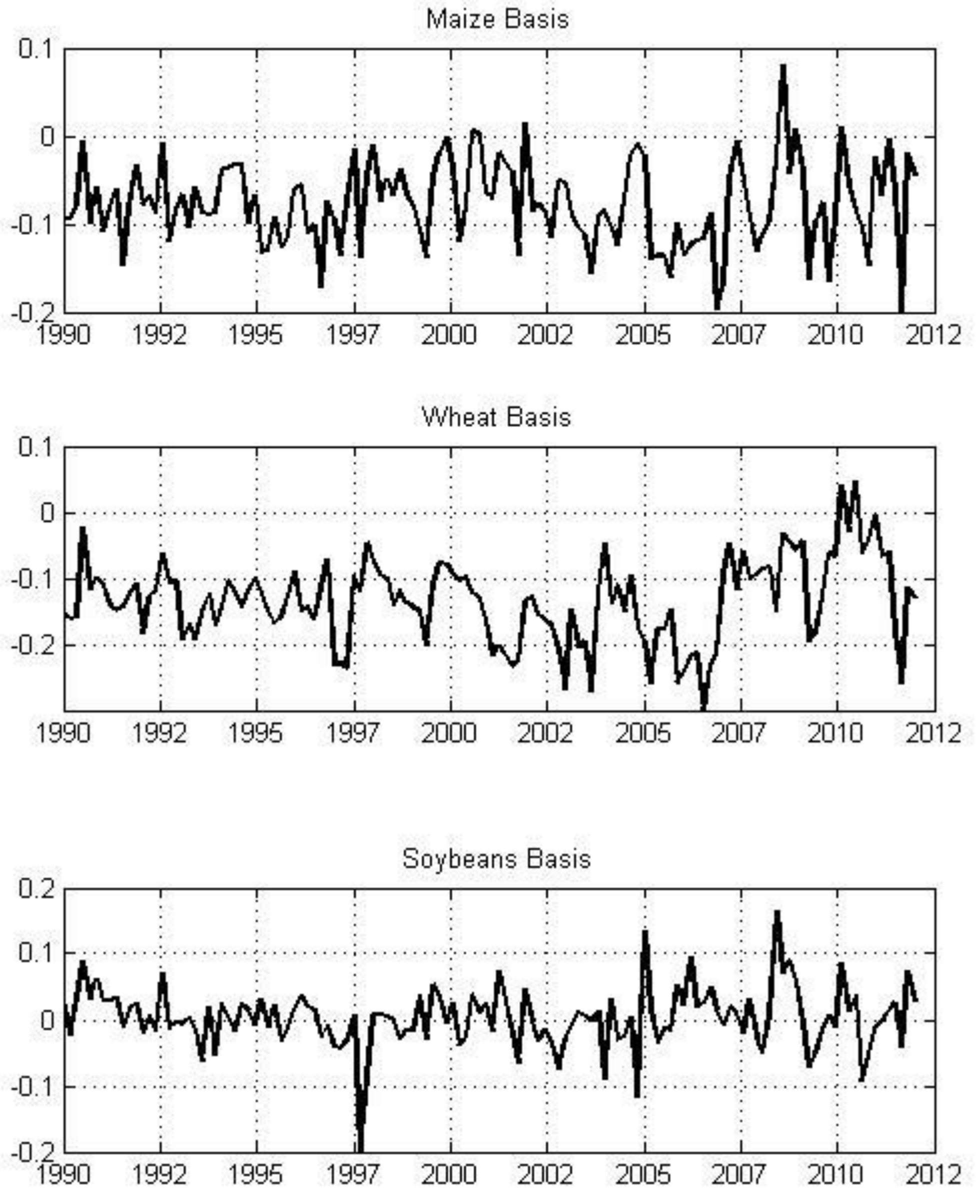


Figure 7:2-month percentage change in futures-spot difference (basis) for maize, wheat and soybeans, from January 1990 to December 2011.



Appendix

Table a: Predicting 2-month variance of maize futures prices

		(1)	(2)	(3)	(4)	(5)
Intercept	Coef.	0.027***	-0.001	0.001	0.188**	0.167**
	t-stat	(4.775)	(-0.271)	(0.283)	(2.397)	(2.031)
Realized Variance	Coef.	0.581***		0.149*	0.085	0.099
	t-stat	(6.027)		(1.669)	(0.859)	(0.978)
Implied Variance	Coef.		0.936***	0.767***	0.834***	0.832***
	t-stat		(10.374)	(6.259)	(6.471)	(4.386)
Implied Skewness	Coef.			0.004	0.001	0.003
	t-stat			(1.424)	(0.349)	(1.223)
Hedging Pressure	Coef.				0.004	0.006
	t-stat				(0.207)	(0.295)
Log (Inventories)	Coef.				-0.012**	-0.011**
	t-stat				(-2.403)	(-2.236)
Production Index	Coef.					0.280
	t-stat					(0.412)
M2 growth	Coef.					-0.670
	t-stat					(-0.868)
US-Tbill3	Coef.					0.047
	t-stat					(0.232)
NBER - Recession	Coef.					0.015
	t-stat					(1.691)
% R^2		34.5	50.5	51.7	53.5	54.2
% R^2 adjusted		34.0	50.2	50.5	51.6	50.8

The t-statistics reported in parentheses are corrected for autocorrelation and heteroscedasticity using the Newey – West (1987) estimator. *denotes significance at the 10% level, ** at the 5% level and *** at the 1% respectively.

Source: Computed by authors

Table b: Predicting 2-month variance of wheat futures prices

		(1)	(2)	(3)	(4)	(5)
Intercept	Coef.	0.025***	0.008**	0.090*	-0.034	0.035
	t-stat	(4.780)	(2.053)	(1.907)	(-0.571)	(0.465)
Realized Variance	Coef.	0.678***		0.040	0.007	-0.071
	t-stat	(9.499)		(0.039)	(0.067)	(-0.647)
Implied Variance	Coef.		0.918***	0.903***	0.930***	0.884***
	t-stat		(13.083)	(8.263)	(8.585)	(8.861)
Implied Skewness	Coef.			0.005	0.008	-0.001
	t-stat			(0.954)	(1.438)	(-0.114)
Hedging Pressure	Coef.				0.024*	0.034**
	t-stat				(1.795)	(2.087)
Log (Inventories)	Coef.				0.003	-0.001
	t-stat				(0.659)	(-0.153)
Production Index	Coef.					0.048
	t-stat					(0.134)
M2 growth	Coef.					0.630
	t-stat					(0.593)
US-Tbill3	Coef.					-0.479*
	t-stat					(-1.853)
NBER - Recession	Coef.					0.011
	t-stat					(0.793)
% R^2		47.0	68.3	68.4	68.8	70.6
% R^2 adjusted		46.6	68.0	67.6	67.6	68.4

The t-statistics reported in parentheses are corrected for autocorrelation and heteroscedasticity using the Newey – West (1987) estimator. *denotes significance at the 10% level, ** at the 5% level and *** at the 1% respectively.

Source: Computed by authors

Table c: Predicting 2- month variance of soybeans futures prices

		(1)	(2)	(3)	(4)	(5)
Intercept	Coef.	0.025***	0.025***	0.015***	0.074	0.099
	t-stat	(5.905)	(3.279)	(2.829)	(1.490)	(1.553)
Realized Variance	Coef.	0.545***		0.344***	0.306***	0.268***
	t-stat	(5.954)		(4.144)	(3.136)	(2.915)
Implied Variance	Coef.		0.420***	0.279***	0.289***	0.242***
	t-stat		(3.194)	(3.174)	(3.089)	(2.908)
Implied Skewness	Coef.			0.014***	0.014**	0.016**
	t-stat			(2.695)	(2.438)	(2.454)
Hedging Pressure	Coef.				-0.014	-0.015
	t-stat				(-0.793)	(-0.811)
Log (Inventories)	Coef.				-0.004	-0.006
	t-stat				(-1.140)	(-1.316)
Production Index	Coef.					-0.512
	t-stat					(-1.206)
M2 growth	Coef.					0.125
	t-stat					(0.238)
US-Tbill3	Coef.					0.003
	t-stat					(0.018)
NBER - Recession	Coef.					0.013
	t-stat					(0.946)
% R^2		30.3	29.1	42.9	43.6	46.3
% R^2 adjusted		29.8	28.6	41.5	41.3	42.3

The t-statistics reported in parentheses are corrected for autocorrelation and heteroscedasticity using the Newey – West (1987) estimator. *denotes significance at the 10% level, ** at the 5% level and *** at the 1% respectively.

Source: Computed by authors

Table d: Predicting 2-month returns of maize futures (rolling contract)

		(1)	(2)	(3)	(4)	(5)
Intercept	Coef.	-0.093***	0.002	-0.097***	0.051	-0.016
	t-stat	(-6.192)	(0.227)	(-6.734)	(0.345)	(-0.110)
Basis	Coef.	-1.277***		-1.264***	-1.371***	-1.350***
	t-stat	(-6.732)		(-7.273)	(-7.528)	(-7.153)
VRP	Coef.		-0.720***	-0.689**	-0.742**	-0.894**
	t-stat		(-3.776)	(-2.205)	(-2.342)	(-2.089)
Implied Skewness	Coef.			-0.012	-0.008	-1.015
	t-stat			(-0.989)	(-0.750)	(-1.178)
Historical returns	Coef.				0.104	0.114
	t-stat				(1.187)	(1.124)
Hedging Pressure	Coef.				0.108**	0.093
	t-stat				(2.025)	(1.632)
Log (Inventories)	Coef.				-0.010	-0.007
	t-stat				(-1.081)	(-0.741)
Realized variance	Coef.					0.196
	t-stat					(0.752)
Production Index	Coef.					0.692
	t-stat					(0.593)
US-Tbill3	Coef.					-0.091
	t-stat					(-0.192)
M2-growth	Coef.					0.194
	t-stat					(0.101)
NBER - Recession	Coef.					-0.008
	t-stat					(-0.254)
% R^2		31.2	7.0	38.4	43.1	43.9
% R^2 adjusted		30.7	6.3	37.0	40.3	38.7

The t-statistics reported in parentheses are corrected for autocorrelation and heteroscedasticity using the Newey – West (1987) estimator. *denotes significance at the 10% level, ** at the 5% level and *** at the 1% respectively.

Source: Computed by authors

Table e: Predicting 2-month returns of wheat futures (rolling contract)

		(1)	(2)	(3)	(4)	(5)
Intercept	Coef.	-0.037	0.010	-0.035	-0.302	-0.419
	t-stat	(-1.394)	(1.086)	(-1.300)	(-0.869)	(-1.339)
Basis	Coef.	-0.336**		-0.326**	-0.344**	-0.488***
	t-stat	(-2.262)		(-2.127)	(-2.082)	(-2.972)
VRP	Coef.		-0.562**	-0.556**	-0.585*	-0.986***
	t-stat		(-2.139)	(-2.094)	(-1.870)	(-3.003)
Implied Skewness	Coef.			0.007	0.049***	0.025
	t-stat			(0.364)	(2.769)	(1.066)
Historical returns	Coef.				-0.034	-0.015
	t-stat				(-0.268)	(-0.127)
Hedging Pressure	Coef.				0.250***	0.294***
	t-stat				(5.767)	(5.843)
Log (Inventories)	Coef.				0.018	0.022
	t-stat				(0.738)	(1.022)
Realized variance	Coef.					0.535**
	t-stat					(2.196)
Production Index	Coef.					1.092
	t-stat					(0.927)
US-Tbill3	Coef.					-0.286
	t-stat					(-0.332)
M2-growth	Coef.					-0.509
	t-stat					(-0.319)
NBER - Recession	Coef.					-0.018
	t-stat					(-0.765)
% R^2		4.2	3.0	6.9	21.8	26.3
% R^2 adjusted		3.4	2.3	4.7	18.0	19.5

The t-statistics reported in parentheses are corrected for autocorrelation and heteroscedasticity using the Newey – West (1987) estimator. *denotes significance at the 10% level, ** at the 5% level and *** at the 1% respectively.

Source: Computed by authors

Table f: Predicting 2-month returns of soybeans futures (rolling contract)

		(1)	(2)	(3)	(4)	(5)
Intercept	Coef.	0.008	0.001	-0.0001	-0.310**	-0.298
	t-stat	(0.875)	(-1.000)	(-0.001)	(-2.286)	(-1.533)
Basis	Coef.	-1.152***		-1.271***	-1.313***	-1.275***
	t-stat	(-4.978)		(-6.457)	(-6.658)	(-6.808)
VRP	Coef.		-0.348**	-0.544***	-0.476***	-0.514***
	t-stat		(-2.281)	(-3.272)	(-3.145)	(-3.132)
Implied Skewness	Coef.			-0.015*	-0.006	-0.002
	t-stat			(-1.737)	(-0.639)	(-0.161)
Historical returns	Coef.				-0.030	-0.059
	t-stat				(-0.340)	(-0.666)
Hedging Pressure	Coef.				-0.015	-0.026
	t-stat				(-0.445)	(-0.700)
Log (Inventories)	Coef.				0.023**	0.023*
	t-stat				(2.365)	(1.860)
Realized variance	Coef.					-0.115
	t-stat					(-0.517)
Production Index	Coef.					0.997
	t-stat					(0.892)
US-Tbill3	Coef.					0.037
	t-stat					(0.072)
M2-growth	Coef.					-2.062
	t-stat					(-1.544)
NBER - Recession	Coef.					0.001
	t-stat					(0.042)
% R^2		26.5	3.2	35.0	37.9	41.4
% R^2 adjusted		26.0	2.5	33.4	34.8	35.9

The t-statistics reported in parentheses are corrected for autocorrelation and heteroscedasticity using the Newey – West (1987) estimator. *denotes significance at the 10% level, ** at the 5% level and *** at the 1% respectively.

Source: Computed by authors

Table g: Forecasting uncertainty (MFIV) in agricultural commodity markets during crisis period

		Maize MFIV	Wheat MFIV	Soybeans MFIV
Intercept	Coef.	0.119**	0.192***	0.008
	t-stat	(2.294)	(3.622)	(0.091)
Log (Inventories)	Coef.	-0.006*	-0.011***	0.001
	t-stat	(-1.800)	(-2.914)	(0.211)
Log (Inventories) cris	Coef.	0.001**	0.004***	0.005***
	t-stat	(2.023)	(2.724)	(3.171)
Maize RV	Coef.	0.169***	-0.023	-0.086*
	t-stat	(4.814)	(-0.565)	(-1.899)
Maize RV cris	Coef.	-0.012		
	t-stat	(-0.144)		
Wheat RV	Coef.	0.205***	0.572***	0.394***
	t-stat	(3.436)	(3.761)	(3.166)
Wheat RV cris	Coef.		-0.271	
	t-stat		(-1.604)	
Soybeans RV	Coef.	0.034	-0.063	0.336***
	t-stat	(0.744)	(-0.946)	(3.800)
Soybeans RV cris	Coef.			-0.453*
	t-stat			(-1.957)
Crude Oil RV	Coef.	-0.003	-0.002	-0.011
	t-stat	(-0.403)	(-0.258)	(-1.293)
Crude Oil RV cris	Coef.	0.021	0.027	0.005
	t-stat	(0.704)	(0.844)	(0.099)
US-Tbill3	Coef.	-0.010	-0.103	-0.021
	t-stat	(-0.093)	(-0.901)	(-0.114)
US-Tbill3cris	Coef.	0.059	-0.281	-0.619
	t-stat	(0.265)	(-1.218)	(-1.228)
US-Tbill3 RV	Coef.	-4.682	-4.059	0.269
	t-stat	(-1.176)	(-1.365)	(0.254)
US-Tbill3 RVcris	Coef.	4.213	22.361***	23.358**
	t-stat	(0.906)	(2.723)	(2.623)
Exchange rate RV	Coef.	0.423	-0.243	0.269
	t-stat	(0.432)	(-0.270)	(0.254)
Exchange rate RVcris	Coef.	1.935	1.187	1.319
	t-stat	(1.243)	(0.894)	(0.645)
Industrial Production	Coef.	-0.100	-0.450	-1.079**
	t-stat	(-0.581)	(1.063)	(-2.203)
% R^2		77.7	83.3	66.0
% Adjusted R^2		74.8	81.1	61.5

The t-statistics reported in parentheses are corrected for autocorrelation and heteroscedasticity using the Newey – West (1987) estimator. *denotes significance at the 10% level, ** at the 5% level and *** at the 1% respectively.