

Speculative Bubbles in Agricultural Prices*

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Abstract

Motivated by repeated spikes and crashes in agricultural prices over the last decade, we investigate whether the increasingly financialized markets for corn and wheat are affected by speculative bubbles. From a technical point of view, we draw on the convenience yield model and use commodity dividends to derive corn's and wheat's fundamental value. Afterwards, we apply the Momentum Threshold Auto-Regressive (MTAR) approach to detect periods of substantial overvaluation followed by a crash. The empirical evidence is favorable for speculative bubbles in the corn and wheat price over the last decade.

JEL Classification: G10, G12, G18, Q02, Q14, Q18

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1. Introduction

Commodity prices reached dizzying heights in mid-2008, then collapsed during the world financial and economic crisis and eventually skyrocketed again. Since important agricultural markets were exposed to these price movements as well (FOOD AND AGRICULTURE ORGANIZATION (FAO), 2011), poor countries suffered from a severe food crisis in 2007-2008. In some parts of the developing world, even food riots broke out. Afterwards, farmers were affected by huge income losses until end-2009, before renewed food shortages occurred in most recent times. On the one hand, there are several fundamental factors explaining the global food crisis in 2007-2008.¹ On the other hand, politicians, regulators and part of the media claim that low interest rates, a weakening US dollar and the attractive characteristics of raw materials with respect to portfolio diversification fostered the increasing financialization of commodity markets, and finally led to speculative bubbles in agricultural prices.

Given this ambiguity, solid statistical inference about possible bubbles in agricultural markets appears to be necessary. Until now, testing for speculative bubbles has mostly been focusing on (US) stock markets.² By contrast, to the best of our knowledge, little work has been done with respect to bubbles in markets for raw materials in general and for agricultural commodities in particular. In the latter case, only GILBERT (2010), covering the time period from 2006 to 2008, provides evidence for speculative bubbles in the soybean, but not in the corn and wheat market, using the supplemented Augmented Dickey-Fuller (ADF) test proposed by PHILLIPS ET AL. (2011).

From our point of view, this gap in the literature is regrettable for a variety of reasons. High agricultural and thus food prices have the potential to destabilize countries due to

¹These factors include rising food demand from emerging countries, imposed trade barriers, negative weather shocks, a slowdown in productivity, high oil prices leading to increased production and transport costs, surging demand for biofuels as well as low inventories resulting in an increased sensitivity to shocks (HEADEY AND FAN, 2008, CLAPP, 2009, FRANKEL AND ROSE, 2010).

²GÜRKAYNAK (2008) provides a recent in-depth survey of econometric methods used for detecting asset price bubbles. This survey includes the well-known variance bounds tests, West's two-step method, (co)integration-based tests as well as the concept of intrinsic bubbles and methods treating bubbles as an unobserved variable.

their effects on income distribution, inflation and poverty, as highlighted, for instance, by the special issue on the world food crisis in 2007-2008 (AGRICULTURAL ECONOMICS, 2008). In addition, overshooting food prices may lead to inadequate monetary policy interventions once they distort the consumer price index upwards, which many central banks use to measure inflation and reach their interest rate decisions.³ By contrast, if speculators are not responsible for high agricultural prices, tighter regulation of futures markets would be ineffective, and would unnecessarily reduce the benefits of portfolio diversification offered by raw materials.⁴ According to HEADEY AND FAN (2008), blaming speculators for increased agricultural prices is “an explanation widely discussed but poorly understood and only superficially researched.”

In order to evaluate the agricultural price bubble hypothesis in depth, we use the present-value model for stocks, and adapt it to the corn and wheat market (PINDYCK, 1993), which constitute the two most financialized agricultural commodities. Our sample runs from the mid-1980s to early 2011. Based on the deviations of the corn and wheat price from their fundamental values, we draw on the Momentum Threshold Auto-Regressive (MTAR) approach, which serves as an improvement of the TAR model (TONG, 1978) and was adapted to the cointegration context by ENDERS AND GRANGER (1998) and ENDERS AND SIKLOS (2001). In practice, the MTAR model was applied to data on US stock prices (BOHL, 2003, BOHL AND SIKLOS, 2004, SELF AND MATHUR, 2006, BEHR, 2007, BOUCHER, 2007) and on real estate investment trusts (PAYNE AND WATERS, 2005, 2007, WATERS AND PAYNE, 2007). In contrast

³For instance, the European Central Bank (ECB, 2008) justified its highly criticized move to reinforce its restrictive monetary stance in mid-2008 by stating: “At its meeting on 3 July 2008, the Governing Council of the ECB decided (...) to raise the minimum bid rate on the main refinancing operations of the Eurosystem by 25 basis points to 4.25%. (...) The Governing Council’s decision was taken (...) to counteract the increasing upside risks to price stability over the medium term. (...) These risks include notably the possibility of further increases in energy and food prices.”

⁴For instance in the US, the Dodd-Frank Wall Street Reform and Consumer Protection Act of 2010 includes substantial innovations of US financial market law, and is currently implemented, amongst others, by the Commodity Futures Trading Commission (CFTC) with respect to commodity markets. Similarly, the European Commission prepares a broad-based reform of its “Markets in Financial Instruments Directive” (MiFID) which is also aimed at limiting speculation on commodity futures markets.

to alternative methods such as the Markov regime-switching ADF test, the MTAR approach benefits from the small number of parameters to be estimated. In addition, it has substantial power to detect periodically bursting bubbles, which are characterized by an explosive eruption followed by a sudden crash.

The paper proceeds as follows: In SECTION 2, we discuss the related literature. In SECTION 3, we present the present-value model for commodities and describe the data. In SECTION 4, we show how to calculate the fundamental value of the corn and wheat price, specify the MTAR model and demonstrate its ability to detect speculative bubbles. In SECTION 5, we present the empirical results. In SECTION 6, we conclude.

2. Related Literature

As mentioned in SECTION 1, only GILBERT (2010) explicitly tackles the question of speculative bubbles on agricultural markets, but fails to answer in the affirmative in the case of corn and wheat. In addition, he draws on a very short sample and uses a methodology which suffers from a number of caveats, as mentioned by GILBERT (2010) himself. However, related studies investigate the bi-directional relationship between speculative positions on futures markets and agricultural returns, while others examine whether agricultural markets are affected by herding behavior. That way, they cannot answer our research question as desired, but contribute indirectly to the discussion about speculative bubbles on agricultural markets.

In this context, several studies show that speculative positions lead agricultural returns, and thus earn abnormal profits. Obviously, if speculative net long (short) positions are systematically followed by positive (negative) returns, this may lead to substantial price overshootings (undershootings). The two major explanations for abnormal speculative profits are that speculators get paid by hedgers for bearing unwanted risk exposures, also known as Keynes' theory of normal backwardation, and that speculators possess superior forecasting abilities (CHANG, 1985, LEUTHOLD ET AL., 1994, WANG, 2001, 2003). By contrast, other studies deny the validity of risk

premium flows (HARTZMARK, 1987, CHATRATH ET AL., 1997, BRYANT ET AL., 2006) or superior forecasting abilities (KHAN, 1986, HARTZMARK, 1991, SANDERS ET AL., 2003, 2009, SANDERS AND IRWIN, 2010). A related argument is made by STOLL AND WHALEY (2010) who concentrate on the wheat market and find that commodity index rolls have little futures price impact, and that inflows and outflows from commodity index investment do not cause futures prices to change. In addition, they argue that the failure of the wheat futures price to converge to the spot price at the contract's expiration date has not undermined the futures contract's effectiveness as a risk management tool.

Another strand of literature asks whether agricultural returns lead speculative positions, indicating that speculators apply noise trading strategies. Most studies find that speculators are either trend-followers or contrarians, depending on the type of agricultural commodity and the time period analyzed (SANDERS ET AL., 2003, WANG, 2003, REITZ AND WESTERHOFF, 2007, RÖTHIG AND CHIARELLA, 2007, SANDERS ET AL., 2009). As pointed out by WANG (2003), however, if speculators act as contrarians and earn abnormal profits (due to risk premium flows, superior information or just luck), while hedgers engage in positive feedback trading and show a negative performance, as in his analysis, it is only the latter who exercise a destabilizing influence on agricultural futures markets, which may ultimately lead to speculative bubbles.

Finally and in relation to the noise trading hypothesis, a couple of studies analyze whether agricultural speculators show herding behavior, but only provide ambiguous results. PINDYCK AND ROTEMBERG (1990) and MALLIARIS AND URRUTIA (1996) find strong evidence for excessive co-movements of agricultural prices, whereas DEB ET AL. (1996) and ADRANGI AND CHATRATH (2008) report weak approval at best. In addition, BOYD ET AL. (2010) document that the moderate levels of herding among large speculative traders help to speed the price adjustment process rather than destabilize agricultural markets.

3. Convenience Yield Model and Data

In order to test for speculative bubbles in the corn and wheat market, we make use of the present-value model for actively traded storable commodities (PINDYCK, 1993). In this model, the fundamental value is defined as the sum of discounted expected future commodity dividends. The corn and wheat dividends are approximated by the benefits the holder of the physical commodity experiences in contrast to the owner of a futures contract written on the respective asset. These benefits that inventories provide, including the ability to smooth production, avoid stockouts and facilitate the scheduling of production and sale, are termed convenience yield and allow calculating reasonable levels of corn and wheat prices.

With reference to PINDYCK (1993), we can use futures prices to measure the convenience yield, drawing on the so-called cost-of-carry equation. Under no arbitrage, the (capitalised) flow of convenience yield net of storage costs from T_1 to T_2 per unit of commodity, $CY_{T_1}^{T_2}$, is:

$$CY_{T_1}^{T_2} = F_t^{T_1}(1 + r_t(T_2 - T_1)/365) - F_t^{T_2}, \quad (1)$$

where $F_t^{T_1}$ and $F_t^{T_2}$ are the first- and second-nearby futures prices for delivery at T_1 and T_2 , respectively, and r_t is the risk-free interest rate. Dividing $CY_{T_1}^{T_2}$ by $(T_2 - T_1)$ then leads to the standardized convenience yield, CY_t . Eq. (1) states that in equilibrium the futures price at T_2 must equal the futures price at T_1 adjusted by the opportunity costs and the benefits of holding the physical commodity. Put differently, investing borrowed money only and taking no risk necessarily lead to a terminal wealth of zero.⁵

In order to calculate the convenience yield for corn and wheat, we are in need of futures prices and a proxy for the risk-free interest rate. Daily futures prices of yellow

⁵Apart from eq. (1), the convenience yield can also be approximated with the help of more sophisticated unobserved-components models. In the two-factor model of SCHWARTZ (1997), for instance, the change of the logarithmic spot price and the convenience yield rate are specified as a geometric Brownian motion and an Ornstein-Uhlenbeck process, respectively, whose parameters are estimated by applying the Kalman filtering technique. However, the resulting time series are qualitatively largely the same in comparison to the actual spot price and the convenience yield proxy from eq. (1).

corn no. 2 and soft red wheat no. 2 belong to contracts traded on the Chicago Board of Trade (CBT), which refer to 5,000 bushels (or 136 metric tons) each and mature in March, May, July, September or December. Applying the first-day-of-delivery-month criterion, we always draw on the first-nearby (second-nearby) contract and roll over to the second-nearby (third-nearby) on the first day of the first-nearby's delivery month. The reason to roll over sufficiently prior to the expiration of the first-nearby is that the latter runs out of liquidity close to maturity. Alternatively, we roll over once the second-nearby continuously exhibits a higher open interest than the first-nearby, following the liquidity-peak criterion.⁶ Daily futures prices are available since January 1985 (corn) and January 1983 (wheat), respectively. The sample ends in April 2011.

The risk-free interest rate is approximated by the three-month US Treasury bill interest rate. Alternatively, we use the Federal funds rate. In addition, the calculation of corn's and wheat's fundamental value (see SECTION 4.1) requires daily spot prices, which are already available as continuous time series and thus need not to be prepared further. Finally, we deflate the spot price and the convenience yield time series, making use of the US consumer price index.⁷ We are thus restricted to a monthly frequency and use end-of-month data. All time series are taken from THOMSON REUTERS DATASTREAM. Spot and futures price time series are quoted in US-cents/bushel, while interest rates are given in percent p.a.

4. Momentum Threshold Autoregressive Approach for Bubble Detection

4.1. Test Specification

In order to establish a stable long-run relationship between the commodity price and the convenience yield in real terms, we apply the Engle-Granger methodology. We first analyze the stationarity properties of the single time series, P_t and CY_t , using six

⁶Note, however, that regardless of the roll criterion applied, we do not expect to find significant differences between the resulting futures price time series (CARCHANO AND PARDO, 2009).

⁷Deflating both time series is done by multiplying with the price index of April 2011 and dividing by that one of the respective month, so that the respective data point for April 2011 is identical in both nominal and real terms.

different methods to overcome the potential problems exhibited by unit-root tests, i.e., their poor size and power properties due to the near equivalence of non-stationarity and stationary processes in finite samples. The following unit-root tests are thus applied: the conventional ADF, the Dickey-Fuller Generalized Least Squares de-trended (DFGLS), the Elliott-Rothenberg-Stock Point-Optimal (ERSPO), the Kwiatkowski-Phillips-Schmidt-Shin (KPSS), the Ng-Perron (NP) and the Philipps-Perron (PP) test.⁸ If both time series are integrated of the same order, we move on by running a simple ordinary least squares (OLS) regression of P_t on CY_t :

$$P_t = \alpha + \beta CY_t + u_t, \quad (2)$$

where u_t represents the error term, whose realization we interpret as the deviation of the commodity price from its fundamental value, $FV_t = \hat{P}_t = \hat{\alpha} + \hat{\beta}CY_t$. The slope parameter β is expected to be positive.

MTAR models are designed to empirically capture the characteristics of periodically bursting bubbles in a cointegration framework. If periodically bursting bubbles exist in commodity prices, the residuals, \hat{u}_t , from the cointegrating regression (2) should reflect sequences of sharp increases followed by sudden drops. This behavior can be modelled by running the regression:

$$\Delta \hat{u}_t = \rho_1 I_t \hat{u}_{t-1} + \rho_2 (1 - I_t) \hat{u}_{t-1} + \sum_{k=1}^K \gamma_k \Delta \hat{u}_{t-k} + \varepsilon_t, \quad (3)$$

where the indicator variable, I_t , is defined as:

$$I_t = \begin{cases} 1, & \text{if } \Delta \hat{u}_{t-1} \geq \tau \\ 0, & \text{if } \Delta \hat{u}_{t-1} < \tau, \end{cases} \quad (4)$$

with τ as the value of the threshold. As in the ADF test, lagged differences are included

⁸Since the convenience yield is, by no means, restricted to be strictly positive, we cannot use logarithms of the original time series in order to reduce the impact of outliers. Obviously, this is in contrast to stock dividends. The sign of the convenience yield primarily depends on the type of raw material, its level of inventory and the period under investigation (PINDYCK, 1993).

to allow for autocorrelation in the error term ε_t .⁹ Eq. (3) constitutes a MTAR model once \hat{u}_t exhibits more “momentum” in one direction than in the other. If the system is convergent, $\Delta\hat{u}_{t-1} = \tau$ is the long-run equilibrium value.¹⁰

The theoretical potential for positive speculative bubbles and the characteristic of commodity price increases relative to the convenience yield before a crash suggest an asymmetry in the development of the residuals of the cointegrating regression (2). Periodically bursting bubbles are captured via changes in \hat{u}_{t-1} above the threshold followed by a sharp drop. By contrast, the path of changes in \hat{u}_{t-1} below the threshold does not show bubble eruptions followed by a collapse.

In order to make use of the MTAR approach to detect periodically bursting bubbles, we apply a two-step method. In the first step, we draw on PETRUCELLI’S AND WOODFORD’S (1984) proof that a necessary and sufficient condition for the stationarity of \hat{u}_t is that $\rho_1 < 0$, $\rho_2 < 0$ and $(1 + \rho_1)(1 + \rho_2) < 1$, and establish the three corresponding null hypotheses $\rho_1 = 0$, $\rho_2 = 0$ and $\rho_1 = \rho_2 = 0$. If all null hypotheses can be rejected, the relationship of P_t and CY_t in eq. (2) is called threshold-cointegrated. We thus denote the test statistic of the third null hypothesis by F_C . Finally, the distributions of all test statistics are non-conventional, but critical values are provided by ENDERS AND GRANGER (1998) and ENDERS AND SIKLOS (2001).

In the second step, we test the null hypothesis of symmetric adjustment behavior $\rho_1 = \rho_2$. The test statistic is denoted by F_A and follows the conventional F -distribution. A failure of symmetric adjustment behavior is interpreted as evidence for periodically bursting bubbles, provided that $|\rho_1| > |\rho_2|$. At this point, we see that the conventional

⁹The optimal lag length, K , is determined by starting with $K_{max} = [T^{(1/3)}]$, where $[\cdot]$ denotes the integer part of its argument, and then reducing the model until the last lagged difference has a statistically significant influence at the 5%-level. In the following, we refer to this procedure as the general-to-specific approach.

¹⁰As suggested by BEHR (2007), if the assumed underlying relationship between the commodity price and the convenience yield in eq. (2) is unstable over time due to a very long observation period such as in BOHL (2003) and BOHL AND SIKLOS (2004), who cover more than 130 years, the estimation of one model only using the entire sample at once might be unwarranted. However, given our relatively short sample covering less than 30 years, we see no need to draw on BEHR’S (2007) rolling window estimation strategy in order to allow for time-varying MTAR coefficients.

Engle-Granger test is nested into the MTAR model. While the null hypotheses in the first step are the same for the Engle-Granger test and the MTAR model, the alternative hypotheses differ once we are able to reject symmetric adjustment behavior. In the latter case, ENDERS AND SIKLOS (2001) provide evidence for a plausible range of adjustment parameters that the MTAR approach has better power and size properties than the Engle-Granger test. In sum, the feature of testing the null hypothesis of a unit-root against the alternative of stationarity with MTAR adjustment thus permits an empirical investigation of speculative bubbles in commodity prices.

The MTAR model can be estimated using OLS. Since τ is unknown in reality, the OLS estimates depend on the threshold chosen: $\rho_1(\tau)$, $\rho_2(\tau)$, and $\gamma_k(\tau)$ for all k . Following CHAN (1993), we determine τ by means of a direct search:

$$\hat{\tau} = \arg \min \hat{\sigma}_\varepsilon^2(\tau), \tau \in \Omega, \quad (5)$$

where $\hat{\sigma}_\varepsilon^2(\tau)$ denotes the error term variance of the MTAR regression for a given τ , and

$$\Omega = \{ \tau | \hat{u}_{([\lambda(T-1)])} \leq \tau \leq \hat{u}_{([1-\lambda(T-1)])} \}. \quad (6)$$

In eq. (6), $\hat{u}_{(.)}$ is the residual with rank $(.)$, given that all residuals are ordered ascendingly, $[.]$ denotes the integer part of its argument, and $0 < \lambda < 1$ indicates which portion of the ordered residuals is eliminated both at the lower and at the upper end. Even though CHAN'S (1993) proposal of setting $\lambda = 0.15$ is rather arbitrary, it is widely used in the literature and thus also accepted for our purposes.

Given that threshold-cointegration with asymmetric adjustment is present, we follow ENDERS AND SIKLOS (2001) and estimate the error-correction model (ECM):

$$\Delta P_t = \mu + \delta_1 I_t \hat{u}_{t-1} + \delta_2 (1 - I_t) \hat{u}_{t-1} + \sum_{i=1}^2 \phi_{1i} \Delta P_{t-i} + \sum_{i=1}^2 \phi_{2i} \Delta CY_{t-i} + \nu_t, \quad (7)$$

where \hat{u}_{t-1} is obtained from eq. (2), I_t is defined in eq. (4) and ν_t represents the error term. The ECM implies that if δ_1 (δ_2) is negative and statistically significant, the

spot price adjusts to deviations from its long-run equilibrium for $\Delta\hat{u}_{t-1} \geq (<) \tau$. In addition, testing the null hypotheses $\phi_{11} = \phi_{12} = 0$ and $\phi_{21} = \phi_{22} = 0$ shows whether movements in the spot price are Granger-caused by its own lagged changes and by lagged changes in the convenience yield, respectively. Apart from that, we replace ΔP_t by ΔCY_t on the left-hand side of eq. (7), and analyze the reaction of the convenience yield to deviations of the spot price from its long-run equilibrium. In this case, the ECM implies that if δ_1 (δ_2) is positive and statistically significant, the convenience yield adjusts to deviations of the spot price from its long-run equilibrium for $\Delta\hat{u}_{t-1} \geq (<) \tau$. Finally, testing the null hypotheses $\phi_{11} = \phi_{12} = 0$ and $\phi_{21} = \phi_{22} = 0$ shows whether movements in the convenience yield are Granger-caused by lagged changes in the spot price and by its own lagged changes, respectively.

4.2. Test Evaluation

In order to show the ability of the MTAR technique to detect periodically bursting bubbles, we make use of EVANS' (1991) approach. We employ the standard present-value model for stock prices with constant expected returns:

$$P_t = \frac{1}{1+r} E_t(P_{t+1} + D_{t+1}), \quad (8)$$

where P_t is the real stock price at time t , $0 < 1/(1+r) < 1$ denotes the constant discount factor, $E_t(\cdot)$ stands for the expectations conditional on all information available at time t , and D_{t+1} measures the real dividend paid to the owner of the stock between t and $(t+1)$. Given that the transversality condition holds true, the stock's fundamental value, FV_t , follows from eq. (8) as:

$$FV_t = \sum_{i=1}^{\infty} \left(\frac{1}{1+r} \right)^i E_t(D_{t+i}). \quad (9)$$

Eq. (9) represents the well-known present-value relation stating that the fundamental value is equal to the sum of discounted expected dividends out to the infinite future.

The general solution to eq. (8) is:

$$P_t = FV_t + B_t, \quad (10)$$

where B_t denotes the rational bubble which satisfies the submartingal condition:

$$B_t = \frac{1}{1+r} E_t(B_{t+1}). \quad (11)$$

Real dividends are assumed to be generated as a random walk with drift, μ :

$$D_t = \mu + D_{t-1} + u_t, \quad (12)$$

where $u_t \stackrel{i.i.d.}{\sim} N(0, \sigma^2)$. In line with EVANS (1991), we set $\mu = 0.0373$, $\sigma^2 = 0.1574$ and $D_0 = 1.3$, which belong to the actual dividend process for the S&P 500 sample covering the time period from 1871 to 1980. In addition, we choose $T = 250$, which is the maximal sample size ENDERS AND SIKLOS (2001) provide critical values for, but suffices in order to show the ability of the MTAR approach to detect periodically bursting bubbles. With dividends generated by eq. (12), eq. (9) can be solved to yield:

$$FV_t = \frac{1+r}{r^2} \mu + \frac{1}{r} D_t, \quad (13)$$

where we set $r = 0.01$. Finally, periodically bursting bubbles are specified by:

$$B_t = \begin{cases} (1+r)B_{t-1}v_t, & \text{if } B_t \leq \alpha \\ \left(\delta + \frac{1+r}{\pi_t} \left(B_{t-1} - \frac{\delta}{1+r} \right) \xi_t \right) v_t, & \text{if } B_t > \alpha, \end{cases} \quad (14)$$

where α and δ are scalars with $0 < \delta < (1+r)\alpha$, ξ_t is an i.i.d. Bernoulli process with $\Pr(\xi_t = 0) = (1 - \pi_t)$, $\Pr(\xi_t = 1) = \pi_t$ and $0 < \pi_t < 1$ as the time-varying probability of no bubble bursting, and v_t is an i.i.d. positive random variable with $E_{t-1}(v_t) = 1$, which is independent of ξ_t . Setting π_t and ξ_t equal to unity shows that the equation for $B_{t-1} \leq \alpha$ (i.e., the first regime) is a special case of the equation for $B_{t-1} > \alpha$ (i.e., the second regime). Note that the bubble process in eq. (14) satisfies eq. (11), and

that $B_t > 0$ implies $B_s > 0$ (and thus $P_s > 0$) for all $s > t$. As long as $B_t \leq \alpha$, the bubble grows at mean rate $(1 + r)$. When eventually $B_t > \alpha$, it grows at the faster mean rate $(1 + r)/\pi_t$ as long as the eruption continues, but collapses with probability $(1 - \pi_t)$ in each period. When the bubble collapses, it falls to a mean value of δ , and the process starts again. In line with EVANS (1991), we set $\alpha = 1$ and $\delta = B_0 = 0.5$. v_t is chosen to be i.i.d. lognormal, scaled to have unit mean; that is $v_t = e^{y_t - \psi^2/2}$, where $y_t \stackrel{i.i.d.}{\sim} N(0, \psi^2)$. For the simulation, we set $\psi = 0.05$.

Our modifications of EVANS' (1991) original bubble process belong both to the specification and to the parameterization. While EVANS (1991) assumes the probability of no bubble bursting to be constant over time, we suggest to model it as a function of the fundamental value and the speculative bubble. More precisely, we set:

$$\pi_t = \exp\left(-b \frac{B_t}{FV_t + B_t}\right), \quad (15)$$

where b is a scaling factor to allow for sufficiently small values of π_t .¹¹ The rationale behind our modification of the bubble specification is that we reasonably expect the probability of a bubble bursting to increase in line with the value of the bubble relative to the asset price. With respect to the parameterization, we choose a larger sample size and a lower discount rate compared to EVANS (1991), allowing for a longer-lasting and thus more realistic development of periodically bursting bubbles.

In line with EVANS (1991), the bubble time series generated is then scaled up by a factor of 20, so that the sample variance of ΔB_t is many times the sample variance of ΔFV_t , and then added to the fundamental value according to eq. (10). Afterwards, we apply the battery of unit-root tests to ensure that P_t is I(1), and run the long-run regression (2), replacing CY_t by D_t . Finally, we use the regression residuals to estimate the MTAR model in eq. (3), and test the null hypotheses.

¹¹Evaluating the MTAR approach for sufficiently small values of π_t is particularly important given EVANS' (1991) critique that alternative bubble tests such as in BHARGAVA (1986) suffer from a sharp drop in power once π_t decreases.

Repeating this simulation exercise 10,000 times leads to the following results: The set of conditions that ρ_1 and ρ_2 are individually and jointly statistically significantly smaller than zero and that $|\rho_1| > |\rho_2|$ is fulfilled in 98.29, 97.85 and 96.51 percent of all cases at the 10%-, 5%- and 1%-level, respectively. In addition, asymmetric adjustment behavior (i.e., $\rho_1 \neq \rho_2$) is detected in 97.87, 97.40 and 96.03 percent of all cases at the 10%-, 5%- and 1%-level, respectively. In sum, our simulation results thus extend BOHL'S (2003) Monte-Carlo evaluation of the MTAR approach by drawing on a time-varying probability of a bubble bursting, and support his conclusion that the methodology used is quite powerful to detect periodically bursting bubbles, irrespective of the significance level.

5. Empirical Results

5.1. Descriptive Statistics

We start the empirical analysis with a brief overview of the situation on the futures markets for corn and wheat, and put it in relation to the price movements on the corresponding spot markets. In FIGURES 1 (corn) and 2 (wheat), Panel A shows the number of outstanding futures contracts (open interest), superimposed on the respective spot price chart. In both cases, the open interest increased just modestly from the 1980s to 2004, but then rose sharply, indicating the accelerating financialization process of agricultural markets. In fact, the open interest in futures contracts exceeds the annual harvest of corn and wheat by many times. Against this background, we observe repeated spot price spikes both in the corn and in the wheat market, which may constitute speculative bubbles.

In Panel B, we display the market shares by type of trader from 1992 to 2011. Interestingly, the share of speculators increased from 10% to 30% for corn and from 15% to 35% for wheat, while hedgers constantly accounted for roughly half of each market and small traders' influence decreased from 40% to 15% in the case of corn and from 40% to 10% in the case of wheat. In sum, we interpret this increase in speculative

shares of the corn and wheat market as exemplary evidence for the rising attractiveness of agricultural commodities as a new asset class.

In Panel C, we compare speculative net long positions and spot price movements between 1992 and 2011, answering the question whether speculators are generally on the right side of the market. On the corn market, speculators nearly always hold more long than short positions, and do so in particular during the spot price spikes. By contrast, on the wheat market, speculators are deeply net short before and after the commodity price boom of 2007-2008. Thus, at least in the latter case, we do not find descriptive support for the popular notion that speculators betting on rising prices cause a self-fulfilling prophecy, which may eventually lead to speculative bubbles.

Finally, in Panel D, we plot the price spread between the futures contracts with a maturity of one and 13 month(s) from the 1980s to 2011, indicating whether the respective market is in contango or in backwardation, and put it again in relation to the spot price movements.¹² Interestingly, once the spot price of corn and wheat reaches a relatively low level, the respective futures market tends to be in contango, indicating mostly positive price expectations, and vice versa. Over the last four years, however, some differences appeared between both commodities. While the corn market remained in contango until end-2010, the wheat market was in backwardation from mid-2007 to early 2008, but ever since showed signs of deep contango. In sum, we thus conclude that corn traders generally had positive expectations throughout the entire commodity price boom and bust from 2007 to end-2010, whereas participants in the wheat market were quite pessimistic just at that time when the spot price shot up to its record high.

[FIGURES 1 and 2 about here]

¹²Note that in agricultural markets it is important to compare futures contracts which expire in the same month since the maturity curve usually reflects the more or less pronounced influence of the harvest cycle, making a general assessment of future price expectations less clear than, for instance, in the case of energy or industrial commodities.

5.2. MTAR Results

Next, we turn to the econometric analysis. As outlined in SECTION 3, we use three different ways in order to construct the convenience yield time series as in eq. (1). Model A draws on futures prices based on the first-day-of-delivery-month criterion and the three-month US Treasury bill interest rate. Replacing the Treasury bill rate by the Federal funds rate and constructing continuous futures price time series based on the liquidity-peak criterion, respectively, then leads to Models B and C. For all models, we first deflate the spot price and the convenience yield time series for corn and wheat, and check their stationarity properties, using the battery of unit-root tests. In sum, without showing the results in detail, the vast majority of the unit-root tests indicates that all spot price and convenience yield time series analyzed are $I(1)$.

According to the Engle-Granger methodology, we then regress the spot price on the convenience yield as in eq. (2), establishing a long-run relationship. Panel A of TABLE 1 shows the regression results. Even though the slope parameter is positive for all three models, the convenience yield explains only a relatively small part of the variance of the spot price, as shown by the coefficient of determination (R^2). More important, we also run Quandt-Andrews unknown breakpoint tests measuring the stability of the parameter estimates. As reported in Panel B of TABLE 1, they indicate that the constant and the slope parameter are jointly instable over time, with the most likely breakpoint in end-2006 (corn) and early 1990 (wheat), respectively. However, with focus on the slope parameter only, Panel C of TABLE 1 shows that in this case the most likely breakpoint is in end-2006 both for corn and for wheat.

[TABLE 1 about here]

The results of the Quandt-Andrews unknown breakpoint tests coincide with our visual impression from Panel A of FIGURES 1 (corn) and 2 (wheat), based on which we expect the spot price to possibly be affected by speculative bubbles since 2007.

In order to avoid possible distortions in the long-run relationship, we thus limit the sample for the cointegrating regression up to end-2006. Panel A of TABLE 2 shows the regression results for the shortened sample. As for the full sample, the slope parameter is positive for all three models. In contrast to before, however, the convenience yield now explains a reasonable part of the variance of the spot price, and the parameter estimates are not affected by structural breaks anymore.

The residuals of the long-run relationship are then used for the MTAR regression (3), ending up with the results in Panel B of TABLE 2. Since the threshold always takes relatively high values, the share of observations above τ is relatively low.¹³ In fact, this outcome guarantees that only time points characterized by a sharp increase in the spot price are assigned to the possible bubble regime. Comparing the residuals with the time series of the indicator variable from eq. (4) shows that this is indeed always the case. Apart from this, we find that all MTAR models estimated end up with less than the maximally possible lag length, showing that the general-to-specific approach works quite well.

Finally, the hypothesis tests lead to the following results: Both for corn and for wheat, ρ_1 and ρ_2 are negative and statistically significant in all cases. In addition, the hypothesis that both parameters are jointly equal to zero is clearly rejected, leading us to conclude that P_t and CY_t are threshold-cointegrated. Apart from this, we also find that ρ_1 is always larger than ρ_2 in absolute terms and that both parameters are statistically significantly different. We thus reject the hypothesis of symmetric adjustment behavior and conclude that commodity price increases above the threshold may become substantial, but are generally followed by a sharp drop. By contrast, price changes below the threshold do not show bubble-like eruptions followed by a collapse. In sum, the evidence provided by the MTAR approach can be interpreted in favor of the presence of periodically bursting bubbles in corn and wheat prices.

¹³However, since τ never equals the highest threshold possible (as shown by the rank of the threshold chosen, $\text{Rank}(\tau)$), we are not forced to work with corner solutions.

[TABLE 2 about here]

Following ENDERS AND SIKLOS (2001), the detection of threshold-cointegration with asymmetric adjustment justifies the estimation of the ECM (7). Results are shown in TABLE 3, using ΔP_t (Panel A) and ΔCY_t (Panel B) as dependent variable, respectively. With focus on Panel A of TABLE 3, we see that both for corn and for wheat, δ_1 is negative and statistically significant in the case of Model A and B. This implies that the spot price adjusts to deviations from its long-run equilibrium for $\Delta \hat{u}_{t-1} \geq \tau$. By contrast, in the case of Model C, δ_2 is negative and statistically significant, indicating that the spot price adjusts to deviations from its long-run equilibrium for $\Delta \hat{u}_{t-1} < \tau$. In addition, the clear rejection of the null hypothesis $\phi_{11} = \phi_{12} = 0$ shows that movements in the spot price are Granger-caused by its own lagged changes. That is, the spot price does not seem to be weakly efficient.

With respect to Panel B of TABLE 3, we see that both for corn and for wheat, δ_2 is positive and statistically significant regardless of the model examined. This implies that the convenience yield adjusts to deviations of the spot price from its long-run equilibrium for $\Delta \hat{u}_{t-1} < \tau$. In addition, for corn, δ_1 is positive and statistically significant in the case of Model A and B. That is, the convenience yield of corn adjusts to deviations of the spot price from its long-run equilibrium also for $\Delta \hat{u}_{t-1} \geq \tau$. Finally, the clear rejection of the null hypothesis $\phi_{21} = \phi_{22} = 0$ shows that movements in the convenience yield are Granger-caused by its own lagged changes. In addition, for wheat, movements in the convenience yield are also Granger-caused by lagged changes in the spot price, as indicated by the rejection of the null hypothesis $\phi_{11} = \phi_{12} = 0$ in the case of Model A and B. In sum, the evidence provided by the ECM can be interpreted as a confirmation of the results obtained by the MTAR approach.

[TABLE 3 about here]

6. Conclusion

Motivated by repeated spikes and crashes in agricultural prices over the last decade, we investigate whether the increasingly financialized markets for corn and wheat are affected by speculative bubbles. From a technical point of view, we draw on the convenience yield model and use commodity dividends to derive corn's and wheat's fundamental value. Based on the deviations of the actual commodity price from its fundamental value, we apply the MTAR approach to detect periods of substantial overvaluation followed by a crash. The empirical evidence is favorable for speculative bubbles in the corn and wheat price over the last decade. Our results are thus in contrast to GILBERT (2010) who analyzes the time period from 2006 to 2008 and finds speculative bubbles in the soybean, but not in the corn and wheat market, using the supplemented ADF test.

As generally accepted, futures trading is a valuable activity since it improves price discovery, enhances market efficiency, increases market depth and informativeness and contributes to market completion. Based on our econometric findings, however, we conclude that the increasing financialization of agricultural markets may be held responsible for contributing to food price increases, so that a more efficient regulation appears to be desirable. One possibility of doing so would be to implement effective position limits, as currently executed in the United States (CFTC, 2011) and at least discussed in Europe.

IRWIN ET AL. (2009) argue that the hypothesis of bubbles in agricultural prices suffers from conceptual errors and inconsistent facts. Scope for future research is thus given by applying the MTAR approach to other agricultural commodities which have recently been blamed for exhibiting speculative bubbles as well. In addition, similarly powerful testing procedures should be used to broaden the empirical evidence of speculative bubbles on markets for raw materials in general and for agricultural commodities in particular.

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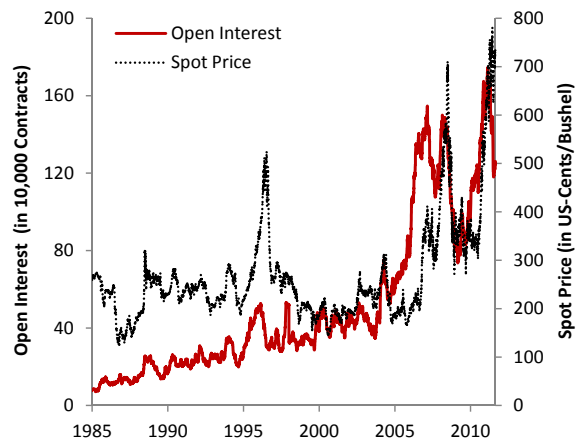
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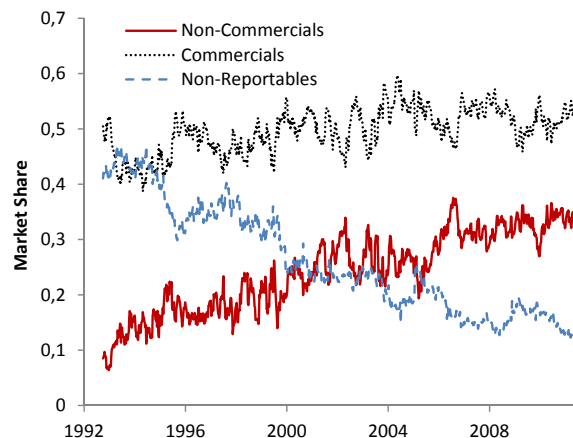
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Figure 1: Descriptive Statistics - Corn

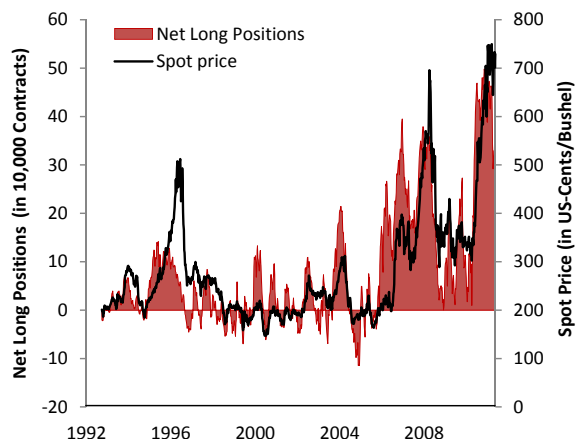
Panel A: Open Interest and Spot Price



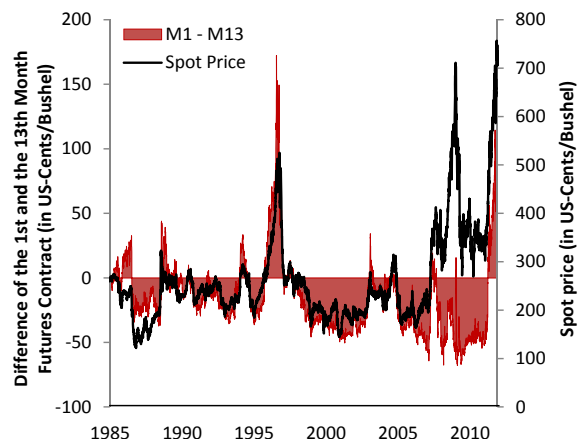
Panel B: Market Shares



Panel C: Speculative Net Long Positions



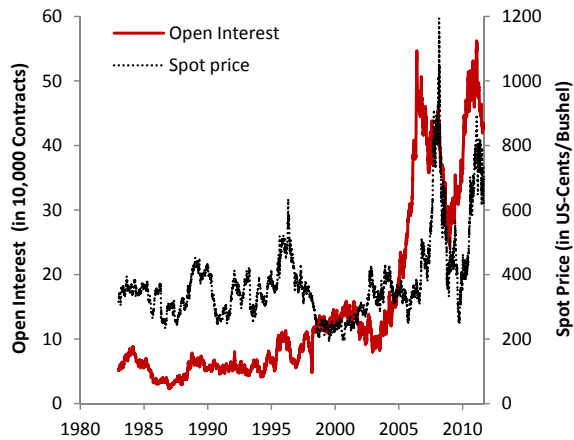
Panel D: Contango/Backwardation



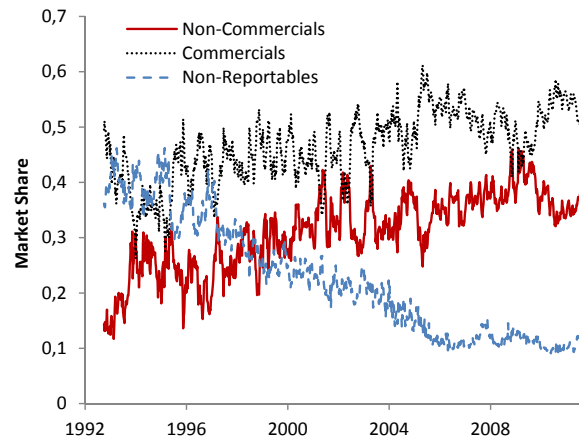
Notes: Panel A shows daily open interest in 10,000 contracts (left) and the daily spot price in US-cents/bushel (right). Panel B displays the shares of Tuesday's closing open interest by type of trader, taken from the weekly Commitments of Traders (COT) report issued by the CFTC, in which the number of outstanding long and short contracts is split up among commercial and noncommercial large traders (i.e., hedgers and speculators) as well as non-reportables (i.e., small traders). Market shares are calculated as the ratios of long plus short (plus two times the speculative spread) positions and two times the aggregate open interest. Panel C shows Tuesday's speculative net long positions in 10,000 contracts (left) and Tuesday's spot price in US-cents/bushel (right). Panel D displays the daily price spread between the futures contracts with a maturity of one and 13 month(s) (left) and the daily spot price in US-cents/bushel (right). In Panels A, C and D, data on open interest and on spot and futures prices are taken from THOMSON REUTERS DATASTREAM.

Figure 2: Descriptive Statistics - Wheat

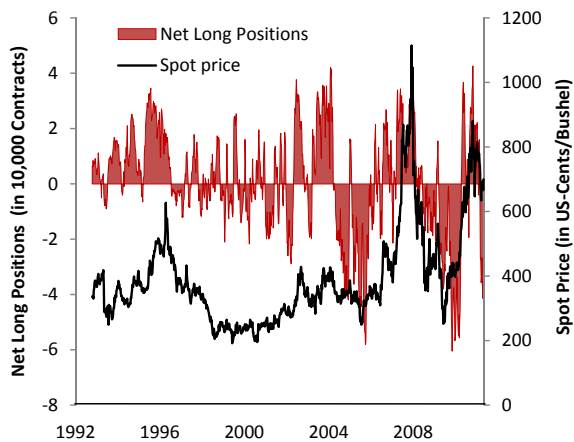
Panel A: Open Interest and Spot Price



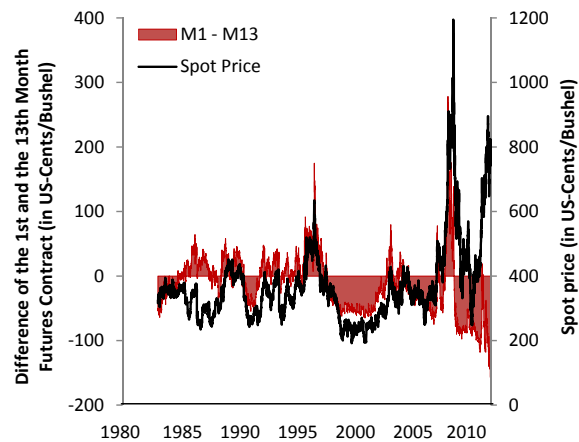
Panel B: Market Shares



Panel C: Speculative Net Long Positions



Panel D: Contango/Backwardation



Notes: Panel A shows daily open interest in 10,000 contracts (left) and the daily spot price in US-cents/bushel (right). Panel B displays the shares of Tuesday's closing open interest by type of trader, taken from the weekly COT report issued by the CFTC, in which the number of outstanding long and short contracts is split up among commercial and noncommercial large traders (i.e., hedgers and speculators) as well as non-reportables (i.e., small traders). Market shares are calculated as the ratios of long plus short (plus two times the speculative spread) positions and two times the aggregate open interest. Panel C shows Tuesday's speculative net long positions in 10,000 contracts (left) and Tuesday's spot price in US-cents/bushel (right). Panel D displays the daily price spread between the futures contracts with a maturity of one and 13 month(s) (left) and the daily spot price in US-cents/bushel (right). In Panels A, C and D, data on open interest and on spot and futures prices are taken from THOMSON REUTERS DATASTREAM.

Table 1: Stability Tests

	Corn			Wheat		
	Model A	Model B	Model C	Model A	Model B	Model C
Panel A						
T	316	316	316	340	340	340
α	371.13	370.40	374.78	533.29	532.10	538.84
β	0.42	0.43	0.50	0.42	0.42	0.64
R^2	0.21	0.21	0.16	0.13	0.14	0.16
Panel B						
SupLR	34.9480***	35.5785***	35.0668***	62.2030***	61.3872***	63.7215***
ExpLR	13.7040***	14.0042***	13.7840***	27.4470***	27.0459***	28.0128***
AveLR	12.2852***	12.0667***	10.8460***	30.7711***	29.3920***	26.6976***
Break	Nov. 2006	Nov. 2006	Dec. 2006	Apr. 1990	Apr. 1990	May 1990
Panel C						
SupLR	15.2346***	15.0044***	23.6069***	34.2089***	31.8625***	17.8545***
ExpLR	4.4562***	4.3541***	8.5526***	13.3480***	12.1971***	5.5645***
AveLR	2.2970***	2.2114***	5.3970***	6.1969***	5.8668***	3.5072***
Break	Nov. 2006	Nov. 2006	Dec. 2006	Nov. 2006	Nov. 2006	Oct. 2006

Notes: Results are shown for the long-run regression (2) in Panel A and for Quandt-Andrews unknown breakpoint tests measuring the stability of the parameter estimates α and β (Panel B) and only β (Panel C), respectively. The convenience yield is calculated as in eq. (1), using (first- and second-nearby) futures prices based on the first-day-of-delivery-month criterion and the three-month US Treasury bill interest rate (Model A), futures prices based on the first-day-of-delivery-month criterion and the Federal funds rate (Model B), and futures prices based on the liquidity-peak criterion and the three-month US Treasury bill interest rate (Model C), respectively. The convenience yield is then adjusted by the difference between the times to maturity of the second- and the first-nearby futures contract. For the long-run regression (2), the spot price and the adjusted convenience yield are deflated by the US consumer price index. T is the number of observations, covering the time period from January 1985 (corn) and January 1983 (wheat), respectively, to April 2011, α and β are the parameter estimates, and R^2 is the coefficient of determination. SupLR, ExpLR and AveLR are the values of the supremum, the exponential and the average likelihood ratio test, respectively. ***, ** and * denote statistical significance at the 1%-, 5%- and 10%-level, respectively. Break denotes the breakpoint.

Table 2: MTAR Results

	Corn			Wheat		
	Model A	Model B	Model C	Model A	Model B	Model C
Panel A						
T	264	264	264	288	288	288
α	354.89	353.91	359.45	513.70	512.14	520.25
β	0.53	0.54	0.56	0.52	0.53	0.83
R^2	0.32	0.33	0.27	0.25	0.26	0.26
Panel B						
T_{MTAR}	316	316	316	340	340	340
τ	96.57	97.32	104.51	148.62	148.62	118.27
Above(τ)	0.02	0.02	0.01	0.02	0.02	0.04
Rank(τ)	215/222	215/222	219/222	222/238	222/238	209/238
ρ_1	-0.6006	-0.6017	-0.3898	-0.3588	-0.3548	-0.2897
se(ρ_1)	0.0754	0.0756	0.0903	0.0769	0.0783	0.0826
ρ_2	-0.0588	-0.0601	-0.0499	-0.0516	-0.0540	-0.0446
se(ρ_2)	0.0321	0.0324	0.0219	0.0233	0.0237	0.0026
$ \rho_1 - \rho_2 $	0.5418	0.5416	0.3399	0.3072	0.3008	0.2451
t_1	-7.9646***	-7.9588***	-4.3154***	-4.6631***	-4.5285***	-3.5089***
t_2	-1.8295*	-1.8567*	-2.2772**	-2.2101**	-2.2768**	-1.6605*
F_C	32.4972***	32.4738***	11.9043***	12.9001***	15.3914***	7.1274**
F_A	46.1097***	45.8273***	13.3719***	14.9427***	19.5931***	8.3472***

Notes: Results are shown for the long-run regression (2) in Panel A and the MTAR regression (3) in Panel B. The convenience yield is calculated as in eq. (1), using (first- and second-nearby) futures prices based on the first-day-of-delivery-month criterion and the three-month US Treasury bill interest rate (Model A), futures prices based on the first-day-of-delivery-month criterion and the Federal funds rate (Model B), and futures prices based on the liquidity-peak criterion and the three-month US Treasury bill interest rate (Model C), respectively. The convenience yield is then adjusted by the difference between the times to maturity of the second- and the first-nearby futures contract. For the long-run regression (2), the spot price and the adjusted convenience yield are deflated by the US consumer price index. T is the number of observations, covering the time period from January 1985 (corn) and January 1983 (wheat), respectively, to December 2006, α and β are the parameter estimates, and R^2 is the coefficient of determination. T_{MTAR} is the number of observations for the MTAR regression (3), covering the time period from January 1985 (corn) and January 1983 (wheat), respectively, to April 2011. τ is the value of the threshold chosen, using the method of CHAN (1993). Above(τ) is the share of observations lying above τ . Rank(τ) is the rank of τ among the ascendingly ordered residuals from the long-run regression (2), excluding the lower and the upper 15%. ρ_1 and ρ_2 are the parameter estimates, and se(ρ_1) and se(ρ_2) are the corresponding standard errors. t_1 ($H_0: \rho_1 \geq 0$) and t_2 ($H_0: \rho_2 \geq 0$) are the values of the t -statistic. F_C ($H_0: \rho_1 = \rho_2 = 0$) and F_A ($H_0: \rho_1 = \rho_2$) are the values of the F -statistic. Asymptotic critical values for t_1 , t_2 and F_C are taken from ENDERS AND SIKLOS (2001). F_A follows the conventional F -distribution. ***, ** and * denote statistical significance at the 1%-, 5%- and 10%-level, respectively.

Table 3: ECM Results

	Corn			Wheat		
	Model A	Model B	Model C	Model A	Model B	Model C
Panel A						
T_{ECM}	309	309	309	333	333	333
μ	1.5371	1.5142	0.9734	1.6098	1.6099	0.0603
δ_1	-0.2922***	-0.2912***	0.4440	-0.4764***	-0.4793***	0.2506**
δ_2	0.0208	0.0215	-0.0510**	0.0046	0.0054	-0.0463**
ϕ_{11}	0.1425**	0.1415**	0.0288	0.1315**	0.1318**	0.0869
ϕ_{12}	0.2222***	0.2229***	0.2081***	0.0687	0.0685	-0.0069
ϕ_{21}	-0.0116	-0.0112	0.0775***	-0.0202	-0.0214	-0.1002***
ϕ_{22}	-0.0323	-0.0337	0.0280	-0.0117	-0.0118	-0.0080
R^2	0.1523	0.1521	0.1328	0.1568	0.1569	0.0470
F_1	9.8795***	9.7753***	8.9497***	5.7945**	5.7874**	0.8822
F_2	1.5071	1.5654	8.8351***	0.5759	0.6245	3.5327*
Panel B						
T_{ECM}	309	309	309	333	333	333
μ	-2.3343	-2.3862	-0.6618	-0.8320	-0.8305	-1.4687
δ_1	0.6446***	0.6423***	0.2353	-0.1667	-0.1784	-0.1317
δ_2	0.1801***	0.1826***	0.0924*	0.1145***	0.1170***	0.0433*
ϕ_{11}	0.0122	0.0167	-0.0578	0.3245***	0.3334***	0.2043**
ϕ_{12}	0.2707*	0.2591	0.1382	0.0600	0.0771	-0.0216
ϕ_{21}	0.0944	0.1029	-0.0367	-0.2183***	-0.2279***	-0.2804***
ϕ_{22}	-0.3342***	-0.3399***	-0.3152***	-0.0737	-0.0821	-0.0930
R^2	0.1883	0.1929	0.1207	0.0860	0.0915	0.0861
F_1	1.4167	1.3571	0.1916	4.6970**	5.3070**	1.5922
F_2	5.8975**	5.7988**	9.2741***	9.5459***	9.8187***	9.5407***

Notes: Results are shown for the ECM (7) with the change in the real spot price (Panel A) and in the real adjusted convenience yield (Panel B) as dependent variable. The convenience yield is calculated as in eq. (1), using (first- and second-nearby) futures prices based on the first-day-of-delivery-month criterion and the three-month US Treasury bill interest rate (Model A), futures prices based on the first-day-of-delivery-month criterion and the Federal funds rate (Model B), and futures prices based on the liquidity-peak criterion and the three-month US Treasury bill interest rate (Model C), respectively. The convenience yield is then adjusted by the difference between the times to maturity of the second- and the first-nearby futures contract. For the long-run regression (2), the spot price and the adjusted convenience yield are deflated by the US consumer price index. T_{ECM} is the number of observations for the ECM, μ , δ_i and ϕ_{ij} , with $i, j = (1, 2)$, are the parameter estimates, and R^2 is the coefficient of determination. F_1 ($H_0: \phi_{11} = \phi_{12} = 0$) and F_2 ($H_0: \phi_{21} = \phi_{22} = 0$) are the values of the F -statistic. ***, ** and * denote statistical significance at the 1%-, 5%- and 10%-level, respectively.