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Assessing the vulnerability to price spikes in agricultural commodity markets

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Abstract

We empirically examine the predictability of the conditions which are associated with a higher probability of a price spike in agricultural commodity markets. We find that the forward spread is the most significant indicator of probable price jumps in maize, wheat and soybeans futures markets, a result which is in line with the "Theory of Storage". We additionally show that some option-implied variables add significant predictive power when added to the more standard information variable set. Overall, the estimated probabilities of large price increases from our probit models exhibit significant correlations with the historical sudden market upheavals in agricultural markets.

Key words: Agricultural price spikes, Tail Risk Measure, Extreme Value Theory, Risk neutral moments, Agricultural Commodities, Basis, Theory of Storage

JEL classification: G13, Q10, Q13, Q18

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1. Introduction

Sudden and large price spikes in agricultural markets can occur because of several events, such as unexpected changes in demand caused by food scares, or supply shocks caused by the destruction of crops by drought or pests. Recent empirical work documents the existence of large unexpected price jumps in agricultural markets (Hilliard and Reis (1999), Koekebakker and Lien (2004)). These unlikely events are very difficult to anticipate and properly hedge, since there is no systematic way to predict them as well as their underlying causes. Nevertheless, the timely anticipation of the conditions under which a price spike in agricultural markets may occur, can increase the likelihood of predictions of subsequent spikes, and is of crucial importance for both farmers and policy-makers who try to shape policies for the risk-prone agricultural sector.

What are the likely determinants of commodity price spikes? Since commodity price spikes are largely unexpected, it seems reasonable to hypothesize that it is unexpected shocks that impinge on prices that are the main causes of spikes. Since such shocks are unexpected, they cannot be predicted. However, the unforeseen changes in the relevant shock variables take place in the context of underlying conditions in the specific commodity market. These conditions affect the vulnerability of the market to various shocks, and hence the way in which any given subsequent sudden change will impact on price and other market variables. Thus, the predictability of subsequent price spikes depends on identifying the variables that render the commodity market sensitive and vulnerable to subsequent unexpected shocks.

In this paper, we examine theoretically and empirically the conditions under which price spikes in maize, wheat and soybeans markets have a high probability of occurring. We define a price spike as an above two-sigma price return for a given month. The sigma is derived from option-implied volatility, rescaled to the holding monthly period, to be directly comparable to monthly returns. Motivated by the theoretical and empirical insights of the ‘Theory of Storage’ (Kaldor, 1939; Brennan, 1958; Telser, 1958; Working, 1948; Fama and French, 1987) we first examine whether the forward spread (the interest adjusted futures-spot price spread) in agricultural futures markets can act as an early warning signal of unexpected price jumps in agricultural markets. According to the “Theory of Storage” the forward spread can be interpreted as the marginal convenience yield for holding physical inventory. Motivated by this theoretical insight we claim and empirically verify that a large negative forward spread is a strong early warning signal of a price spike. We then include the commodity inventory levels as an additional predictor of price spikes. Motivated by the empirical findings of Deaton and Laroque (1992) and Bobenrieth, Wright and Zeng (2013), who find that low inventory levels are associated with subsequent high prices in the respective commodity markets, we empirically examine whether the inventory levels are predictors of subsequent price jumps in agricultural markets.

We find that the forward spread is the most significant predictor of price spikes in maize and wheat commodity markets when considering a short (1-month) forecasting horizon. Our results are in line and provide further empirical support to the findings in the literature according to which rising convenience yields (more negative forward spread) are associated with higher returns in commodity futures markets (Fama and French, 1987; Gordon and Rowenhorst, 2006; Gordon, Hayashi and Rowenhorst, 2013; Szymanowska *et al.* 2014). Our contribution to the relevant literature, is that, while these empirical studies verify the predictive information content of the forward spread on commodity futures returns, we also show that this spread is a robust predictor of the likelihood of subsequent price spikes in agricultural markets. Our empirical findings implicitly show that the market conditions which affect the variability of the forward spread can also act as early warning signals of price jumps in the underlying commodity market.

Independently, the literature on the predictability of stock-market returns (Bollerslev, Tauchen and Zhou, 2009; Bollerslev and Todorov, 2011; Bollerslev, Todorov, and Xu 2015; Kelly and Jiang, 2014; Vilkov and Xiao, 2013) identifies the significant predictive information content of option-implied tail risk measures. Motivated by the findings for the equity markets, we include as additional explanatory variables in our predictive equation some option-implied variables which quantify the conditional expectations of commodity market participants about extreme (tail) risks. Such variables are the option-implied tail risk measure, the variance risk premium, the implied variance, the implied skewness and the implied kurtosis.

We find that the option-implied tail risk measure, the implied variance and the variance risk premium are statistically significant indicators of high probabilities of price jumps and they add significant predictive power when added in the right-hand side of our regression models. Lastly, following the empirical findings of another strand of literature which attributes the commodity price movements to speculation and to the hedging pressure of commodity markets (Bessembinder, 1992; DeRoon *et al.*, 2000), we control for the hedging pressure in our probit regression models and find that hedging pressure does not add significant forecasting power when predicting the unexpected above two-sigma price spikes.

To the best of our knowledge, this is the first paper which utilizes the option-implied information for the modeling of the probability of price jumps in agricultural commodity markets. Empirical studies in the relevant literature on extreme agricultural risk (Morgan, Cotter and Dowd, 2012; Martins-Filho, Yao and Torero, 2018) have used the moments and the tails of the realized price distribution (the distribution of the realized returns of agricultural commodity futures prices) to model the extreme agricultural tail risk. Here we use instead the moments and the tails of the risk neutral option-implied distribution. The advantage of this approach is that, while the tails of the realized distribution are backward looking (they are based on historical observations), the moments and tails of the option-implied risk neutral density function are forward looking since they quantify the conditional expectations of commodity investors about subsequent tail risk. Furthermore, the low correlation coefficients between the variables associated with the 'Theory of Storage' and the option-implied risk measures reveal that the (option-implied) commodity investors' beliefs are driven by economic forces which are structurally different from those determining the "inverse carrying charges".

Our contribution to the field is twofold: first, we show that the change in the commodity futures forward spread can act as an early warning signal of possible extreme returns in agricultural markets. Secondly, our empirical findings show that the option-implied information in agricultural markets is very useful, not only when predicting the volatility of agricultural prices (Giot, 2003; Simon, 2002; Triantafyllou, Dotsis and Sarris, 2015; Manfredo and Sanders, 2004; Wang, Fausti and Quasmi, 2012), but also when predicting the conditions under which the probability of agricultural price spikes significantly increases. Our findings have implications for optimal hedging decisions on agricultural markets since we show that the commodity market participants should avoid hedging (particularly long hedges) when our probit models indicate rising probabilities of price spikes[1]. Our results are in line with the findings of Wilson and Dahl (2009) who show that the hedging efficiency in agricultural markets declines significantly during periods of increased commodity price volatility.

The remainder of the paper is structured as follows. In Section 2, we provide an analytical explanation of the methodology, in Section 3 we describe the relevant data, in Section 4 we present the descriptive statistics for our explanatory variables and we analyze the results of our probit and OLS regression models. Finally, Section 5 concludes and presents some suggestions for further research.

2. Methodology

2.1 Defining price spikes in agricultural markets

The price spike is defined as a monthly price return which is larger than the expected return plus two option implied standard deviations. For an efficient commodity market, the expected return should be slightly positive to cover the storage cost, which, however, is close to zero for small commodity inventory holding periods (Brennan, 1958). Thus, we choose to define a price spike as a monthly price return which is greater than two option-implied standard deviations. More specifically, the categorical monthly variable PS_t which indicates the presence of a price spike is defined as follows:

$$PS_t = \begin{cases} 1 & if \quad ret_t \geq 2\sigma_t \\ 0 & otherwise \end{cases} \quad (1)$$

In (1) σ_t is the rescaled (transformed from annual to monthly) option-implied expected volatility observed at the first trading day of each monthly period according to the equation:

$$\sigma_t = \sqrt{IV_t \frac{30}{360}} \tag{2}$$

where IV_t is the option-implied risk neutral variance at the beginning of each monthly period and its estimation is analytically described in the Appendix. The rescaling of the implied volatility is necessary in order to be comparable to the monthly commodity futures returns. Thus, according to our definition a price spike occurs when the monthly return is more than two expected monthly standard deviations above its expected value. We compute the monthly returns (ret_t) of commodity futures contracts using the nearby (close to maturity) contracts. We choose nearest maturity to correspond to two-month expiration because the expiration dates on maize and wheat commodity futures are the last business days before the 15th of March, May, July, September and December while the maturity dates of soybeans futures contracts are the last business days before the 15th of January, March, May, July, August, September and November. These specificities suggest that the nearby agricultural commodity futures contracts expire roughly every two months. We define the monthly return of a futures contract for an investor who buys the futures contract at the start of the monthly period and keeps it (closes his long position) until the end of the monthly period, as follows:

$$ret_t = \frac{F\left(t_{end}, T\right) - F(t_{start}, T)}{F(t_{start}, T)} \tag{3}$$

Where $F(t_{start},T)$ is the price of the commodity futures contract (which expires at time T) at the beginning of the month t (namely the first trading day of the month) and $F(t_{end},T)$ is the price of the same contract at the end of month t (namely the last trading day of the month). Thus, the commodity futures return ret_t is the monthly return for a commodity investor who keeps his long futures position for the whole monthly period and closes his position in the last trading day of the month.

2.2 Baseline regression models

To assess the vulnerability to price spikes, we rely on estimating, based on historical data, the probability of occurrence of a price spike. We utilize a probit model for this, where both the left hand as well as the right-hand variables are based on theory as well as previous findings. The utilized model is the following:

$$P(PS_t = 1) = F(b_0 + b_1 FS_{t-1} + b_2 SUR_{t-1} + b_3 HP_{t-1} + b_4 TRM_{t-1} + b_5 VRP_{t-1} + b_6 IV_{t-1} + b_7 IS_{t-1} + b_8 IK_{t-1}) \quad (4)$$

Where PS_t is the categorical variable which indicates the occurrence of a price spike at time t, FS_{t-1} is the forward spread, SUR_{t-1} is the stock to use ratio at the beginning of the period HP_{t-1} is the hedging pressure, TRM_{t-1} is the seasonally adjusted tail risk measure, VRP_{t-1} is the variance risk premium, IV_{t-1} is the option-implied variance, IS_{t-1} is the option implied skewness and IK_{t-1} is the option implied kurtosis. All the above variables are observed at time t-1, in order to investigate whether they have predictive power. In the sequel we define and explain the above variables.

We additionally create a variable for Scaled-for-Volatility Returns (SVR_t) which in a sense quantifies the magnitude of a price spike, by dividing the monthly return given in equation (3) above with twice the rescaled monthly expected (option-implied) volatility given in equation (2). Thus, the SVR_t variable is larger than one for the month during which a price spike occurs and smaller than one for the other months. By this transformation we essentially capture the magnitude of a price spike for a given month. We then estimate the following predictive OLS regression model on the rescaled commodity futures returns:

$$SVR_t = b_0 + b_1 FS_{t-1} + b_2 SUR_{t-1} + b_3 HP_{t-1} + b_4 TRM_{t-1} + b_5 VRP_{t-1} + b_6 IV_{t-1} + b_7 IS_{t-1} + b_8 IK_{t-1} + \varepsilon_t \quad (5)$$

The estimates of the above model provide additional robustness to our probit model since the variable *SVR* variable is continuous (instead of binary) and consequently quantifies both the occurrence and magnitude of price spikes.

2.3 Storage and convenience yield

Any assessment of the probability of subsequent commodity price spikes must be based on a model of commodity price behavior. Bobenrieth, Wright and Zeng (2013) indicate that there is a well-established model of commodity price behavior based on competitive storage arbitrage. Prices by themselves are inadequate predictors of subsequent price spikes. In their effort to expand the range of variables that can be used as valid predictors of price spikes, Bobenrieth, Wright and Zeng (2013) find that global stock data, imperfect as they are by their nature, still provide information that can be used in conjunction with price information to obtain a better assessment of subsequent price shocks.

Existing commodity theory suggests that the behavior of commodity futures and spot prices is related to storage costs, inventory levels and convenience yields (Working, 1948, Brennan, 1958, Telser, 1958, Bresnahan and Suslow, 1985, Williams and Wright, 1989, 1991). It is the level of stocks in relation to demand (or the Stocks to Use Ratio (SUR) according to Bobenrieth, Wright and Zeng, 2013) which provides the appropriate cushion to shocks, and hence is related to the likelihood of a subsequent price increase.

Stocks are not easy to observe, so we need other variables that reflect stock scarcity. One of these is the futures-spot price spread (the difference between the price of the nearest futures contract, namely that which expires at a date nearest to the current time, and the cash or spot price). We call this the "forward spread"[2]. This forward spread is directly related to the level of stocks. When stocks are ample the forward spread is positive, stable, and equal to the marginal physical storage cost between the period of observation and the period of expiration of the nearest future contract. When stocks are low the forward spread is negative and can become very negative, as it is largely determined by the willingness of operators to pay for the convenience of having stocks at the current period.

The agricultural commodity futures forward spread is defined as the proportional price spread between the current futures price $F_{t,T}$ (namely the price of the futures contract traded at time t (present) and with maturity date T) and the corresponding spot price of the commodity S_t. The monthly time series for the agricultural cash prices are obtained from US Department of Agriculture (USDA). To better capture the marginal convenience yield which is included in the forward spread, we remove the cost-of-carry factor of the forward spread by subtracting the short-term interest cost (for the time interval used in the calculation of the forward spread) from the relative futures-spot price spread. Following the empirical approach of Fama and French (1988), we estimate the interest-adjusted agricultural commodity futures forward spread ($FS_{t,T}$) as follows:

$$FS_{t,T} = \left(\frac{F_{t,T} - S_t}{S_t} - r(t,T) \right) * 100 \tag{6}$$

Where t is the day of observation and T is the maturity date of the commodity futures contract. $F_{t,T}$ represents at time t the price of the futures contract that matures at time T. The variable $r(t,T)$ is the rate of interest for the period between time t and T, using the 3-month US-Treasury Bill rate. We take t to be the first trading day of each month. The variable S_t is the commodity spot price at time t[3]. We additionally follow the methodology of Fama and French (1987) and Geman and Nguyen (2005) and compute the forward spread using the nearby (near maturity) commodity futures prices as proxies for spot prices (S_t). Our additional results on forward spread using nearby futures contracts as proxies for cash prices can be found in our Appendix.

2.4 Realized variance

The monthly realized variance is calculated using the daily closing prices of the nearby commodity futures of a given maturity over a calendar month. For the calculation of the realized variance we construct a time series of prices following the methodological approach of Wang, Fausti and Qasmi (2012) who estimate the realized variance for corn commodity futures. For each trading day in a monthly period, among the available futures contracts we select the one which has the closest maturity to 60 days and at the same time has less than 90 days and more than 27 days to expiration. We estimate the monthly realized variance of commodity futures as the variance of the daily returns of these selected futures contracts. In order to be annualized, the realized variance of daily returns is multiplied by 252.

2.5 Option-implied agricultural market risk measures

2.5.1 The option-implied risk neutral distribution of commodity prices

Commodity option prices contain investors' probability assessments about the future price distribution of the underlying commodity. For example, the price of a call option with a strike price K reveals the assessment by commodity investors of the probability that the underlying commodity futures price will be larger than K. Consequently, the prices of options contracts which are written on the same commodity futures contract and have the same maturity date but different strike prices, can reveal an assessment (by option writers) of the conditional probability distribution of the underlying commodity price, and can be used to infer the unobservable option-implied distribution of the underlying agricultural commodity futures prices. In this paper we estimate the option-implied distribution of agricultural commodity prices by applying the tool of risk neutral valuation which goes back to contingent claim valuation and Arrow-Debreu securities. (See Arrow (1964), Debreu (1959)).

Risk neutral valuation is used extensively in mathematical finance as an easier way to price securities. The idea of risk neutral valuation is that any security can be reconstructed (replicated) as a weighted average of a set of primary (or Arrow-Debreu) securities, whose prices in turn can be inferred from prices of securities observed in the market. The price of the security can then be derived as the same weighted average of the prices of the primary securities. The risk neutral probability measure consists of the rescaled prices of the primary securities, which then look like probabilities.

The underlying economics behind risk neutrality, is that, unlike the real world, an artificial risk neutral world discounts all future events using the same risk-free rate r. In an artificial risk neutral world, the expected returns are not affected by the risk preferences of investors, and consequently, no risk premia exist. The risk neutral pricing measure Q is practically useful because of its uniqueness. In the real world (or under the physical pricing measure P), we need many different discount factors to price different risky assets, while in the risk neutral world we use the risk-free rate as the unique discount factor for all the different risky assets. Further details about the estimation of the risk neutral distribution for agricultural commodity prices can be found in our on-line Appendix.

2.5.2 Variance, skewness and kurtosis of the option-implied distribution

The shape of the option-implied risk neutral distribution reveals significant information regarding the expectations of market participants, and it is measured by estimating the moments of the distribution. The option-implied variance, skewness and kurtosis are useful because they quantify commodity investors' expectations about future volatility and tail risk. For example, Han (2008) shows that the risk neutral skewness which is backed-out from S&P 500 equity options, is associated with a bullish (bearish) equity market, while Jiang and Tian (2005) show that the option-implied risk neutral variance subsumes all the information contained in the Black and Scholes (1973) implied volatility and in the past realized volatility of the S&P 500 stock-market index. In our on-line Appendix we present the methodology for the estimation of the higher order moments of the option-implied risk neutral distribution of agricultural markets. More specifically, we estimate the variance, the skewness and the kurtosis of the risk neutral distribution using the methodology of Bakshi, Kapadia and Madan (2003).

2.5.3 Variance Risk Premium

The variance risk premium represents the compensation demanded by investors for bearing variance risk and is defined as the difference between realized variance (RV_t). and a risk-neutral implied variance (IV_t). According to Bliss and Panigirtzoglou (2004) and Carr and Wu (2009) the variance risk premium is a reliable measure of risk aversion in financial markets. More specifically, following Carr and Wu (2009) and Christoffersen, Kang and Pan (2010), we define the variance risk premium as the difference between the *P*-measure (namely the real-world) realized variance and the *Q*–measure expected variance, using the following formula:

$$VRP(t,T) = E_t^P\left(RV(t,T)\right) - E_t^Q\left(RV(t,T)\right) \equiv RV_t - IV_t \tag{7}$$

where RV_t stands for the realized monthly variance and IV_t stands for the option-implied risk neutral variance at the first trading day of the month.

2.5.4 Tail Risk Measure of the option-implied distribution

The option-implied Tail Risk Measure (*TRM*) is the probability mass which is contained in the right tail of the option-implied risk neutral density function and represents the option-implied expectations of agricultural investors about tail risk. In other words, the *TRM* shows the probability assigned by commodity option writers that the underlying commodity futures price will be higher than a high strike price *K* (namely, the probability that a deep-out-of-the money call option will not expire worthless). The right tail of the risk neutral distribution is estimated by using the deep-out-of-the-money call options contracts whose strike price *K* is significantly larger when compared to the price of the current (at-the-money) commodity price.

Motivated by the relevant literature in equity markets (Bollerslev and Todorov, 2011; Bollerslev, Todorov, and Xu, 2015; Vilkov and Xiao, 2013) which shows that the *TRM* is systematically priced in the equity market and is a significant predictor of extreme equity market returns, we estimate the *TRM* and examine its predictive power on the price jumps in agricultural commodity markets. Unlike equity markets for which the unexpected price jumps are usually negative because of the leverage effect, in commodity markets the prices and volatility are positively correlated because they are both negatively correlated with stocks (this is the inverse leverage effect). The underlying economic justification for the occurrence of a relatively higher number of price spikes compared to price drops in commodity markets, is that price jumps are potentially unbounded because low stocks cannot prevent prices from increasing, while price drops will be mitigated by stock accumulations. For this reason, we estimate the TRM as the probability mass of the right tail of the risk neutral distribution which captures investors' expectations (fears) about the occurrence of price spikes. The analytical formulas and methodology for the estimation of the TRM can be found in our on-line Appendix.

3. Data

3.1 Agricultural commodity options and futures data

We obtained daily option and futures data for maize, wheat and soybeans from the Chicago Board of Trade (CBOT). The options and futures data for maize, wheat and soybeans cover the period from January 1990 to December 2011. In the empirical analysis, we use the option and futures daily settlement prices, the strike prices for option contracts and the respective time to maturity for both options and futures.

3.2 Hedging Pressure and Stocks-to-Use Ratios

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

$$Hedging\ Pressure_t = \frac{(\#\ of\ short\ hedge\ positions)_t - (\#\ of\ long\ hedge\ positions)_t}{(\#\ of\ total\ hedge\ positions)} \quad (8)$$

Bi-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. We compute the monthly hedging pressure using the number of short and long hedge positions in the first bi-weekly period of each monthly period.

Concerning inventory data, we obtained quarterly inventory data for maize, wheat and soybeans from the US National Agricultural Statistics Service for the period 1990 till 2011[4]. We then obtained yearly data for US aggregate consumption for maize, wheat and soybeans from the USDA/FAS/PSDO. Following the methodology of Bobenrieth, Wright and Zheng (2013) for the computation of Stocks-to-Use Ratios (SURs), we normalize (detrend) the quarterly commodity inventory series by dividing them by the yearly US consumption of the respective commodities. These ratios are our quarterly SURs. To remove the seasonalities from the SURs, we de-seasonalize the quarterly SUR series using the Dagum (1978) X-11 ARIMA methodology. We then estimate our monthly SUR series by applying linear interpolation on the de-seasonalized quarterly SURs.

4. Empirical results

4.1 Descriptive statistics

We first present in Table 1 the descriptive statistics for our most significant explanatory variables. In Table 1, *FS* is the forward spread, *INV* is the logarithm of the inventory level, *TRM* is the tail risk measure, *VRP* is the variance risk premium, *IV* is the option-implied variance, *HP* is the hedging pressure and *RET* is the monthly returns of agricultural commodity futures.

[Insert Table 1 here]

The numbers in Table 1 show that the average forward spread is positive for maize, soybeans and wheat market. Furthermore, the variance risk premium is statistically indistinguishable from zero for all agricultural markets considered. The hedging pressure is also positive for all agricultural markets analyzed. The percentage of price spikes in the sample is approximately 5% of the total time series sample for all agricultural markets considered. Furthermore, we conduct unit root tests for all our explanatory variables and for the residuals of our multivariate probit model. We reject the hypothesis of a unit root for our explanatory variables and for maize, wheat and soybeans probit regression residual series at a 1% confidence level. The results of our unit root tests can be found in our on on-line Appendix. In Table 2 we present the correlation coefficients between our explanatory variables.

[Insert Table 2 here]

The Table 2 indicates low correlation coefficients between our explanatory variables, hence low multicollineariarity issues. The very low correlation coefficients between the forward spread and the all the other commodity specific and option-implied variables indicate that the forward spread has statistically and economically different predictive information compared to the option-implied variables.

It can be inferred by these results that commodity investor's option-implied expectations are not driven by the convenience yield for holding physical inventory.

There must be other microeconomic or macroeconomic forces driving the expectations and the risk premiums in agricultural commodity option markets.

In Figures 1, 2 and 3 we present the time series of the commodity futures Forward Spread (FS), of Stocks-to-Use Ratios (SURs) and of TRM respectively.

[Insert Figure 1 here]

[Insert Figure 2 here]

[Insert Figure 3 here]

The time-variation in commodity investors' perception of tail risk (quantified by the tail risk measure of maize, wheat and soybeans markets) significantly increased in the 2006-2008 commodity crisis period. In addition, the forward spread of agricultural commodity futures remains positive in nearly all the periods and becomes negative only when a significant fall in SURs occurs. For example, in early 1996 the negative forward spread in maize and wheat market coincides with a significant drop in the SURs of maize and wheat respectively during the same period. Figures 1 and 2 show a negative correlation between SURs and agricultural futures forward spread. These results are in line with the findings of Joseph, Irwin and Garcia (2016) who empirically verify the existence of the Working supply of storage curve for maize, wheat and soybeans futures markets by showing that the agricultural futures forward spread is positive for high inventory levels and negative for low inventory levels.

4.2 Assessing the probability of agricultural price spikes

4.2.1 Probit regression models

In this section, we present the results of our probit models in which we estimate the onset of unexpected price spikes in commodity markets according to equation (4). Tables 3, 4 and 5 summarize the regression results of our univariate and multivariate probit models for maize, wheat and soybeans markets respectively.

[Insert Table 3 here]

[Insert Table 4 here]

[Insert Table 5 here]

From Tables 3, 4 and 5 we observe that the sign of the coefficient of the forward spread is negative and statistically significant when forecasting the one-month ahead price jumps of maize and wheat markets. It can be inferred by this result that a more negative forward spread in agricultural futures markets (a rise in convenience yields) at the beginning of each monthly period is associated with higher probability of a price spike during this period[5]. This result is in accordance with the Theory of Storage (see Brennan, 1958; Telser, 1958; Working, 1948), as the forward spread represents the marginal convenience yield of holding physical inventory. Thus, according to our findings, when agricultural commodity producers and consumers hold low physical inventories (more negative forward spread), the probability of a price spike occurring is significantly increased. Our findings are in line with the more recent empirical findings of Bobenrieth, Wright, and Zeng (2013) who find that agricultural stocks-to-use ratios, which are essentially driven by convenience yields and inverse carrying charges, are significant indicators of subsequent spikes in agricultural markets.

Furthermore, our econometric analysis shows that the forecasting ability of our probit models is significantly increased when we include in the right-hand side of the regressions the option-implied variables which are associated with the expectations of commodity investors about volatility and tail risk. We find that the tail risk measure, the variance risk premium and the risk neutral variance contain statistically significant predictive power and result in a large improvement of the explanatory power of our probit models when added into the right-hand side of the probit equations[6]. More specifically, Tables 3 to 5 show that the Mc Fadden R^2 increases from 5.8% to 26.9%, from 18.8% to 29.4% and from 6.8% to 27.9% for maize, wheat and soybeans price spike forecasting respectively[7]. We find that the Variance Risk Premium (*VRP*) and the Implied Variance (*IV*) in the maize options market increase the probability of predicting a subsequent spike in the price of maize[8]. The statistically significant coefficient of these option-implied risk measures shows that maize commodity investors' fears about tail risk indicate a higher probability of an extreme (above two-sigma) return in the maize futures market. The estimated coefficient for the Tail Risk Measure (*TRM*) is also negative and statistically significant when forecasting the timing of price spikes in the soybeans market[9].

Figure 4 shows the estimated probabilities of our multivariate probit model versus the actual (realized) above two-sigma returns for each monthly period along with the respective time series of maize, wheat and soybeans spot prices. The forecasting horizon of the probit regressions is one month.

[Insert Figure 4 here]

Figure 4 shows that the estimated (by the probit model) probabilities of extreme returns significantly increase prior to the realization of the extreme two-sigma returns in agricultural markets. Even though the timing of extreme returns in commodity markets is by default a highly unpredictable process, our econometric analysis indicates that our explanatory variables can act as early warning signals of extreme-returns in agricultural commodity markets. As a robustness check, we also examined the predictability of extreme returns for intermediate (two-month and three month) forecasting horizons and our main findings regarding the predictability of the forward spread, the implied variance and the variance risk premium remain unaltered. These additional results can be found in our Appendix.

4.2.2 OLS regression models

In this section we present the OLS regressions in which we use the same regression specification as in our probit models. In these regression models our dependent variable is the Scaled-for-Volatility-Return (*SVR*). Our baseline OLS regression model is given in equation (5). Table 6 presents the respective OLS regression results for maize, wheat and soybeans markets.

[Insert Table 6 here]

The results of Table 6 provide robustness to our probit regression results since we show that the *FS*, the *TRM*, the *IV* and the *VRP* are significant determinants of these volatility-adjusted returns which, apart from the timing, capture the magnitude of price spikes in agricultural markets. We also run the same OLS regression model for the financialization period (post-2000) of commodity markets and our basic results and conclusions remain unaltered. We lastly provide out-of-sample evidence of the predictive power of the OLS regression models by running rolling regressions on the scaled-for-volatility returns using an initial 10-year time series window. Our out-of-sample estimates show the robust predictive power of the forward spread and of the option-implied risk measures. These additional regression results can be found in our Appendix.

5. Conclusions

We empirically show that the more negative forward spread, apart from indicating higher convenience yield for holding physical inventory, is also associated with higher probabilities of above 2-sigma price jumps in agricultural commodity futures markets. Furthermore, the option-implied tail risk measure, the risk neutral variance and the variance risk premium significantly increase the forecasting power of our regression models when added as additional predictors of the conditions which are associated with a higher probability of agricultural commodity price spikes. Overall, we conclude that the unexpected above 2-sigma price spikes are associated with changes is commodity futures forward spread, thus they can largely be attributed to the variables related with the 'Theory of Storage'. In addition, we show that the option-implied information significantly improves the predictive power of models which forecast the above 2-sigma jumps in maize, wheat and soybeans markets.

These empirical findings indicate that the combined predictive information content of commodity futures forward spread and option-implied risk measures can be used as risk management tools for commodity producers, investors and policy makers which have as an objective the timely forecasting and management of agricultural risk. Nevertheless, the determination of the key drivers of time-varying option-implied perceptions of tail risk and of agricultural commodity futures forward spread remains an unresolved issue. We leave the further exploration of the factors influencing these as an open question for further research.

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Table 1. Descriptive statistics of the explanatory variables and of agricultural commodity futures returns.

Panel A: Maize

	FS (%)	SUR	TRM	IV	VRP	HP	RET
Mean	7.698	0.577	0.070	0.073	-0.007	0.013	0.002
Median	7.495	0.566	0.066	0.060	-0.015	0.031	0.000
Max	38.133	1.078	0.251	0.293	0.422	0.323	0.278
Min	-24.220	0.219	0.012	0.008	-0.165	-0.372	-0.231
St. Dev.	7.883	0.108	0.027	0.045	0.052	0.148	0.077
Skew	0.165	0.500	1.613	1.271	3.243	-0.293	0.022
Kurt	5.804	5.361	11.198	5.074	24.426	2.313	3.774

% of price spikes in the sample: 3.8%

Panel B: Wheat

	FS (%)	SUR	TRM	IV	VRP	HP	RET
Mean	4.201	1.109	0.064	0.075	0.005	0.078	0.002
Median	1.760	1.067	0.060	0.060	-0.004	0.036	0.000
Max	77.415	1.734	0.168	0.344	0.244	0.570	0.278
Min	-19.389	0.512	0.014	0.015	-0.106	-0.287	-0.231
St. Dev.	11.128	0.206	0.026	0.048	0.044	0.187	0.077
Skew	2.018	0.296	1.051	1.870	1.752	0.545	0.022
Kurt	11.067	3.466	4.524	7.581	9.331	2.582	3.774

% of price spikes in the sample: 4.2%

Panel C: Soybeans

	FS (%)	SUR	TRM	IV	VRP	HP	RET
Mean	1.482	1.125	0.069	0.061	-0.005	0.130	0.002
Median	1.034	1.087	0.066	0.050	-0.010	0.148	0.000
Max	39.226	2.611	0.258	0.199	0.423	0.654	0.278
Min	-17.730	0.524	0.016	0.005	-0.158	-0.354	-0.231
St. Dev.	5.667	0.244	0.026	0.037	0.045	0.192	0.077
Skew	1.458	1.674	2.312	1.502	4.188	-0.154	0.022
Kurt	11.416	10.550	15.356	5.012	37.100	2.509	3.774

% of price spikes in the sample: 4.5%

Note: The *SUR* and the *TRM* variables refer to the seasonally adjusted Stocks-to-Use Ratio (SUR) and on the seasonally adjusted *TRM* series which are used in the time series regressions. The Forward spread variable is expressed in percentages. We do not include in this table the descriptive statistics of our higher order option-implied moments (skewness and kurtosis) in order to save space and because our econometric analysis shows that these are not significant determinants of agricultural price spikes.

Source: Computed by authors

Table 2. Correlations between explanatory variables

Panel A: Maize

	FS	SUR	HP	TRM	IV	VRP	SKEW	KURT
FS	1.00							
SUR	0.13	1.00						
HP	0.26	-0.11	1.00					
TRM	0.01	-0.15	0.12	1.00				
IV	0.07	-0.28	0.23	0.62	1.00			
VRP	-0.08	-0.10	-0.03	-0.01	-0.05	1.00		
SKEW	0.13	-0.17	-0.09	0.27	0.45	0.05	1.00	
KURT	-0.13	0.24	0.08	-0.28	-0.52	-0.08	-0.91	1.00

Panel B: Wheat

	FS	SUR	HP	TRM	IV	VRP	SKEW	KURT
FS	1.00							
SUR	0.23	1.00						
HP	-0.30	-0.10	1.00					
TRM	0.38	0.08	-0.29	1.00				
IV	0.54	-0.02	-0.31	0.78	1.00			
VRP	-0.01	-0.09	-0.06	0.08	0.12	1.00		
SKEW	0.27	0.17	-0.54	0.34	0.34	0.08	1.00	
KURT	-0.31	-0.12	0.54	-0.32	-0.40	-0.10	-0.94	1.00

Panel C: Soybeans

	FS	SUR	HP	TRM	IV	VRP	SKEW	KURT
FS	1.00							
SUR	0.19	1.00						
HP	0.24	-0.11	1.00					
TRM	0.14	-0.17	0.12	1.00				
IV	0.21	-0.14	0.06	0.56	1.00			
VRP	0.09	-0.12	-0.02	-0.01	0.09	1.00		
SKEW	0.19	-0.14	0.03	0.30	0.52	0.09	1.00	
KURT	-0.17	0.13	0.11	-0.25	-0.56	-0.07	-0.93	1.00

Note: The *SUR* and the *TRM* variables refer to the seasonally adjusted Stocks-to-Use ratio and on the seasonally adjusted *TRM* series which are used in the time series regressions.

Source: Computed by authors

Table 3. Probit regressions of the incidence of price spikes in the maize futures market

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Const	Coef.	-1.539***	-0.449	-1.778***	-1.907***	-1.383***	-1.820***	-1.725***	-1.644***	0.079
	t-stat	(-9.180)	(-0.540)	(-12.749)	(-4.997)	(-4.766)	(-11.901)	(-11.106)	(-7.404)	(-0.056)
FS	Coef.	-0.044**								-0.065*
	t-stat	(-2.195)								(-1.937)
SUR	Coef.		-2.393							-1.204
	t-stat		(-1.572)							(-0.591)
HP	Coef.			-0.871						1.158
	t-stat			(-0.944)						(0.759)
TRM	Coef.				1.841					14.974
	t-stat				(0.375)					(1.595)
IV	Coef.					-6.129				-25.478***
	t-stat					(-1.417)				(-2.732)
VRP	Coef.						5.619**			7.982**
	t-stat						(2.618)			(2.470)
SKEW	Coef.							0.076		0.123
	t-stat							(0.703)		(0.353)
KURT	Coef.								-0.012	-0.023
	t-stat								(-0.720)	(-0.380)
% Mc Fadden R^2		5.8	3.1	1.1	0.2	2.9	7.0	0.6	0.7	26.9

Source: Computed by authors

Table 4. Probit regressions of the incidence of price spikes in the wheat futures market

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Const	Coef.	-1.859***	-1.455*	-1.725***	-1.468***	-1.365***	-1.870***	-1.735***	-1.693***	-2.971**
	t-stat	(-9.764)	(-1.922)	(-11.620)	(-3.728)	(-4.463)	(-11.529)	(-11.878)	(-7.065)	(-2.220)
FS	Coef.	-0.096***								-0.101***
	t-stat	(-3.377)								(-2.966)
SUR	Coef.		-0.251							1.185
	t-stat		(-0.369)							(1.277)
HP	Coef.			-0.086						-0.441
	t-stat			(-0.117)						(-0.429)
TRM	Coef.				-4.268					13.645
	t-stat				(-0.694)					(0.925)
IV	Coef.					-5.527				-12.662
	t-stat					(-1.240)				(-1.178)
VRP	Coef.						7.180***			10.122**
	t-stat						(2.764)			(2.335)
SKEW	Coef.							-0.014		-0.366
	t-stat							(-0.879)		(-0.661)
KURT	Coef.								-0.005	-0.074
	t-stat								(-0.194)	(-0.737)
% Mc Fadden R^2		18.8	0.2	0.1	0.6	2.2	7.7	0.1	0.4	29.4

Source: Computed by authors

Table 5. Probit regressions of the incidence of price spikes in the soybeans futures market

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Const	Coef.	-1.691***	-0.690	-1.623***	-0.328	-1.176***	-1.695***	-1.569***	-1.401***	1.960
	t-stat	(-11.823)	(-0.945)	(-10.654)	(-0.680)	(-3.811)	(-12.314)	(-11.027)	(-6.498)	(0.916)
FS	Coef.	-0.071**								-0.058
	t-stat	(-2.465)								(-1.519)
SUR	Coef.		-0.914							-0.610
	t-stat		(-1.355)							(-0.653)
HP	Coef.			-0.527						0.947
	t-stat			(-0.772)						(0.854)
TRM	Coef.				-22.281***					-20.292*
	t-stat				(-2.726)					(-1.729)
IV	Coef.					-9.747				-12.753
	t-stat					(-1.651)				(-1.236)
VRP	Coef.						3.812			4.161
	t-stat						(1.684)			(0.795)
SKEW	Coef.							0.240*		0.327
	t-stat							(1.867)		(0.812)
KURT	Coef.								-0.026	-0.020
	t-stat								(-1.484)	(-0.330)
% Mc Fadden R^2		6.8	2.1	0.6	9.6	3.9	2.5	4.5	2.9	27.9

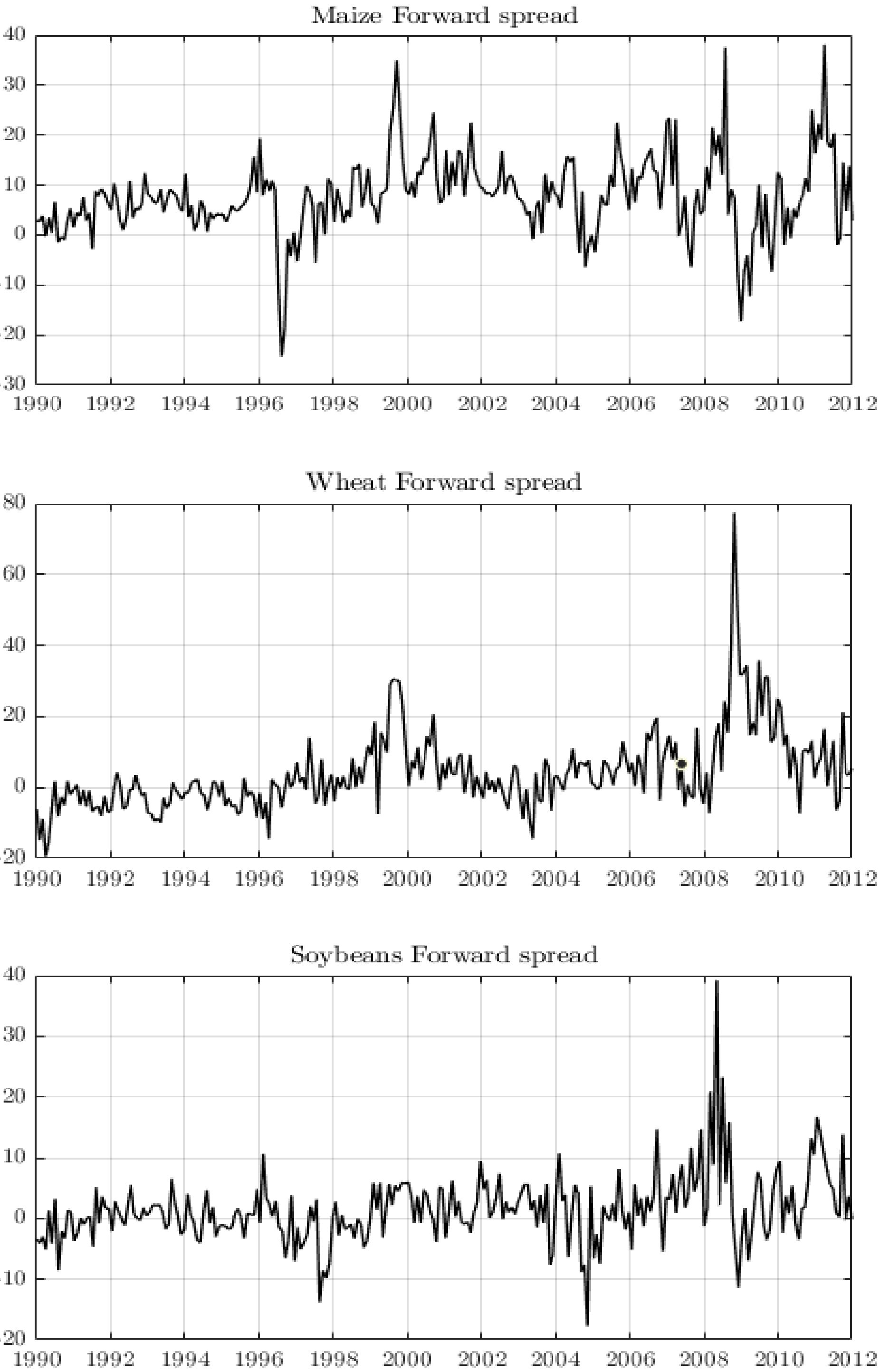
Source: Computed by authors

Table 6. OLS regressions on scaled-for-volatility monthly returns in agricultural futures markets for medium-term forecasting horizons. The model estimated is the following:

$$SVR_t = b_0 + b_1 FS_{t-k} + b_2 SUR_{t-k} + b_3 HP_{t-k} + b_4 TRM_{t-k} + b_5 IV_{t-k} + b_6 VRP_{t-k} + b_7 IS_{t-k} + b_8 IK_{t-k} + \varepsilon_t$$

		Maize (k=1)	*Maize (k=2)*	*Maize (k=3)*	*Wheat (k=1)*	*Wheat (k=2)*	*Wheat (k=3)*	*Soybeans (k=1)*	*Soybeans (k=2)*	*Soybeans (k=3)*
Const	Coef.	0.052	0.012	-0.375**	-0.476**	-0.047	-0.077	0.092	0.320*	0.128
	t-stat	(0.241)	(0.058)	(-1.980)	(-2.077)	(-0.233)	(-0.386)	(0.423)	(1.673)	(0.674)
FS	Coef.	-0.016***	0.003	0.003	-0.021***	0.004	0.002	-0.040***	0.006	-0.004
	t-stat	(-3.728)	(0.721)	(0.106)	(-5.225)	(1.396)	(0.068)	(-4.500)	(1.094)	(-0.736)
SUR	Coef.	0.401	0.297	0.445	0.342**	-0.027	0.126	0.204	-0.031	0.115
	t-stat	(1.126)	(1.215)	(1.611)	(2.399)	(-0.177)	(0.855)	(1.474)	(-0.242)	(0.841)
HP	Coef.	0.547**	0.092	-0.185	-0.182	-0.058	-0.215	0.257*	-0.179	-0.323*
	t-stat	(2.492)	(0.443)	(-0.830)	(-0.901)	(-0.311)	(-1.500)	(1.704)	(-1.045)	(-1.939)
TRM	Coef.	2.320*	-1.242	2.661**	-0.944	-2.655*	-1.154	0.859	0.667	1.183
	t-stat	(1.716)	(-0.783)	(2.217)	(-0.590)	(-1.715)	(-0.629)	(0.431)	(0.855)	(0.812)
IV	Coef.	-3.069***	-0.553	-1.064	2.407*	0.450	0.591	-3.525**	-3.397***	-3.290***
	t-stat	(-2.881)	(-0.547)	(-1.124)	(1.850)	(0.474)	(0.525)	(-2.379)	(-3.258)	(-2.821)
VRP	Coef.	1.035	-0.770	-0.862	2.531***	-1.326**	-1.166*	0.459	-0.270	-0.605
	t-stat	(0.988)	(-1.074)	(-1.383)	(3.315)	(-2.327)	(-1.709)	(0.741)	(-0.526)	(-0.982)
SKEW	Coef.	-0.007	-0.026	0.041	0.074	0.287***	0.001	0.026	-0.003	0.101*
	t-stat	(-0.223)	(-0.752)	(1.212)	(0.796)	(3.039)	(-0.015)	(0.458)	(-0.056)	(1.875)
KURT	Coef.	-0.006	-0.006	0.006	0.016	0.045***	0.003	-0.005	-0.005	0.003
	t-stat	(-0.949)	(-0.724)	(1.231)	(1.010)	(3.046)	(0.158)	(-0.668)	(-0.594)	(0.472)
% Adj. R^2		12.2	2.6	4.7	17.8	5.4	1.9	20.4	4.4	7.5

Figure 1. Interest-adjusted forward spread of agricultural commodity markets

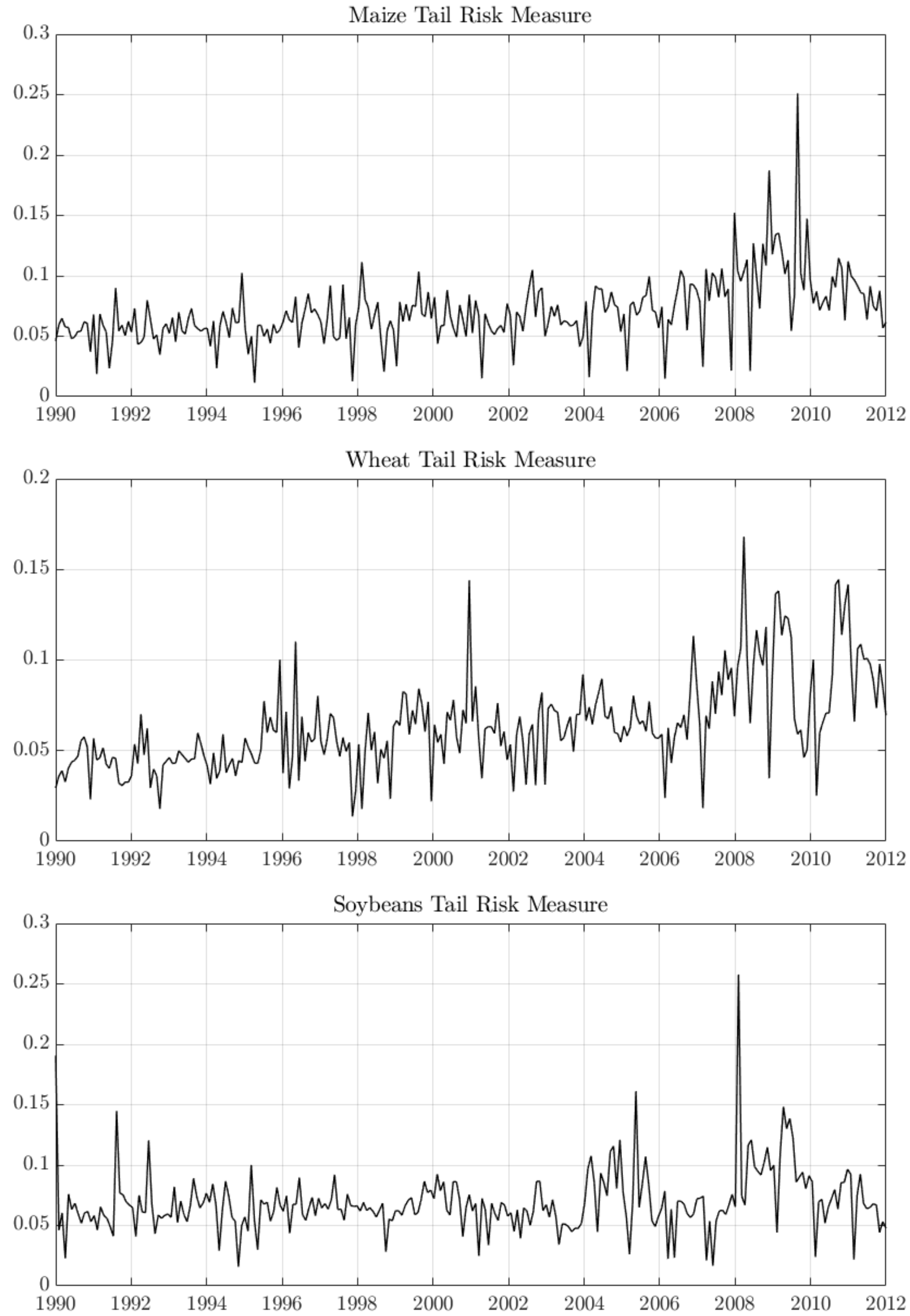


Source: Computed by authors

Figure 2. Stocks-to-Use Ratio (SUR) for agricultural commodity markets

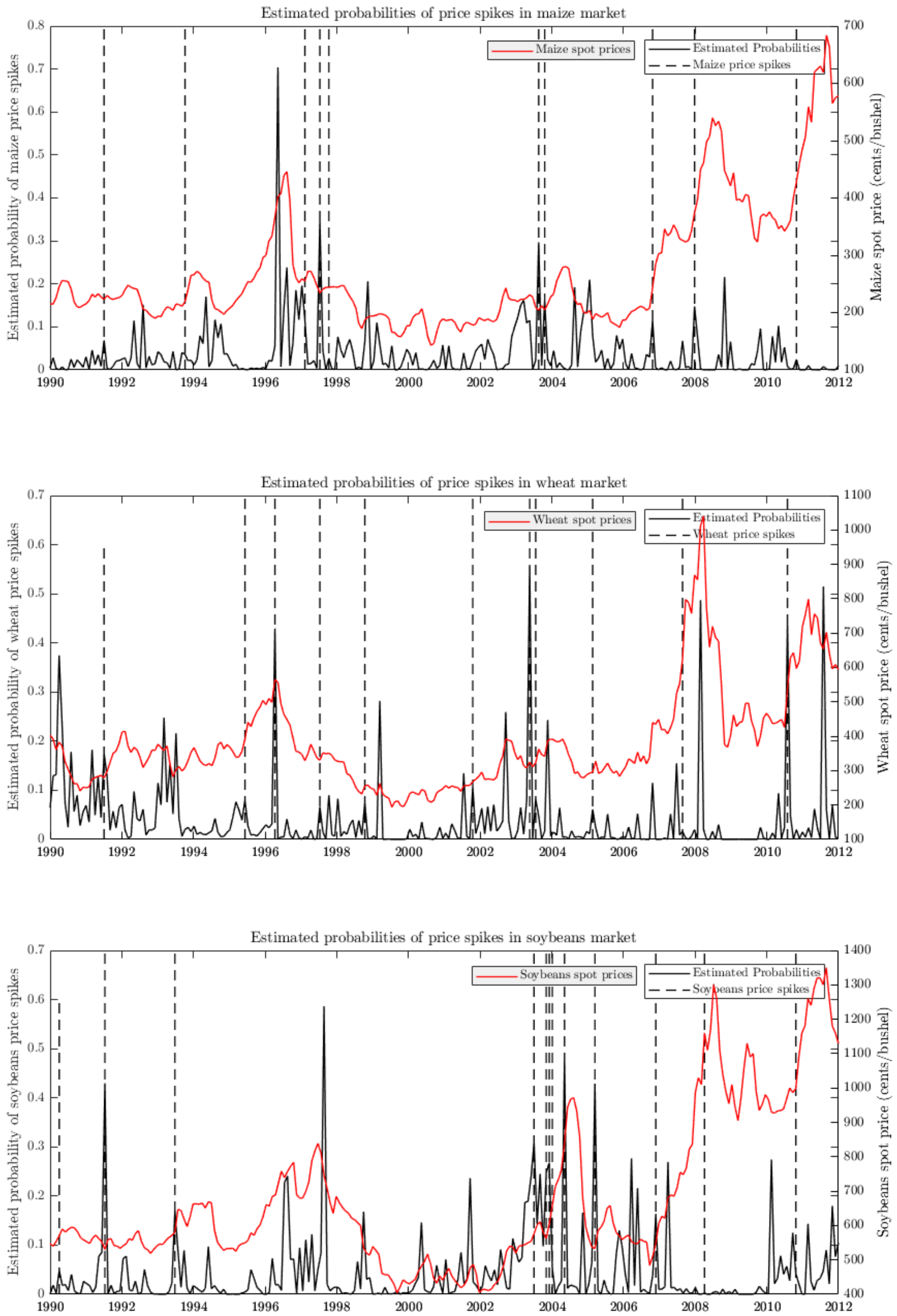
Source: Computed by authors

Figure 3. Option-implied Tail Risk Measure (TRM) of agricultural commodity markets



Note: The TRM series are the de-seasonalized series of the estimated Tail Risk Measure.
Source: Computed by authors

Figure 4. Estimated probabilities of the incidence of price spikes in agricultural commodity futures markets (multivariate probit model of equation (4))



The black line shows the probabilities implied by the probit model, the red line shows the monthly time series of maize, wheat and soybeans spot (cash) prices and the dashed vertical line represents the historical timing of the above 2-sigma price jumps in agricultural markets.

Source: Computed by authors

Footnotes

[1] In general, the higher basis risk may lead to improvement or worsening of a hedger position. When the forward spread strengthens unexpectedly (the spot prices increase more than the corresponding commodity futures prices), the long hedge position worsens while the short hedge position improves in terms of hedging cost and efficiency. Thus, it is optimal for a hedger to avoid long hedges in the agricultural market when a commodity price jump occurs and, according to our empirical findings, a synchronous rise in agricultural convenience yields is anticipated.

[2] In order to avoid confusion, we define the percentage difference between futures and spot prices as forward spread. We avoid defining this difference as the basis, since, while the commodity futures basis is defined as the futures-spot price difference in some empirical studies (Fama and French, 1987; Josheph, Irwin and Garcia, 2016), it is defined as the spot-futures spread in some other relevant studies (Fausti, Qasmi and Mc Daniel, 2017).

[3] To compute the two-month maturity forward spread we use futures contracts with maturities close to 60 days.

[4] Since commodity prices are global, the more appropriate inventories series for our analysis would be the global level of inventories. Unfortunately, reliable global inventory data do not exist (at least in monthly or quarterly frequency), so we decide to use the US inventory data series as the next best proxy for global inventories.

[5] We provide robustness to the predictive power of the forward spread by using alternative methods for estimating the forward spread. More specifically, we follow the empirical approach of Fama and French (1987) and Geman and Nguyen (2005) and use equation (6) to compute the forward spread using the nearby futures prices (and not the USDA cash prices which we use in the paper) as proxies for spot prices (S_t). Under this alternative methodology for the estimation of the forward spread, our findings on the predictive power of the forward spread remain unaltered. These additional regression results can be found in our Appendix.

[6] To control for the high correlation between the *TRM* and *IV* as shown in Table 2, we estimate additional probit models in which we include only the *TRM* or the *IV* in our right-hand side of the regression equation and show that our basic findings remain unaltered. These additional results can be found in our on-line Appendix.

[7] We must state here that relying solely to Mc-Fadden R^2 values as a goodness of fit measure is a bit controversial. The adjusted R^2 values of our OLS regression models which are presented at Subsection 4.2.2. of the paper are more reliable measures of goodness of fit.

[8] We provide robustness to our baseline multivariate probit model given in Equation (4) by estimating the coefficients for the marginal probabilities of our regressions which are included in our probit model and our findings remain unaltered. Moreover, we provide robustness to the goodness of fit of our model by showing that the correlations between the residuals of our multivariate probit model and our explanatory variables are less than 3%. These additional results can be found in our Appendix.

[9] The negative sign of the estimated coefficients of the tail risk measure and risk neutral variance in the soybeans market indicates that these option-implied risk measures increase only after the extreme event has occurred and can be interpreted as an overreaction of agricultural commodity investors (Bates, 1991). The statistically significant negativity of the coefficients of risk neutral variance and *TRM* when forecasting the timing of extreme returns, indicates that these option-implied risk measures increase only after the occurrence of the price spike and not prior to it.