Speculative bubbles in agricultural commodity markets[†]

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Abstract

Numerous factors have been proposed in the literature as explaining the recent commodity price movements. In this paper we focus on one of the most widely discussed factors, the impact of speculative bubbles. We investigate whether commodity prices during the spike of 2007–2008 might have deviated from their intrinsic values based on market fundamentals. To do this, we use a bootstrap methodology to compute the finite sample distributions of recently proposed tests. Monte-Carlo simulations show that the bootstrap methodology works well, and allows us to identify explosive processes and collapsing bubbles for wheat, corn and rough rice. There was less evidence of exuberance in soya bean prices.

Keywords: commodity prices, bubbles, bootstrap, unit root tests

JEL classification: G14, Q14, C12, C15

1. Introduction

The recent rise in international agricultural commodity prices, after the shocking boom and bust of 2007–2008, has enlivened the debate on what the determinants of commodity price behaviour are and has reawakened interest in coordinated policy actions at both the national and international level.

Although numerous factors have been proposed in the literature as explaining recent commodity price movements, there is no general consensus on the relative weight that should be attributed to each of them. Many authors have stressed that more consideration should be given to the effects of growing food demand in developing countries, especially in China and India, and also to the lower production growth rate as being among the causes of the recent food price spike (see for example Von Braun, 2007; Dewbre *et al.*, 2008;


Trostle, 2008; Krugman, 2011). Other studies have argued that biofuel programmes in the United States and European Union are behind the run-up in food prices. These programmes provide subsidies for biofuels leading to a greater use of corn and vegetable oil and resulting in price increases for these commodities (see Headey and Fan, 2008; Mitchell, 2008). On the other hand, Baffes and Haniotis (2010) suggested that the link between food prices and energy prices is the main factor in recent commodity price movements. Energy prices affect food commodity prices by influencing the cost of inputs, such as nitrogen fertiliser, and the cost of transport. The use of agricultural commodities to produce biofuels is also an additional reason for a possible link between energy and food commodity prices. Besides the above-mentioned factors, the list of possible causes analysed in the recent literature includes the decline of commodity stocks (Abbott, Hurt and Tyner, 2008; Piesse and Thirtle, 2009), a weak US dollar (Abbott, Hurt and Tyner, 2008; Mitchell, 2008), panic buying (Timmer, 2009), bans on exports (Dollive, 2008; Headey, 2011) and, above all, speculation (Cooke and Robles 2009; Gilbert, 2010a; 2010b; Irwin, Sanders and Merrin, 2010; Sanders, Irwin and Merrin, 2010).

In this paper, we focus on speculative bubbles. The astonishing rise in 2007–2008 of agricultural commodities prices and then their sudden decline convinced many researchers and policy-makers that speculation, and not fundamentals, was behind the commodity price boom and bust. This view was reinforced by comments of Desai (2008), the testimony of the financiers George Soros to the US Senate Commerce Committee (Soros, 2008) and Michael Masters to the US Senate Committee on Homeland Security and Governmental Affairs (Masters, 2008), and by Gensler (2009), the chairman of the Commodities Futures Trading Commission at the US Senate, who testified 'We ... experienced, in my view, an asset bubble in commodity prices ... I believe that commodity index funds and other financial investors participated in the commodity asset bubble' (Gensler 2009: 1). The warnings of the dangers of speculation have become so strong that they convinced Nicolas Sarkozy, who recently became President of the G20, to put speculation on the next G20 Agenda.[1]

To gauge the importance of the speed of the bubble, we should bear in mind that, in February 2008, the Chicago Board of Trade (CBOT) wheat future price was 280 per cent higher than in January 2006, and only six months later it had fallen by 40 per cent. There were similar movements in the prices of other primary commodities such as corn, soya beans and rice. Media interest in the role of speculation in commodity markets was further increased by the recent steep rise in primary commodity prices, beginning in the second half of 2010 (see Figure 1).[2]

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1 Press Conference of the French Presidency of the '*G20 and G8 2011, Nouveau Monde Nouvelles Idées*', Paris, January 2011.

2 If measured relative to the average values in August 2010, in February 2011 CBOT corn, wheat, rough rice and soya beans future prices were, respectively, 68.5, 21.5, 39.7 and 8.9 per cent higher.
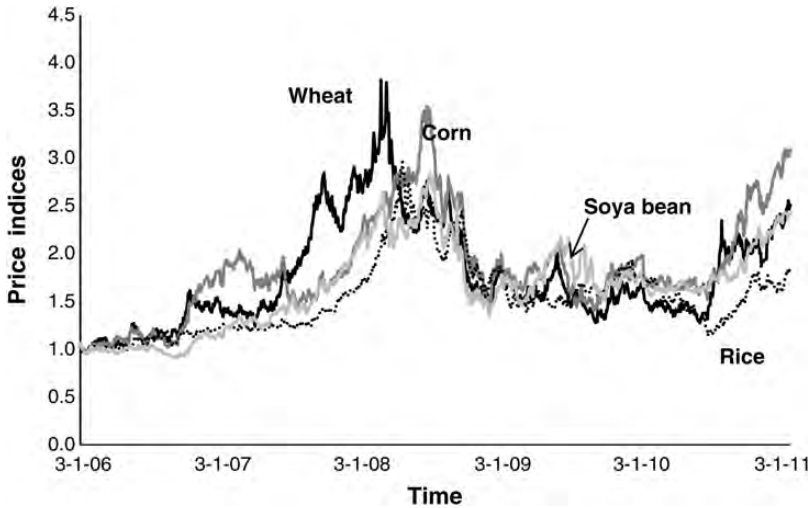
Fig. 1. Daily CBOT future price indices: January 2006 – February 2011 (January 2006 = 1)

The rapid surge in commodity spot and future prices has sparked an intense debate on whether financial investments, mainly by long-only index funds, were affecting the markets and creating a commodity bubble. According to Masters (2008) often cited testimony, assets allocated to commodity indices[3] rose from USD 13 billion at the end of 2003 to USD 260 billion in March 2008. However, the Commodity Future Trading Commission (CFTC) (2008) has estimated the notional value of index trading to be lower, placing it at USD 200 billion in June 2008, with 24 per cent held by index funds, 42 per cent held by pension funds and endowment funds, 9 per cent held by sovereign wealth funds and finally 25 per cent held by retail investors.

However, Irwin *et al.* (2010) and Sanders and Irwin (2010) have found little evidence that the commodity boom and bust was driven by index funds. For example, Irwin *et al.* (2010) used Granger non-causality tests to show that money flows from index funds to commodity indices do not help in forecasting the future price changes of many agricultural commodities, including those of wheat, corn and soya beans.

On the other hand, Cooke and Robles (2009) and Gilbert (2010b) used the same methodology, i.e. Granger non-causality tests, to provide evidence that financial activity in the futures markets, and other proxy variables for

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3 A commodity index, such as the S&P and Goldman Sachs commodity index or the Dow Jones-UBS index, comprise selected commodity futures contracts. Index traders sell these index instruments to hedge funds, pension funds and other investors who desire to invest in the commodity market without actually buying any commodities. To offset their financial exposure to changes in commodity prices, index traders typically buy the futures contracts on which the index-related instruments are based. It is through the purchase of these futures contracts that commodity index traders may affect the futures markets, see US Senate Committee on Homeland Security and Governmental Affairs (2009).

speculation, may be of use in explaining the change in food prices. Irwin *et al.* (2009) and Sanders and Irwin (2010) also found a number of 'conceptual errors' in the hypothesis that speculation by index funds was behind the commodity bubble. These 'conceptual errors' were also discussed in Gilbert (2010a).

Recently, Phillips and Yu (2009b) and Phillips, Wu and Yu (2011) provided a method of testing for the possible presence of speculative bubbles. Their method relies on recursive and rolling regressions coupled with sequential right-sided unit root tests. Unlike standard unit root tests where the researcher is interested in testing for the alternative stationary hypothesis which is located on the left-side of the probability distribution of the test statistic, here the alternative is on the right-side of the probability distribution, where the test statistics for an explosive root is located. The main advantage of the method is that it allows one to test, period by period, for the possible non-stationary behaviour of the price time series against mildly explosive alternatives. Mildly explosive behaviour may be modelled by an autoregressive process with a root that exceeds, but that is still near to, unity. Thus if an explosive root holds, i.e. the alternative hypothesis of mildly explosive behaviour is not rejected, then the Phillips and Yu (2009b) and Phillips *et al.* (2011) procedure provides a tool for identifying bubble behaviour and consistent dating of its origin and collapse. Phillips and Magdalinos (2009) recently provided the large sample asymptotic theory of mildly explosive process. Identifying an explosive root in the commodity price series is interesting, because this is compatible with various different explanations of speculative bubbles, such as rational bubbles, Campbell, Lo and MacKinlay (1998), fads or feedback behaviour, Shiller (1984, 2005) and De Long *et al.* (1990). Gilbert (2010b) applied Phillips *et al.*'s (2011) recursive procedure to three CBOT future prices, wheat, corn and soya beans. His conclusion was that during the commodity boom and bust of 2007–2008 there was explosive behaviour only in the CBOT soya beans future prices and not in the wheat and corn prices.

In this paper, like Gilbert (2010b), we use Phillips and Yu (2009b) and Phillips *et al.* (2011) test statistics but, unlike them, we suggest a nonparametric bootstrap methodology to compute the empirical distribution and the critical values of the previous test statistics. The bootstrap method allows one to replace the asymptotic sampling distribution with an exact distribution that acts as if the empirical distribution of the sample is the population distribution. A large number of studies in the literature shows that bootstrapping, if appropriately used, helps one to compute the critical values of test statistics in finite samples more accurately than those based on asymptotic theory, see for example Hall (1992) and Horowitz (2001). Using the bootstrapped distribution we are able to compute the *p*-value of the test statistic for each observation, i.e. the probability under the null hypothesis of obtaining a test statistic at least as extreme as the one that was actually observed. Unlike Gilbert (2010b), we use the rolling procedure of Phillips and Yu (2009b) and Phillips *et al.* (2011) instead of the recursive method. Banerjee, Lumsdaine and Stock

(1992) showed that both recursive and rolling regression-based Dickey–Fuller statistics are important tools for detecting the unit root properties of the time series. However, we use a Monte-Carlo simulation experiment to show that the rolling method is more powerful than the recursive method in detecting possible speculative bubbles, especially when the explosive root is near unity and the bubbles are located at the end of the sample. We also use a further Monte-Carlo analysis to show that the bootstrap procedure seems to be a good way of detecting where the bubbles are located.

We apply our method to four daily agricultural commodity future price series observed from 1985 to 2010. Futures markets perform a risk-transfer role reallocating the productive activity risk from producers (hedgers) to speculators. Futures markets are also usually considered to perform a fundamental price discovery function, transmitting to future prices actual and expected supply, demand and inventory news. Hernandez and Torero (2010) recently showed that price changes in the futures markets for wheat, corn and soya beans lead to price changes in the spot markets more often than the reverse happening. These findings suggest that futures prices should be used rather than spot prices. The idea of using futures prices and not spot prices to analyse commodity price movements is not new, and many authors, see Fama and French (1987), Gibson and Schwartz (1990) and Bessembinder *et al*. (1995), caution that there is no true spot market for some commodity markets because of the delay in delivery. There is also the recent problem of lack of convergence between commodity future and cash prices (Irwin *et al*., 2009). For these reasons, we investigated the possible explosive characteristics of the wheat, corn, soya beans and rough rice CBOT daily futures prices. In brief, we found that there was strong evidence of explosive behaviour in CBOT wheat, corn and rice futures prices in 2007–2008. Minor signs of price exuberance were detected for the soya beans futures prices.

The paper is organised as follows. In Section 2, we briefly analyse some theoretical models that allow price exuberance and in Section 3 we describe a bootstrap procedure that allows testing for possible price explosions. In Section 4, we apply this bootstrap procedure to a set of commodity futures prices. Finally, in Section 5 we present our conclusions.

2. Bubble models

The analysis of why asset prices tend to show excess volatility when compared with simple efficient market models has attracted an enormous amount of theoretical and empirical research. The notion that asset prices or commodity prices might deviate from their intrinsic values based on market fundamentals because of 'speculative bubbles' (Tirole, 1982; 1985) or 'fads' (Shiller, 1984) or 'information bubbles' (De Long *et al*., 1990) is widely accepted in literature. All these types of bubbles can be well subsumed under Stiglitz's (1990: 13) famous definition: '[I]f the reason that the price is high today is only because investors believe that the selling price is high tomorrow – when "fundamental" factors do not seem to justify such a price – then a

bubble exists.' In other words, movements in asset or commodity prices can be based on the self-fulfilling prophecies of the market participants and these do not depend on the fundamental values.

One of the best-known models allowing for bubbles is the present value model of rational commodity pricing. In this model, the commodity price P_t equals the sum of the expected future price and expected future payoff, or benefit, from ownership of the asset, both discounted at the constant rate R. The model can be represented by the following equation

$$P_t = \frac{E_t(P_{t+1} + \Psi_{t+1})}{1+R},\qquad(1)$$

where, for a storable commodity, the variable Ψ_t is the convenience yield. The convenience yield is a well-known concept. Early authors, for example Kaldor (1939) and Working (1949), defined the convenience yield as a negative component of the carrying charges, i.e. storage costs, insurance costs and finance charges paid to store a physical commodity, in an effort to explain the often-observed phenomenon of spot prices being higher than futures prices.[4] In this case, the convenience yield is a benefit that accrues to inventory holders from the increased utility associated with availability in periods when supplies are scarce. Pindyck (1993) uses equation (1), and the above-mentioned convenience yield definition, to explain the pricing of storable commodities. If aggregate storage is always positive, as it usually is for agricultural commodities, equation (1) holds and the present value model provides a simple explanation for changes in the price of a commodity. In other words, the present value model of rational commodity pricing can be viewed as a highly reduced form of a dynamic supply and demand model. We use a log-linear framework suggested in Campbell, Lo and MacKinlay (1998) to explain how the present value model can be usefully used to explain price exuberance. The major advantage of working with a log-linear approximation is that the relationship between price, convenience yields and possible bubbles will be tractable under empirically plausible assumptions. Taking logs of both sides of equation (1), we approximate the nonlinear function (1) by using the first-order Taylor expansion of the arguments. Finally, using the law of iterated expectations, we end up with the following solution of the difference equation (1)

$$p_t = p_t^f + b_t,\qquad(2)$$

where the term p_t^f in equation (2) is defined as the fundamental price and b_t is the bubble variable. Thus, using the log-linear approximation, the log of commodity price p_t can be split into a fundamental component p_t^f and a bubble component b_t.

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4 See Garcia and Leuthold (2004) for a survey on this and other themes connected to the agricultural future markets.

These components can be written as[5]

$$p_t^f = \frac{\kappa - \gamma}{1 - \rho} + (1 - \rho) \sum_{i=0}^{\infty} \rho^i E_t \psi_{t+1+i},$$

$$b_t = \lim_{i \to \infty} \rho^i E_t p_{t+i}, \tag{3}$$

where $\psi_t = \ln(\Psi_t)$, $\gamma = \ln(1 + R)$, $\rho = 1/(1 + \exp(\overline{\psi - p}))$, with $\overline{\psi - p}$ being the average convenience yield–price ratio, $0 < \rho < 1$, and

$$\kappa = -\ln(\rho) - (1 - \rho)\ln\left(\frac{1}{\rho} - 1\right). \tag{4}$$

We can see from equation (2) that when $b_t = 0$, $b_t = \lim_{i \to \infty} \rho^i E_t p_{t+i} = 0$, i.e. imposing the transversality condition, the price p_t is fully determined by the fundamental price p_t^f or, in other words, by the discounted expected future convenience yield ψ_t, see (3). If $b_t \neq 0$, there exists an infinite number of solutions to equation (1) and any solution can be written as equation (2). Campbell, Lo and MacKinlay (1998) call the term b_t a 'rational' bubble. The adjective 'rational' is used because the presence of b_t in equation (2) is fully consistent with rational expectations and constant expected returns. The word 'bubble' is a reference to episodes of financial exuberance in which investors appeared to be betting that other investors would drive prices even higher in the future, and far higher than could be explained by fundamentals. In this case, from equation (4), we can always write

$$b_t = \frac{1}{\rho} b_{t-1} + \varepsilon_t \equiv (1 + g)b_{t-1} + \varepsilon_t \tag{5}$$

where $g = (1/\rho) - 1 = \exp(\overline{\psi - p}) > 0$ is the growth rate of the natural logarithm of the bubble and ε_t is a random error. Thus as $\exp(\overline{\psi - p}) > 0$, b_t will be explosive as well as the price p_t, irrespective of whether the convenience yield ψ_t is or is not a stationary variable. Moreover, $\Delta p_t = p_t - p_{t-1}$ will also be explosive. This finding explains the method used by Diba and Grossman (1988) to test for explosive rational bubbles. They proposed investigating the stationarity properties of the price series. To be more precise, if Δp_t is a stationary variable, the presence of explosive rational bubbles is ruled out. If not, the rational bubble hypothesis can hold. Rational bubble models have been criticised for both economic and methodological reasons (see for a survey Camerer, 1989). In terms of economics, rational bubbles for commodity prices can be ruled out if there is a substitute with an infinitely elastic supply curve. In this case, we can imagine that there is an upper limit on the price of the commodity. However, commodity markets are usually characterised by low short-run

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5 See Campbell and Shiller (1988).

supply elasticities. Thus, in the short-run, and especially for tight markets where the stocks are minimal, commodity prices can show periods of exuberance. In terms of the methodology, Evans (1991) showed that when this method is applied to periodically collapsing rational bubbles, testing for the stationarity of Δp_t as proposed, for example, in Diba and Grossman (1988), may lead to the incorrect conclusion that bubbles are not present. This is because b_t in equation (5) will appear to be a stable linear autoregressive process unless the probability that the bubble does not collapse is very high. Thus, the testing procedure will erroneously come to the conclusion that bubbles are not present.

A second way to model explosive processes or bubbles in commodity prices is to use fad models where deviations from the price fundamental are caused by social or psychological forces. This idea captures Keynes's notion that markets are sometimes driven by animal spirits unrelated to economic realities. If this is the case, commodity markets may show excess volatility and overreact to new information (Shiller, 1984; Summers, 1986). A simple fad model can be written as

$$
\begin{aligned}
p_t &= p_t^f + F_t, \\
F_{t+1} &= \gamma F_t + e_t
\end{aligned}
\tag{6}
$$

where F_t is the fad, γ is a parameter measuring the speed of convergence or decay of the fad and e_t is a zero-mean independent error term. If $\gamma = 0$, any fads disappear immediately. If $\gamma = (1 + g)$, the fad is a rational bubble as described in equation (5).[6] Thus, fad models may show price explosiveness, but they can be criticised because they use the same economic and methodological arguments as rational bubble models.

Feedback models have introduced additional ideas into why prices in certain periods may be explosive. Shiller (2005) uses these models to explain various speculative bubbles. The basic idea here is that rising commodity prices may attract positive feedback traders. Rational speculators can anticipate feedback traders and will buy more today and thus driving prices up higher than fundamentals would suggest. If the feedback is not stopped, it may produce many rounds of speculative bubbles, in which high expectations of further price increases support high current prices (De Long et al., 1990). Gilbert (2008) suggests a simple extrapolative model where commodity prices show explosive behaviour. One of the advantages of using these types of models is that the behaviour of commodity prices is not linked to strong assumptions as in the case of rational bubble models. However, Park and Irwin (2007) underline the importance of rational expectation models and behavioural models in the technical trading strategies on futures markets.

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6 Note that both rational bubbles and fads may exist. We simply add the bubble term in equation (2) to the fad model (6).

3. Testing for bubbles: a bootstrap procedure

Recently, two seminal papers by Phillips and Yu (2009b) and Phillips *et al.* (2011) suggested a method to first test for explosive bubbles and then, if bubbles hold, to date the origin and collapse of the bubbles.[7] The method is mainly based on the recursive and rolling implementation of right-side unit root tests. Thus, and unlike standard unit root tests where the researcher is interested in testing for the alternative stationary hypothesis located on the left-side of the probability distribution of the test statistic, here the alternative is on the right-side where the test statistic for an explosive root is located.

In our case, the method requires estimating the augmented Dickey–Fuller (ADF) regression

$$y_t = c + \rho y_{t-1} + \sum_{i=1}^{k-1} \beta_i \Delta y_{t-i} + \varepsilon_t, \, t = 1, \dots, T \tag{7}$$

where y_t is the log of the agricultural commodity price p_t, c is a constant, k is a lag parameter and ε_t is an identically and independently distributed error term. Equation (7) is estimated repeatedly, using subsets of the sample data. Recursive ADF test statistics are computed using subsamples $t = 1, \dots, m$, for $m = m_0, \dots, T$, where m_0 is a start-up value and T is the size of the full sample. For the rolling method, the ADF statistics are computed using subsamples that are a constant fraction δ_0 of the full sample, rolling through the sample. Both recursive and rolling statistics are aggregate in order to construct the following single test statistic

$$\sup_{\text{rec}} \text{ADF} = \sup_{m \in \{1, [T\delta]\}} \text{ADF}_m, 0 < \delta_0 \leq \delta \leq 1 \tag{8}$$

for the recursive case, and the following test statistic for the rolling case

$$\sup_{\text{rol}} \text{ADF} = \sup_{m \in \{T(\delta - \delta_0)+1, T\delta\}} \text{ADF}_m, 0 < \delta_0 \leq \delta \leq 1. \tag{9}$$

Phillips and Yu (2009b) and Phillips *et al.* (2011) suggest comparing the estimates of equation (8), for the recursive method, or equation (9) for the rolling method, with the right-tailed critical values of their distributions being used to test for a unit root, $\rho = 1$ in equation (1), against explosive bubbles, i.e. $\rho > 1$. Thus, if the estimated test statistics $\sup_{\text{rec}}$ ADF or $\sup_{\text{rol}}$ ADF are higher than the right-side critical value, we can reject the null hypothesis of a unit root $H_0 : \rho = 1$ for the alternative hypothesis, $H_A : \rho > 1$.

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7 Recently, Nielsen (2005) proposed using a vector autoregression (VAR) analysis to investigate for the possible presence of a cointegrated explosive process. This is an interesting topic in studying explosive processes but beyond the scope of this work.

Now, if the test (8) or (9) allows rejecting the null hypothesis in favour of the alternative hypothesis of a mildly explosive process, Phillips and Yu (2009b) and Phillips *et al.* (2011) propose a method that allows dating the origin, τ_s^o, and the collapse, τ_s^c, of a bubble. Using their notation, the origin of a bubble is estimated as

$$\hat{\tau}_s^o = \inf_{s \geq m}\{s : \mathrm{ADF}_m > cv_\alpha^{\mathrm{ADF}}\} \tag{10}$$

and the collapse of the bubble is estimated as

$$\hat{\tau}_s^c = \inf_{s \geq m}\{s : \mathrm{ADF}_m < cv_\alpha^{\mathrm{ADF}}\} \tag{11}$$

where cv_α^{ADF} is the right-side critical value of the ADF statistic based on $\tau = [T\delta]$ observations in the case of recursive case and $\tau = [T\delta_0]$ observations in the case of rolling method. Thus, if the ADF test in the interval $t \in (\delta_0 T, T)$ is greater than the critical value, we define this date as the origin of the bubble. The first date where the ADF test is lower than the critical value is defined as the collapse of the bubble. The asymptotic distribution of the previous test statistics is non-standard. Under the null hypothesis of a unit root, the OLS estimator of ρ in equation (7) and the $t_{\hat{\rho}}$ ADF statistic are both functions of a Wiener process, see for example Hamilton (1994), and thus also $\sup_{\mathrm{rec}}$ ADF or $\sup_{\mathrm{rol}}$ ADF test statistics will be functions of a Wiener process, see Gutierrez (2011). Phillips and Yu (2009b) and Phillips *et al.* (2011) use a Monte-Carlo simulation to derive the asymptotic critical values.

Rather than adopting this method, we use a bootstrap to draw inferences from the empirical distribution of the test statistics. The main advantage of bootstrap over asymptotic methods is that they provide answers to a large class of statistical inference problems without stringent structural assumptions on the underlying random data-generating process (Lahiri, 2003). In our case, the bootstrap idea is to consider the residuals ε_t from fitted model (7) as 'approximately independent' and then re-sample the residuals (with a suitable centring adjustment) in order to define the bootstrapped observations through equation (7). The bootstrapped observations can then be used to compute the empirical distribution of the test statistics (8) and (9), as well as those of (10) and (11), and their quantiles.

We use a sieve bootstrap method to construct the bootstrap tests. The sieve bootstrap was given this name by Buhlmann (1997) because the method allows approximating any general linear, possibly infinite, process by a finite autoregressive process of order k and thus resampling from a finite autoregression. The sieve bootstrap has been found to be better than other bootstrap methods such as block-bootstrap methods in approximating the general linear process, see for example Palm, Smeekes and Urbain (2008).

In our case, the sieve bootstrap comprises the following steps:

1. Step 1: Fit the following autoregressive process by OLS,

$$\Delta y_t = \alpha_0 + \sum_{i=1}^{k} \alpha_i \Delta y_{t-i} + \varepsilon_t \tag{12}$$

2. Step 2: Denote by $\hat{\alpha}_i$ with $i = 1, \ldots, k$ the OLS estimates and $\hat{\varepsilon}_t$ the OLS residuals in regression (12). Now resample ε_t^* from the centred residuals $(\hat{\varepsilon}_t - \bar{\varepsilon})$ where $\bar{\varepsilon}$ is the average of the residuals.[8]
3. Step 3: Generate y_t^* using the OLS estimates $\hat{\alpha}_i$, $i = 1, \ldots, k$ and the residuals ε_t^*, i.e.

$$y_t^* = y_{t-1}^* + \sum_{i=1}^{k} \hat{\alpha}_i \Delta y_{t-i}^* + \varepsilon_t^*. \tag{13}$$

4. Step 4: Using y_t^*, compute the statistics (8) or (9) and repeat Step 2 to Step 4 B times to obtain their bootstrapped distribution. Moreover, y_t^* can be also used to compute the bootstrap distribution of the ADF test and the quantiles of equations (10) and (11).

The above-mentioned bootstrap procedure needs some additional explanation. First, Chang and Park (2003) and Palm *et al.* (2008) show that the asymptotic distribution of the ADF bootstrap statistics under the null is the same as the asymptotic distribution of the original ADF statistic. Thus given that the sup(·) operator in equations (8) and (9) is a continuous function and applying the continuous mapping theorem, one can assume that Chang and Park (2003) and Palm *et al.* (2008) results will also hold for the bootstrapped test statistics (Hamilton, 1994). Secondly, we impose the null hypothesis of a unit root in equation (12), because Basawa *et al.* (1991) showed that the unit root must be imposed in order to achieve consistency of the bootstrap. Third, the auto-regression (13) must be initialised to obtain the bootstrap sample. We fix the first $k + 1$ of y_k^* to zero in order to avoid nonstationary autoregressive processes.

3.1 Monte-Carlo simulations

Before presenting the empirical results, it is useful to check first which testing procedure, the recursive or the rolling regressions method, performs better and second, whether bootstrap methods are better for dating bubbles than asymptotic methods. To do this we use a Monte-Carlo simulation model similar to those presented in Phillips *et al.* (2011) and compare the power of $\sup_{\text{rec}}$ ADF and $\sup_{\text{rol}}$ ADF test statistics. Phillips *et al.* (2011) propose the following model

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8 To generate a valid approximation of equation (12), the residuals have to be centred given that $k + 1$ residuals are lost in step 3.

$$y_t = y_{t-1}1\{t < \tau^o\} + \rho y_{t-1}1\{\tau^o \le t \le \tau^c\}$$

$$+ \left(\sum_{k=\tau^c+1}^{t} \varepsilon_k + y_{\tau^c}^*\right)1\{t > \tau^c\} + \varepsilon_t\{t < \tau^c\} \tag{14}$$

where $1\{\}$ is the indicator function, τ^o and τ^c are, respectively, the date of origin and collapse of the exuberance, $y_{\tau^c}^*$ is the new initial value of the variable after the collapse and ε_t is a pseudorandom normal variate. As do Phillips *et al.* (2011), we compute 1,000 sample path replications, setting $\rho = 1.01, 1.02,$ 1.05 and the number of bootstrap replications set to $B = 999$.[9]

We analyse the power of the two ADF test statistics for the values of $\tau^o = 0.35$ and $\tau^c = 0.45$, for $\tau^o = 0.55$ and $\tau^c = 0.65$, and finally for $\tau^o = 0.85$ and $\tau^c = 0.95$. Finally, we fix $\delta = \delta_0 = 0.2$ in equations (8) and (9).

From Table 1, it appears that the power of rolling and recursive methods is similar for higher value of ρ but the rolling method performs better than the recursive method, especially for low values of ρ and when bubbles are located at the end of the sample. This is particularly interesting when testing for the possible 2007–2008 commodity price bubble, because the period of price exuberance is situated at the end of the sample. The rolling method probably performs better because the signal of rolling regressions will be comparatively stronger than recursive regressions as the number of observations in each regression are shorter for the former.

We now turn to the Monte-Carlo analysis of asymptotic versus bootstrap methods' performance in dating bubbles. The asymptotic theory required to obtain the critical values of Phillips and Yu (2009a) test is very complicated. The authors propose using an (arbitrary) expansion rule and fixing the critical value for the ADF test to $(2/3)\ln\ln^2(t)$, which increases slowly with the sample size T.[10] They claim that this rule produces a significance level close to the 1 per cent level and which seems acceptable as it reduces the risk of choosing the explosive alternative when this is not true. Thus we also use the 1 per cent quantile (on the right-side of the bootstrapped distribution of the ADF test) in the Monte-Carlo simulation. Finally, as do Phillips *et al.* (2011), we impose the (small infinity) duration condition that $\hat{\tau}^c - \hat{\tau}^o \ge \ln(t)/t$. In Table 2 we report the mean, standard error and root mean square error (RMSE) of the bootstrap and the Phillips *et al.* (2011) asymptotic method for rolling regressions with for $\tau^o = 0.4$ and $\tau^c = 0.6$.

Some interesting results emerge. First, both methods seem to work well in detecting τ^o and τ^c and the true values are inside the two standard deviations of the estimated values. Second, the τ^c is estimated better than τ^o. Third, when the explosive behaviour is stronger, it is easier to estimate τ^o and in this

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9 Setting $B = 999$ is a common choice in bootstrap procedures. The results do not change much any more for larger number of iterations.

10 Gilbert (2010b) uses these critical values in dating bubbles. Interestingly, a different expansion rule, given by $\ln\ln^2(t)/4$, has been proposed in Phillips and Yu (2009b).

Table 1. The power of $\sup_{\text{rec}}$ ADF and $\sup_{\text{rol}}$ ADF test statistics.

ρ	$\tau^o = 0.35;\ \tau^c = 0.45$		$\tau^o = 0.55;\ \tau^c = 0.65$		$\tau^o = 0.85;\ \tau^c = 0.95$	
	$\sup_{\text{rec}}$ ADF	$\sup_{\text{rol}}$ ADF	$\sup_{\text{rec}}$ ADF	$\sup_{\text{rol}}$ ADF	$\sup_{\text{rec}}$ ADF	$\sup_{\text{rol}}$ ADF
1.01	0.399	0.457	0.445	0.537	0.494	0.613
1.02	0.802	0.831	0.821	0.861	0.810	0.893
1.05	0.994	0.994	0.991	0.991	0.990	0.994

Table 2. Monte-Carlo estimates of $\hat{\tau}^o$ and $\hat{\tau}^c$ based on ADF test critical values: Rolling regressions method, $\tau^o = 0.4$ and $\tau^c = 0.6$, $T = 1.000$

	$\rho = 1.035$		$\rho = 1.040$		$\rho = 1.045$		$\rho = 1.050$	
	$\hat{\tau}^o$	$\hat{\tau}^c$	$\hat{\tau}^o$	$\hat{\tau}^c$	$\hat{\tau}^o$	$\hat{\tau}^c$	$\hat{\tau}^o$	$\hat{\tau}^c$
Bootstrap simulation results[a]								
Mean	0.4346	0.6004	0.4307	0.6011	0.4280	0.6010	0.4248	0.6006
Std	0.0237	0.0152	0.0212	0.0040	0.0197	0.0035	0.0180	0.0080
RMSE	0.0419	0.0152	0.0373	0.0040	0.0342	0.0035	0.0307	0.0080
Asymptotic simulation results								
Mean	0.4381	0.6006	0.4335	0.6008	0.4298	0.6007	0.4262	0.6007
Std	0.0268	0.0122	0.0245	0.0104	0.0218	0.0103	0.0186	0.0104
RMSE	0.0465	0.0122	0.0415	0.0104	0.0369	0.0104	0.0321	0.0104

[a]Based on 999 iterations.

case both the bias and the standard error become smaller, while minor changes are seen for τ^c. Finally, the bootstrap procedure provides better estimates and standard deviations for smaller values of T while the differences between the two methodologies become negligible for larger values of T. Of course the bootstrap procedure is more time-consuming than the asymptotic approach. However, the additional computational requirements are quite modest.[11]

In synthesis, the results from the two Monte-Carlo simulation experiments show that the rolling regressions method performs better than the recursive regressions method in detecting periods of price explosions and that the boot-strap method seems to date bubbles well.

4. Empirical results

Our data were collected from the CBOT and refer to the daily future prices of four commodities: wheat, corn, soya beans and rough rice. Wheat, corn and soya beans are widely traded commodities while the rice market is very

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11 All the results of Monte Carlo simulation analysis and the GAUSS procedures are available upon request.

thin. For example, the average trading volume in December 2008 for wheat and corn futures contracts were 132 times the daily volume for rough rice (Timmer, 2009). However, CBOT rough rice prices show clear signs for price explosions on the same days that the governments of India and Thailand announced export bans. Thus, given the world-wide price linkages, we think that analysing the CBOT rice futures prices will detect signs of price exuberance in this important market.

We use settlement prices, i.e. closing prices recorded after a trading section. The first nearby futures price is employed as a proxy for cash prices in commodity markets. However, commodity futures contracts have a finite life span limited by their maturity and analysts need to create futures continuation series not only to test academic hypotheses, but also to study and develop different trading systems that they can use for speculative or hedging purposes. Thus we have a problem. We have to choose the rollover date, i.e. the point in time when we switch from the front contract series to the next one. We use two methods. First, we construct a unique price series using only the data of the nearest futures contract up to its maturity, usually the business day prior to the 15th calendar day of the contract month, and link with the following contract on the next day. However, in the last weeks of the life of a futures contract commodity prices may be abnormally volatile (see Samuelson, 1965) and for this reason Ma, Mercer and Walker (1992) suggest to generally avoid using rolling over at the maturity date. The second method rolls contracts on the first day of the final month of trading (also used by Gilbert, 2010b). Even though both methods may introduce possible outliers in the commodity price process, we did find only minor differences when testing for price explosiveness and dating bubbles.

Table 3 provides summary statistics for the time series analysed. The maximum value for all commodity future prices was found in the first 7 months of 2008. The wheat price reached its maximum of 1280 US-cents per bushel at the end of February 2008 and the rough rice price reached its maximum of 24.5 US-cents per hundredweight in April 2008. Corn and

Table 3. Summary statistics of commodity prices: March 1985–January 2011.[a]

Data	Sample size[b]	Frequency	Min. price US-cents	Date (Min.)	Max. price US-cents	Date (Max.)
Wheat (bushel)	6,517	Daily	280.0	13 December 1999	1,280.0	27 February 2008
Corn (bushel)	6,517	Daily	142.8	13 February 1987	754.8	27 June 2008
Soya beans (bushel)	6,517	Daily	410.0	8 July 1999	1,658.0	3 July 2008
Rough Rice (hundredweight)	5,491	Daily	3.43	6 May 2002	24.5	23 April 2008

Source: Chicago Board of Trade.
[a]For the rough rice prices the period of analysis is December 1988–January 2011.
[b]Number of trading days.

Table 4. Test results for futures prices and convenience yields explosiveness and estimates of bubbles origin and collapse.[a]

	Rolling regressions			
	Wheat	Corn	Soya beans	Rough rice
Commodity prices				
sup$_{rol}$ ADF	1.858 (0.036)	2.389 (0.010)	1.667 (0.066)	2.334 (0.010)
Bubble origin	22 August 2007	14 January 2008	11 June 2008	6 February 2008
Bubble collapse	22 April 2008	1 August 2008	17 July 2008	3 October 2008
Bubble n. days	168	140	26	168
ADF (full period)	-1.353 (0.400)	-1.145 (0.317)	-1.730 (0.578)	-1.396 (0.425)
Convenience yields				
sup$_{rol}$ ADF	0.178 (0.832)	0.289 (0.783)	1.307 (0.171)	0.012 (0.488)

[a]*p*-Values in parentheses.

soya beans maximum prices were, respectively, June and July 2008. All commodity prices rose considerably higher in 2008 when compared with the minimum values observed during the period of analysis. Wheat increased by 357 per cent, rice by 614 per cent, corn by 428.5 per cent and soya beans by 304 per cent.

In Table 4, we present the test values and the right-side critical values obtained from the bootstrapped distribution of the test statistics. They refer to the rolling regression method.[12] For the wheat, corn and soya beans CBOT future prices, the initial start-up sample for the rolling regressions covers the period from March 1985 to May 1990 for a total of 1300 daily observations. For the rough rice prices, the start-up sample for the rolling regressions covers the period December 1988 to August 1993, with 1098 daily observations. The price series are expressed in natural logarithms and are constructed from the rolling contracts on the first day of the final month of trading. The maximum lag order k in equations (7) and (12) has been fixed at $k = 10T^{1/4}$. The optimal lag length is determined sequentially testing for significance at the 5 per cent level, and leading to the selection of the model for which the coefficient of the last included lag is significant at the 5 per cent level.

Several conclusions can be drawn from the table. First, if we were to follow the convention and apply the ADF test to the full sample, that is from March 1985 to January 2011 for wheat, corn and soya bean future prices and from December 1988 to January 2011 for rough rice price, the tests could not reject the null hypothesis $H_0 : \rho = 1$ in favour of the right-tailed alternative hypothesis $H_A : \rho > 1$, and therefore one would conclude that there was no significant evidence of exuberance in the agricultural commodity prices.

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12 Similar results, not reported for brevity but available upon request, were obtained from the recursive method.

This result is consistent with Diba and Grossman (1988), as well as with the recent findings of Phillips and Yu (2009b) and Phillips *et al.* (2011) for a set of stock price indices, house price indices and commodity prices. However, the ADF test results are open to the criticism expressed by Evans (1991) because this unit root test applied to the full sample has difficulties detecting period-ically collapsing bubbles. Second, and unlike the previous results, both the $\sup_{rec}$ ADF and $\sup_{rol}$ ADF tests provide evidence of explosiveness in the price data for wheat, corn and rough rice. Our results are probably independent of sampling frequency. In fact, Pierse and Snell (1995) show that the power of the ADF unit root tests with the same data span is independent of sampling frequency. Thus using daily or weekly data might not affect the testing pro-cedure. For soya beans future prices, the rolling regressions method rejects the null of a non-stationary process at the 10 per cent level of confidence while it is strongly rejected by the recursive method. Thus, the bootstrap method allows highlighting the possible presence of speculative bubbles for wheat, corn and rough rice prices. Minor evidence of price exuberance was detected for soya bean prices. These results differ from Gilbert (2010b). Unlike us, he detected bubbles for the CBOT soya beans and not for wheat and corn. This result may due to the more efficient bootstrap method used here and by the different method used in defining the critical values.[13]

Focusing now on the origin and collapse of bubbles, we use the test statis-tics (10) and (11). Note that, using the bootstrap method, we are able to con-struct the empirical distribution of the ADF statistics for each rolling date, and thus we are able to define the critical value as well as the *p*-values. Using the 5 per cent level of significance, we find that for wheat prices the bubble origi-nated on 22 August 2007. The bubble finally collapsed on 22 April 2008. The total duration of the wheat price exuberance was 168 trading days. For corn prices the bubble started later, in January 2008 and collapsed in August 2008. Interestingly, Gilbert (2010b) concluded that index traders appear to have amplified price movements for wheat, corn and soybeans and Cooke and Robles (2009) showed that financial activity in the futures markets and/or speculation can help to explain the behaviour of these prices in 2007–2008. For rough rice, price exuberance started on 6 February 2008, thus later than the wheat and corn bubbles, and collapsed on 3 October 2008, a total number of trading days. Interestingly, in February 2008, India announced a ban on exports of non-Basmati rice. In Thailand, the world's largest exporter of rice, rice prices exploded in March 2008 fol-lowing discussions by the new government on introducing export restrictions (Timmer, 2009). Thus it may be that hoarding by small traders and consumers reacting to actual or discussions of export bans caused panic and consequently

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13 As shown in Phillips, Wu and Yu (2011), the critical values used in Gilbert (2010a, 2010b) are near the 4 per cent significance level while we used a 5 per cent significance level. Further, Monte-Carlo experiments, not reported in the paper but available upon request, show that the ADF and $\sup_{rol}$ ADF, $\sup_{rec}$ ADF test statistics are very sensitive to the choice of lag *k* in equation (7). Because Gilbert (2010b) does not say how *k* was fixed, we cannot say whether our different results may be due to this.

a bubble in rice markets. Finally, to find a bubble for soya beans, we have to accept a level of significance of 10 per cent. We note in this case that the soya beans bubble was very short in duration, less than 1 month.

It is important to mention that finding periods of price exuberance for commodity prices may seem curious, given that there are daily price limits for trading in future contracts. However, the standard custom of raising limits on the daily movements of contract prices when prices arrive at the limits may have reduced the importance of this instrument, Schnepf (2008).[14]

If we now apply the rolling method to the price series constructed using only the data of the nearest futures contract up to its maturity, we find similar results. The $\sup_{rol}$ ADF statistics for wheat, corn and rough rice reject the null hypothesis of non-stationarity for the alternative of an explosive root at the 5 per cent significance level.[15]

If we adopt the rational speculative bubble model, the explosive characteristics in p_t could in principle arise from explosive behavior in the convenience yield ψ_t. This is why we analyse whether the convenience yield showed exuberance during the period of analysis. As indicated in Section 2, instead of using rational expectation models, one could resort to feedback models to explain bubbles. These models allow overcoming the strong hypothetical aspects implicit in rational bubble models. However, given the importance of rational bubble models in the literature, we investigate their statistical properties. We measure the convenience yield as

$$\Psi_t = P_t - \mathrm{PF}_{t,T}\mathrm{e}^{-(i(t,T)(T-t))/365} \tag{15}$$

where the first term on the right-hand side of equation (15) is the settlement price of the nearby future contract and the second term on the right-hand side of equation (15), $\mathrm{PF}_{t,T}$, is the settlement price of the next-to-expire futures price. The variable $\mathrm{PF}_{t,T}$ is net, from the cost of storage computed as a product of the CBOT daily storage cost times the number of days between the first delivery date for the expiring and next-to-expire futures contracts, see Irwin *et al.* (2009). Focusing on wheat contracts, starting from 2000, the CBOT wheat storage rates were set at USD 0.0015 per bushel per day. This rate remained until the July 2008 contract, when the storage rate was increased to USD 0.00165 per bushel per day. Starting from July 2009 a seasonal wheat storage rate schedule was introduced. It established a storage rate of USD 0.00265 per bushel per day from July 18 to December 17. From December 18 to July 17, the storage rate decreased to its original level of USD 0.00165 per bushel per day. We also use the previous storage cost for corn and soya beans prices. For rough rice, the cost of storage was fixed at USD 0.0034 per hundredweight per day. The index t is the time of observation, T

14 CBOT daily price limits were raised in February 2008 for wheat, and March 2008 for corn, soya beans and rough rice future prices.
15 In this case, the $\sup_{rol}$ ADF test statistic for wheat is equal to 1.613 (0.042), for corn is equal to 1.858 (0.038), for rice is equal to (0.018) and finally for soya beans the test statistic is equal to 1.607 (0.071), with the bootstrapped *p*-values in parentheses.

is the time of expiration, $i(t, T)$ is the value of the 3-month US Treasury Bond rate over the interval and $(T-t)$ the number of days until expiry. The source for this series is the Federal Reserve System database.

This discounting procedure is similar to that proposed in Brennan (1986). Interestingly, the results are quite different from the price statistics. In brief, all the convenience yield series are non-explosive. In fact, the $\sup_{rol}$ ADF tests statistics strongly reject the alternative hypothesis of $H_A : \rho > 1$. More importantly, because the convenience yield is not explosive, it immediately follows from equation (3) that the fundamental price must be a non-explosive process. Observing equation (2) in addition, the only way to explain the commodity rice bubbles detected in 2007–2008 for actual wheat, corn and rough rice prices is from a rational explosive bubble b_t or a positive feedback behaviour (De Long *et al.*, 1990).

In synthesis, under the assumption of a constant discount rate, the test results show that there was price exuberance or bubble activity for wheat, corn and rough rice commodity prices. Minor signs of exuberance were found for soya bean prices. However, because equation (7) may be exclusively interpreted as a reduced form of an unknown structural model, our approach only allows us to detect periods where actual prices deviated from fundamentals and not to attribute these deviations to a specific factor such as financial speculation, hoarding or the actions of positive feedback traders. Structural models are needed to investigate these issues.

5. Conclusions

We provide evidence that commodity prices might have deviated from their intrinsic values based on market fundamentals during the recent price spike of 2007–2008. Using a bootstrap method computing the finite sample probability distribution of the tests recently proposed in Phillips and Yu (2009b) and Phillips *et al.* (2011), we find that there was evidence of explosiveness in the future prices of wheat, corn and rough rice in 2007–2008. Bubbles were not synchronised. The first signals of price exuberance were registered in the wheat market in the last week of August 2007. Corn prices started to show explosive behaviour in January 2008, followed by rough rice prices in February 2008. The wheat bubble collapsed in April 2008, while the corn and rough rice prices bubbles burst later, in August and October 2010, respectively. Minor signs of price exuberance were detected for soya bean prices.

Thus our empirical results may help to support the testimony of Gensler (2009), the chairman of the Commodities Futures Trading Commission at the US Senate, who in June 2009 stated: 'We … experienced, in my view, an asset bubble in commodity prices … '. Unfortunately, because we are using a reduced form and not a structural model, we cannot identify which factors were behind the commodity price explosions and their collapse. Whether financial speculation caused the 2007–2008 bubbles in wheat and corn prices is still debated. Hoarding by small traders and consumers in reaction to export bans by some governments may have caused a bubble in the rice

market. Furthermore, the behaviour of positive feedback traders with high expectations of further price increases may have contributed to the high prices registered in 2007–2008. In synthesis, additional research is needed to understand which factors may have affected agricultural commodity price dynamics. Knowing where the bubbles are located may help us to identify the crucial variables.

Acknowledgements

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