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Assessing the Vulnerability to Price Spikes in Agricultural Commodity Markets

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Abstract

We examine empirically the predictability of conditions 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 historical sudden market upheavals in agricultural markets.

Keywords: *agricultural price spikes*; *extreme value theory*; *risk neutral moments*; *tail risk measure*; *theory of storage*.

JEL classifications: *G13, Q10, Q13, Q18*.

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. Previous 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

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either the spikes themselves or their underlying causes. Nevertheless, the identification of the conditions under which a price spike in agricultural markets could occur, would improve the anticipation of subsequent spikes, and would be important for farmers, their marketing chains, and policy-makers who try to shape policies for a risk-prone agricultural sector.

What are the likely determinants of commodity price spikes? Since commodity price spikes are largely unexpected, it is reasonable to assume that unexpected shocks that impinge on prices 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 a 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; Working, 1948; Brennan, 1958; Telser, 1958; 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. Our contribution to the relevant literature is that, while empirical studies verify the predictive information content of the forward spread on commodity futures returns (Fama and French, 1987; Gordon and Rowenhorst, 2006; Frankel and Rose, 2010; Gordon *et al*., 2013), we also examine whether this spread is a robust predictor of the likelihood of subsequent price spikes in agricultural markets. 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 *et al*. (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.

Independently, the literature on the predictability of stock-market returns (Bollerslev *et al*., 2009; Bollerslev and Todorov, 2011; Vilkov and Xiao, 2013; Kelly and Jiang, 2014; Bollerslev *et al*., 2015) 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. These variables are the option-implied tail risk measure, the variance risk premium, the implied variance, the implied skewness and the implied kurtosis. Lastly, following the empirical findings of another strand of literature which attributes 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.

To the best of our knowledge, this is the first paper that utilises the option-implied information for the modelling of the probability of price jumps in agricultural commodity markets. Empirical studies in the relevant literature on extreme agricultural risk (Morgan *et al.*, 2012; Martins-Filho *et al.*, 2018) have used the moments and the tails of the realised price distribution (the distribution of the realised 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 realised 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 future 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 test whether the change in the commodity futures forward spread can act as an early warning signal of possible extreme returns in agricultural markets. Secondly, we investigate empirically whether option-implied information in agricultural markets is useful, not only when predicting the volatility of agricultural prices (Simon, 2002; Giot, 2003; Manfredo and Sanders, 2004; Wang *et al.*, 2012; Triantafyllou *et al.*, 2015), but also when identifying the conditions under which the likelihood of agricultural price spikes increases significantly.

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

2. Methodology

2.1. Defining price spikes in agricultural markets

A 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, our categorical monthly variable PS_t which indicates the presence of a price spike is defined as:

$$PS_t = \begin{cases} 1 \; if \; re\ t_t \geq 2\sigma_t \\ 0 \quad otherwise \end{cases} \tag{1}$$

In equation (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 Online Appendix. The rescaling of the implied volatility makes it comparable to the monthly commodity futures returns. 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 approximately every 2 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 until closing the long position on the last trading day of the monthly period, as follows:

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

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).

2.2. Baseline model

To assess the vulnerability to price spikes, we estimate the probability of occurrence of a price spike as a function of several variables that appear *a priori* to affect the vulnerability, based on historical data. Our model is:

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

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

We include the forward spread as it is related to the level of inventories. According to the theory of storage (Kaldor, 1939; Working, 1948; Brennan, 1958) the lower the current inventories, the higher the difference between the current and the forward price – that is, the lower the forward spread. But low current inventories signify a market sensitive to shocks, and hence more likely to experience price spikes. Similarly, the stock to use ratio of the previous period denotes market sensitivity to shocks and is an alternative to forward spread. As stocks are measured imperfectly, the variable FS may better reflect current stock conditions. Both of these variables should enter with a negative sign in the empirical equation. Hedging pressure is included since the hedging pressure hypothesis is that a positive HS (net short hedging activity) predicts a subsequent increase in futures prices and *vice versa*. We also include a set of predictive variables (TRM, VRP, IV, IS, IK) extracted from option prices. These predictive variables (explained in detail in section 2.4) capture various segments of the option-implied distribution and reflect expectations blended with risk premiums of agricultural commodity investors.

We estimate the probit model given in equation (4) using maximum likelihood and we base our conclusions regarding the predictive power of our covariates on the statistical significance of the respective probit estimators using standard asymptotic theory results. We also create a variable for Scaled-for-Volatility Returns (SVR_t) 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:

$$\begin{aligned} SVR_t \; &= b_0 + b_1 FS_{t-1} + b_2 SUR_{t-1} + b_3 HP_{t-1} + b_4 TRM_{t-1} + b_5 VRP_{t-1} \\ &\quad + b_6 IV_{t-1} + b_7 IS_{t-1} + b_8 IK_{t-1} + \varepsilon_t \end{aligned} \tag{5}$$

The estimates of this model provide additional support to our probit model, since the variable SVR is continuous (rather than 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 behaviour. Bobenrieth *et al*. (2013) indicate that there is a well-established model of commodity price behaviour 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 *et al*. (2013) find that global stock data, imperfect as they are, 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 behaviour 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 *et al*., 2013] that 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 other variables reflecting stock scarcity would be useful. 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' ($FS_{t,T}$).[1] This forward spread is directly related to the level of stocks. When stocks are ample the

[1]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; Joseph et al., 2016), it is defined as the spot-futures spread in some other relevant studies (Fausti et al., 2017).

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 agents to pay for the convenience of having stocks at the current period.

The monthly time series for the agricultural cash prices are obtained from the 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 define 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.[2] 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 Online Appendix provides additional results on forward spread using nearby futures contracts as proxies for cash prices.

2.4. *Option-implied Agricultural Market Risk Measures*

2.4.1. *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. The conditional probability distribution of prices, in turn, is the market assessment of subsequent risk and hence spikes. 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 Debreu, 1959; Arrow, 1964).

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)

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

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 Online Appendix.

2.4.2. 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, and these in turn are related to the probability of a spike. For example, Han (2008) shows that the risk neutral skewness, which is derived 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 realised volatility of the S&P 500 stock-market index. Hence it seems that these variables should be related to the subsequent probability of spikes. In our Online 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 *et al.* (2003).

2.4.3. Variance risk premium

The variance risk premium represents the compensation demanded by investors for bearing variance risk and is defined as the difference between realised variance (RV_t) and risk neutral implied variance (IV_t). According to Carr and Wu (2009) the variance risk premium is a reliable measure of risk aversion in financial markets. If this is also the case in commodity markets, then a high VRP should indicate that market participants are very sensitive to subsequent shocks.

Following Carr and Wu (2009) and Christoffersen *et al.* (2010), we define the variance risk premium as the difference between the P-measure (namely the real-world) realised variance and the Q-measure expected variance, using the following formula:

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

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

The monthly realised 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 realised variance we construct a time series of prices following the methodological approach of Wang *et al.* (2012) who estimate the realised 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 realised variance of commodity futures as the variance of the daily returns of these selected futures contracts. The realised variance of daily returns is then multiplied by 252 to convert the measure to an annual basis.

2.4.4. Tail risk measure of the option-implied distribution

The option-implied tail risk measure (*TRM*) is the probability mass that 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). Thus, the TRM is a variable which measures directly the probability of a price spike. 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; Vilkov and Xiao, 2013; Bollerslev *et al.*, 2015) 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 Online 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:

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

Bi-weekly data for the number of short and long hedge positions for wheat, maize and soybeans futures were obtained from the US 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 until 2011.[3] We then obtained yearly data for US aggregate consumption for maize, wheat and soybeans from the USDA/FAS/PSDO. Following the methodology of Bobenrieth *et al.* (2013) for the computation of stocks-to-use ratios (SURs), we normalise (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-seasonalise 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-seasonalised quarterly SURs.

4. Empirical Results

4.1. Descriptive statistics

We first present in Table 1 the descriptive statistics for our explanatory variables. In Table 1, *FS* is the forward spread, *SUR* is the stocks-to-use ratio, *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.

Table 1 shows 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 these markets. The zero mean variance risk premium across all agricultural markets shows that in our sample period the variance risk is not systematically priced in agricultural commodity options and futures markets. The hedging pressure is also positive for all agricultural markets analysed. The percentage of price spikes in the sample is approximately 5% of the total time series sample for these three agricultural markets. 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

[3]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 decided to use the US inventory data series as the next best proxy for global inventories, given that US inventories compose the bulk of global inventory data.

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

	FS (%)	*SUR*	*TRM*	*IV*	*VRP*	*HP*	*RET*
Panel A: Maize							
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							
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							
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%							

Notes: 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.

and soybeans probit regression residual series at a 1% confidence level. The results of our unit root tests can be found in our Online Appendix. In Table 2 we present the correlation coefficients between our explanatory variables.

Table 2 indicates low correlation coefficients between our explanatory variables, hence low multicollinearity issues. The very low correlation coefficients between the forward spread and 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 investors' 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.

4.2. Assessing the probability of agricultural price spikes

4.2.1. Probit regression models

Table 3 summarises the regression results of our multivariate probit models for maize, wheat and soybeans markets respectively, according to equation (4).

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, which implies 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 a higher probability of a price spike during this period.[4] This result is consistent with the Theory of Storage (Working, 1948; Brennan, 1958; Telser, 1958), 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 *et al.* (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 the option-implied variables that 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 substantial improvement of the explanatory power of our probit models when added into the right-hand side of the probit equations.[5] We find that the variance risk premium (*VRP*) and the implied variance (*IV*) in the maize options market are statistically significant predictors of a subsequent spike in the price of maize.[6] Moreover, our analysis shows that the *VRP* is a statistically significant predictor of price spikes in the wheat 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 soybean market. However, the signs of the estimated coefficients of the option implied risk measures suggest when risk perception in the option market is low the probability

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[4]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 Online Appendix.

[5]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 Online Appendix.

[6]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 Online Appendix.

Table 2. Correlations between explanatory variables

	FS	*SUR*	*HP*	*TRM*	*IV*	*VRP*	SKEW	KURT
Panel A: Maize								
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	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	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.

of a future spike increases.[7] This is an unexpected result that deserves further investigation. A promising avenue for future research would be to develop a theoretical model to pin down the exact economic mechanism(s) behind this relationship. Given the empirical nature of our paper, one plausible interpretation is that low risk, as measured in options markets, induces commodity investors to take on more risk and commodity markets become more vulnerable to negative shocks.[8]

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[7]The positive coefficients of variance risk premium show that the probability of a price spike increases when risk aversion in agricultural markets decreases. Since VRP is defined as the difference between realised and implied variance, then the more negative VRP is associated with higher risk aversion and the rising VRP reveals a lower market price of variance risk.

[8]We additionally perform the probit analysis using the realised variance (RV) [instead of the implied variance (IV)] as predictor of agricultural price spikes, and the estimated coefficients of RV are also negative (and statistically significant for the case of maize). These additional probit regression results can be found in our Online Appendix.

Table 3. Probit regressions of the incidence of price spikes in agricultural commodity markets.The baseline multivariate probit model is the following:

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

Commodity	Maize	Wheat	Soybeans
Constant			
Coef.	0.079	−2.971**	1.960
t-stat	(−0.056)	(−2.220)	(0.916)
FS			
Coef.	−0.065*	−0.101***	−0.058
t-stat	(−1.937)	(−2.966)	(−1.519)
SUR			
Coef.	−1.204	1.185	−0.610
t-stat	(−0.591)	(1.277)	(−0.653)
HP			
Coef.	1.158	−0.441	0.947
t-stat	(0.759)	(−0.429)	(0.854)
TRM			
Coef.	14.974	13.645	−20.292*
t-stat	(1.595)	(0.925)	(−1.729)
IV			
Coef.	−25.478***	−12.662	−12.753
t-stat	(−2.732)	(−1.178)	(−1.236)
VRP			
Coef.	7.982**	10.122**	4.161
t-stat	(2.470)	(2.335)	(0.795)
SKEW			
Coef.	0.123	−0.366	0.327
t-stat	(0.353)	(−0.661)	(0.812)
KURT			
Coef.	−0.023	−0.074	−0.020
t-stat	(−0.380)	(−0.737)	(−0.330)
% Mc Fadden R^2	26.9	29.4	27.9

Note: *, ** and *** denote statistical significance at the 10%, 5% and 1% level, respectively.
Source: Computed by authors.

Furthermore, in order to provide robustness to our main probit regression results, besides the McFadden R^2, we compute the Count-R^2 as an additional goodness-of-fit measure of the timing of commodity market turbulence. We use the estimated coefficients from the probit model to compute the model-implied probabilities $P_t = F(\alpha + b\,x_t)$ at each point in time during the sample period. If the probability P_t is greater than 0.5 (closer to 1), we assume that our model predicts a price spike in agricultural markets. Otherwise (if the probability is less than or equal to 0.5), we assume that our model predicts a normal period. Thus, we construct a variable T_t which takes the value of 1 when P_t>0.5 and the value of 0 when $P_t \leq 0.5$. Then, we compare the values of T_t with the actual values of the extreme event indices presented in equation (1). We also use different thresholds for our estimated probabilities (70% and 90%) assuming that our model predicts a spike when the estimated probability is more than 0.7 or 0.9 respectively. For each observation (t = 1,.., n), we count the

Table 4. Count-R^2 values for the baseline multivariate probit model (equation 4)

Probability threshold (%)	Maize (%)	Wheat (%)	Soybeans (%)
50	73.9	84.7	71.1
70	70.8	83.7	65.4
90	70.7	83.3	61.9

Notes: This table shows the Count-R^2 values of the baseline multivariate regression model described in equation (4). The probability threshold is the threshold value above which we assume that the probit model predicts a price spike. The Count-R^2 goodness of fit measure is defined as the ratio of correct predictions of the probit model divided with the total number of time series observations. Hence, the Count-R^2 gives the percentage of correct predictions (according to the estimated probabilities the probit model) in the data sample.
***Source*:** Computed by authors.

number of correct predictions and then compute the Count-R^2 as the ratio between the number of correct predictions to the total number (n) of observations. Table 4 reports the Count-R^2s for our multivariate baseline probit model.

The Count-R^2s are always higher when predicting wheat price spikes, and they are always more than 62% for all agricultural markets considered. In our Online Appendix we present time series plots with the estimated probit probabilities along with the incidence of the price spikes. As a robustness check, we also examined the predictability of extreme returns for intermediate (2-month and 3-month) forecasting horizons. 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 Online Appendix. As an additional robustness test, we estimate the same set of regression models using alternative spike definitions and show that our findings are insensitive to the methodology chosen for the identification of price spikes. These additional results can also be found in our Online Appendix.

Finally, since the explanatory variables linked with the 'Theory of Storage' – FS and SUR – exhibit fat tails (deviation from normality), we estimate the baseline probit model using the White (1980) robust standard errors which correct for heteroskedasticity in the probit estimators. Moreover, in order to relax the normality assumption, we estimate a multivariate logit and generalised extreme value (GEV) binary model on agricultural price spikes (Horowitz and Savin, 2001; Calabrese and Osmetti, 2013; Calabrese and Giudici, 2015). Using all these alternative types of models, we show that our main findings remain unaltered.[9] The normality tests along with the additional probit, logit and GEV regression results can be found in our Online Appendix.

4.2.2. Implications of the storage model

One of the well-known stylised facts of the theoretical commodity storage model is its pronounced non-linearity. In order to examine the empirical and theoretical importance of our econometric results, which are based on linear regression models, we also

[9]We thank an anonymous referee for his valuable suggestions and comments on including models which relax the normality assumption and take into account the fat-tailed distributions of our covariates.

examine the robustness of our price spike predictions in the presence of non-linear effects.[10]

The storage model, first introduced by Working (1948), indicates that the relationship between agricultural inventory levels and the forward spread (the Working storage supply curve) is non-linear, since it is positive (or very close to storage cost) for high inventory levels and becomes significantly negative only to the extreme situation of falling inventories and inventory stock-outs due to the rising convenience yield for holding physical inventory during times of scarce inventory levels. The validity of the Working curve (which identifies an asymmetric and non-linear relationship between inventories and forward spread) has been extensively empirically verified for agricultural commodity markets (see Joseph *et al.*, 2016). We examine the implication of the storage model by adding a non-linear (squared) term for the SUR in the right-hand side of the equation of our baseline forecasting probit model. Table 5 reports the respective regression results of the multivariate non-linear model in which we include a squared term for SUR.

The probit regression results of Table 5 show that for the case of maize, the estimated coefficient of SUR is positive and significant while the coefficient of SUR^2 is negative and significant. According to our findings, the relationship between inventories and the probability of maize price spike, is negative and non-linear. This is another useful implication of the storage model for price spike predictions in the maize market.

4.2.3. 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.

The results of Table 6 provide robustness to our probit regression results since we show that the *FS*, 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. More specifically, our OLS regression results show that IV is a significant predictor of maize and soybeans extreme returns, while the VRP is a significant predictor of wheat extreme returns. As expected, the predictive power of our models is high for 1-month horizon and deteriorates for 2- and 3-month forecasting horizons. On the other hand, our OLS regression analysis shows that the TRM, SKEW and KURT are not significant determinants of extreme returns in agricultural markets. We also run the same OLS regression model for the financialisation 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 SVRs 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 Online Appendix.

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[10]We thank an anonymous referee for this suggestion to include a non-linear model in our analysis like the storage model suggests.

Table 5. Non-linear probit regression models on the incidence of price spikes. The baseline probit regression model is given below:

$$P(PS1_t = 1) = F(b_0 + b_1 FS_{t-1} + b_2 SUR_{t-1} + b_3 SUR^2_{t-1} + b_4 HP_{t-1} + b_5 TRM_{t-1} + b_6 IV_{t-1} + b_7 VRP_{t-1} + b_8 IS_{t-1} + b_9 IK_{t-1})$$

Commodity	Maize	Wheat	Soybeans
Constant			
Coef.	−15.853*	−8.288	0.521
t-stat	(−1.876)	(−1.756)	(0.143)
FS			
Coef.	−0.076*	−0.121***	−0.067
t-stat	(−1.732)	(−3.095)	(−1.609)
SUR			
Coef.	60.920*	10.878	0.495
t-stat	(1.883)	(1.365)	(0.079)
SUR^2			
Coef.	−58.701*	−4.218	−0.425
t-stat	(−1.919)	(−1.212)	(−0.155)
HP			
Coef.	0.905	−0.458	−20.305*
t-stat	(0.513)	(−0.440)	(−1.726)
TRM			
Coef.	10.578	15.841	−12.173
t-stat	(1.046)	(1.029)	(−1.169)
IV			
Coef.	−27.253**	−12.954	4.492
t-stat	(−2.505)	(−1.160)	(0.850)
VRP			
Coef.	12.259**	11.028**	0.297
t-stat	(2.732)	(2.426)	(0.729)
SKEW			
Coef.	0.132	−0.621	−0.023
t-stat	(0.303)	(−1.068)	(−0.365)
KURT			
Coef.	−0.015	−0.105	−0.425
t-stat	(−0.192)	(−1.031)	(−0.155)
% Mc Fadden R^2	34.1	32.2	28.4

Note: In these regression models SUR^2 is the stocks-to-use ratio variable squared. *, ** and *** denote statistical significance at the 10%, 5% and 1% level, respectively.
***Source*:** Computed by authors.

5. Conclusions

We show empirically 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. 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

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 ($k = 3$)
Constant									
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

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

spread) are associated with higher returns in commodity futures markets (Fama and French, 1987; Gordon and Rowenhorst, 2006; Gordon *et al*., 2013). 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. Overall, we conclude that the unexpected above 2-sigma price spikes are associated with changes in commodity futures forward spread, and thus that 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. More specifically, our analysis shows that 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 that are associated with a higher probability of agricultural commodity price spikes. The signs of the estimated coefficients from the probit models suggest that when some option implied risk measures are low, the probability of a future spike in commodity prices increases. This is a counterintuitive result that certainly deserves further investigation, mainly from a theoretical point of view. Given that our paper is largely empirical, we hypothesise that when volatility risk is low, commodity investors may be induced to take on more risk and as a result commodity markets become more vulnerable to unexpected adverse shocks.[11]

Our findings have implications for optimal hedging decisions in 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.[12] 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. Overall, our 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, whose objectives include 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 and is an open question for further research.

[11]Note that this interpretation of the empirical results shares some similarities with Minsky's (1992) financial instability hypothesis. Danielsson *et al*. (2018) examine empirically Minsky's hypothesis using cross-country equity data and find that low equity volatilities increase the probability of banking and stock market crisis.

[12]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.

Supporting Information

Additional supporting information may be found online in the Supporting Information section at the end of the article.

Supplementary Material

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