Paper prepared for the 123rd EAAE Seminar

PRICE VOLATILITY AND FARM INCOME STABILISATION

Modelling Outcomes and Assessing Market

and Policy Based Responses

Dublin, February 23-24, 2012

Testing for Speculative Bubbles in Agricultural Commodity Prices: A Regime Switching Approach

Xiaoliang Liu, Guenther Filler and Martin Odening

Department of Agricultural Economics, Humboldt-Universität zu Berlin, Germany

liuxiaoz@agrar.hu-berlin.de

Testing for Speculative Bubbles in Agricultural Commodity Prices: A Regime Switching Approach

Xiaoliang Liu, Guenther Filler and Martin Odening

Abstract

The sharp increase in agricultural commodity prices in 2008 and in 2011 has triggered an intensive debate on the causes for these price booms. Speculative bubbles have been quoted as one factor among others for the price peaks. Against this background, our paper contributes to this discussion by implementing a novel test procedure for speculative bubbles which has been suggested in the stock market literature. We use a regime switching regression model to test the hypothesis that agricultural prices are driven by periodically collapsing bubbles. The analysis is conducted for wheat, which is one of the most important crops worldwide. Our results show that the data do not support this particular bubbles hypothesis.

Keywords: Agricultural commodity market, net convenience yield, speculative bubbles, regime switching, fundamental values.

JEL classification: C12, Q13, Q14.

1. INTRODUCTION

The sharp increase in agricultural commodity prices in 2008 and in 2010 has triggered an intensive debate on the causes for these price booms. There seems to be a consensus among agricultural economists that this development cannot be traced back to one single factor. Rather several factors contributed to the price increase (e.g. Sarris 2009; Headey and Fan 2008; von Braun et al. 2008). Among them are crop failures simultaneously occurring in major production regions of the world as well as an increased demand for biofuels (cf. Roberts and Schlenker 2009; Liu et al. 2011). The most controversial discussion, however, is about the impact of financial investors and speculative activities on prices of agricultural commodity futures. The fact that the price peak in 2008 occurred subsequent to an increase of the trading volume of commodity futures held by index funds led to the conjecture that a speculation drives agricultural prices (e.g. Robles et al. 2009). This viewpoint has been adopted by some agricultural politicians who then called for regulative measures in order to limit the influence of financial investors on food prices. The partially dogmatic discussion on this issue has different aspects and facets. A fundamental concern is whether agricultural commodities serving basic human needs should be subject of speculation at all or if this should be ruled out for ethical reasons. The role of speculators has also been discussed from an economic viewpoint. A comprehensive overview about the pros and cons is provided by Sanders et al. (2010) and Sanders and Irwin (2010). Proponents argue that speculation contributes to price discovery in information efficient markets, provides liquidity to otherwise illiquid markets, and is a necessary counterpart to hedging activities. Also, Milton's classical argument that profitable speculation has a stabilizing effect on prices has been recalled (Gilbert 2009). On the other hand

it has been emphasized that rational as well as irrational speculation can set price trends which may be self-enforced by herd behaviour and result in prices bubbles. Moreover, noise trading has been identified as a source of risk that deters rational market participants from betting against erroneous beliefs (De Long et al. 1990). Prices, in turn, deviate from their fundamental values and do no longer reflect solely demand and costs of production.

Numerous studies deal with the empirically validation of the aforementioned arguments. Two different foci can be distinguished[1]. A first group of papers analyses the causal relation between financial investors/speculators and commodity prices. Robles et al. (2009) conduct Granger causality tests in order to test whether speculative activities in futures markets can help explaining price movements of spot prices for agricultural commodities. They provide evidence that speculation affects prices of wheat, rice, maize, and soybeans. This finding is questioned by Sanders et al. (2010) who decompose open interest in commodity future markets into commercial and non-commercial positions. Using Working's index of speculation they find that speculative activities did not show a significant change over the last years, i.e. speculation was not "excessive". A similar finding is reported by Sanders and Irwin (2010) who could not find a significant relationship between returns in commodity futures markets and long positions held by index funds. A second type of empirical work is related to the detection of speculative bubbles in commodity prices. Gilbert (2009) looks for evidence of trend-following behaviour in the commodity price process. Using a positive augmented Dickey-Fuller-Test he finds that index-based investment in commodity futures had an impact on the prices of wheat, corn, and soybeans and that these investments generated a bubble in futures prices. Liu and Tang (2010) likewise conjecture that a bubble exists in futures prices of corn and sugar. They report that spot prices were co-integrated with the convenience yields before 2004, but a structural break occurred in 2004 in a sense that prices and convenience yields sometimes trend oppositely. This is not in line with the present value of asset pricing. Went et al. (2009) investigate the presence of rational speculative bubbles in 28 commodities traded in the U.S. markets. Based on duration dependence tests on the stochastic interest-adjusted basis they conclude, that 11 of 28 (amongst them wheat) commodities experienced some episodes of rational speculative bubbles.

Our paper contributes to the question if speculative bubbles are actually present in agricultural commodity prices. The analysis was motivated by the impression that many of the existing empirical studies on bubbles in agricultural commodity prices do not fully take into account the available statistical tools and models that have been developed for detecting bubbles in financial asset markets. Actually, testing for bubbles has a long tradition in financial economics. Thus it is not surprising that a variety of statistical tests is available. These approaches have specific strengths and weaknesses that one has to consider when choosing the empirical test approach. The next section provides a brief overview about testing for speculative bubbles. In section 3, a switching regime regression model that has been proposed by van

[1] Irwin and Sanders (2011) provide a comprehensive overview about the existing empirical studies on bubbles in agricultural commodity prices.

Norden and Schaller (1993) is explained in greater details. To our knowledge this model has not been applied to the detection of speculative bubbles in agricultural commodity prices before. In section 4 we use this model to test for bubbles in wheat prices. The paper ends with a discussion on the influence of speculative behaviour on commodity prices and the measures that have been proposed to confine speculation.

2. REVIEW OF TESTS FOR SPECULATIVE BUBBLES

Asset price bubbles are typically associated with sharp price increases and followed by price collapses (Kindleberger 1978). Prominent examples are the Dutch tulip mania (1636-1637) and the dot-com bubble (1998-2000). Economists associate a bubble with an asset price that rises above the level justified by economic fundamental values. Therefore, the answer to the question whether a bubble is present or not heavily depends on the definition of the fundamental price of an asset. The present value model of asset prices defines the fundamental price by the discounted stream of expected future cash flows that will accrue to the owner of the asset. Under the assumption of rational expectations, the price of an asset should fully equal the discounted expected future dividend payment, or the market fundamental value. For a more formal description of the present value model recall the definition of the net simple return on an asset, $R_{t+1} \equiv \frac{P_{t+1}+D_{t+1}}{P_t} - 1$, where P_t denotes the price in period t and ψ_t is a dividend. For simplicity of exposition, we assume the expected return on an asset is equal to a constant R, i.e. $\mathbb{E}_t[R_{t+1}] = R$. Thus, defining $\delta := (1+R)^{-1}$ and rearranging the above return definition, it yields a relation between the current asset price and the next period's expected asset price and dividend:

$$P_t = \delta \cdot \mathbb{E}_t[P_{t+1} + \psi_{t+1}]. \tag{1}$$

After solving this equation T periods forward and using the fact that $\mathbb{E}_t\big[\mathbb{E}_{t+1}[X]\big] = \mathbb{E}_t[X]$, we obtain:

$$P_t = \mathbb{E}_t\left[\sum_{i=1}^{T} \delta^i \cdot \psi_{t+i}\right] + \mathbb{E}_t[\delta^T \cdot P_{t+T}]. \tag{2}$$

If the asset price is not expected to grow faster than with rate R, the second term on the right hand side of (2) converges to zero as T towards infinity, i.e.

$$\lim_{T\to\infty} \mathbb{E}_t[\delta^T \cdot P_{t+T}] = 0. \tag{3}$$

In that case, we are left with the following expression

$$P_t^* \equiv \mathbb{E}_t\left[\sum_{i=1}^{T} \delta^i \cdot \psi_{t+i}\right]. \tag{4}$$

Equation (4) is referred to as the market fundamental solution (or the present value model). However, if the terminal condition (3) does not hold, an additional bubble term B_t occurs in the solution to equation (1)

$$P_t = P_t^* + B_t. \quad (5)$$

Solving (5) one period forward yields

$$P_t = P_t^* + \delta \cdot \mathbb{E}_t[B_{t+1}]. \quad (6)$$

Note that both, equation (5) and (6), are solutions to $P_t = \delta \cdot \mathbb{E}_t[P_{t+1} + \psi_{t+1}]$ if and only if

$$\mathbb{E}_t[B_{t+1}] = B_t/\delta = (1+R) \cdot B_t. \quad (7)$$

In other words, the bubble term B_t appears in the price process because it is expected to be present in next period with an expected value $(1+R)$ times its current value. Since the presence of B_t is entirely consistent with the rational expectation framework, this term is also called a rational bubble. Of course there are other arguments explaining the existence of financial bubbles, among them exaggerated or heterogeneous belief, herding behaviour of investors (Brunnermeier 2001), asymmetric information (Allen and Gorton 1993), limited arbitrage (Nagel and Brunnermeier 2003) and noise trading (De Long et al. 1990).

Since testing for existence of speculative bubbles has a long tradition in financial economics, it is not surprising that numerous statistical tests are available. In general, two classes of tests can be distinguished: indirect and direct tests. Originally, indirect tests focused on studying the validity of the present value model or other kind of relationships between actual prices and their fundamental values without specifying a particular bubbles process (Salge 1997). Any rejection of the validity of the present value model is then regarded as an evidence for the presence of rational bubbles. Typical approaches are tests on variance bounds violations, specification tests, bubble premium tests, tests on bubbles as an unobserved variable, a set of integration and co-integration tests, and (sequential) unit-root tests.

Variance Bounds Tests (LeRoy 1989; Shiller 1992), sometimes named as volatility tests or tests of excess volatility, were originally proposed for testing the efficient market hypothesis. According to the present value model (4), the asset price equals the discounted expected value of future dividends if bubbles are absent. In that case the actual (observable) price is the expectation of the unobservable fundamental price conditional on the available information and thus it constitutes an optimal forecast for P_t. It follows that under the null hypothesis of no bubbles the variance of the fundamental price sets an upper bound to the variability of the actual asset price, i.e. $H_0: Var(P_t) \leq Var(P_t^*)$. Thus variance bounds tests interpret an excess volatility as an indication for price bubbles. However, West (1988) points out that excess volatility may also be caused by variations in expected returns or by fads. Furthermore, volatility tests suffer from a small sample bias.

West (1987) develops a test which utilizes the notion of a Hausman specification test and focuses more directly on the presence of the rational bubbles. The basic idea is to estimate the present value model (4) with two different equations. The first one implies the validity of the

terminal condition (3) and thus rules out bubbles by definition. The second estimation equation is more general and explains the asset price as the sum of two components, the fundamental and the bubble (equation (5)). Under the null hypothesis that no bubble exists, the parameter estimates of both equations will be equal apart from random errors. If a bubble exists, on the contrary, the estimates of the restricted equation will be biased because of an omitted variable.

Early bubble tests have been criticized because they do not provide insight into the behavior and the characteristics of the bubble process. Moreover, Evans (1991) demonstrated by means of simulation experiments that unit root tests and co-integration tests unable to detect price bubbles even if they are present by construction. As a response to this criticism direct bubble tests have been developed. Direct bubble tests investigate whether the characteristics of the data are consistent with a specific bubble process that is explicitly modeled, i.e., whether the chosen form of the speculative bubble has any explanatory power for asset price movements. Several types of bubble processes have been studied in the literature. For example, Flood and Garber (1980) propose a deterministic function for B_t in equation (5) to capture the explosiveness of price levels in periods of hyperinflations. Motivated by the empirical observation that price bubbles are periodically collapsing, Blanchard (1979) and Blanchard and Watson (1982) introduce a stochastic model in which the price bubble moves randomly between two states, a collapsing and a surviving state. Their basic idea has been econometrically implemented by means of regime switching models. Van Norden and Schaller (1993) take up the Blanchard model and relax three restrictive assumptions. First, they allow for time varying probabilities. It is assumed that the probability of a bubble being in the surviving state in the next period depends on the bubble size in the current period. Second, the bubble size in the current period is also assumed to be a function of the size of previous bubbles. This ensures that the bubble does shrink, but not to zero in a single period. Third, negative bubbles are not ruled out in contrast to the original Blanchard model. On this basis, van Norden and Schaller (1993) and van Norden (1996) specify a two-regime-switching regression model and apply it to test the existence of a such kind of bubbles for the Toronto Stock Exchange Composite Index and four of the world most traded currencies. The following section describes the regime switching approach model in greater details.

3. A REGIME SWITCHING MODEL FOR BUBBLE TESTING

3.1. General model

We target at a regression model that explains asset returns under two alternative regimes: a surviving (growing) state and a collapsing (shrinking) state of the price bubble. For that purpose, we proceed as follows: We define a stochastic process that describes how the bubble evolves in time under the two regimes. Two important assumptions have to be made. The first one describes a functional relationship between the expected bubble size and the current bubble size in the collapsing state. The second one defines a functional relationship between the probability of being in the surviving state and the bubble size. Based on these assumptions, it is

possible to calculate conditional expected returns from holding the asset which form the basis for the regime switching model.

According to Blanchard and Watson (1982) the rational bubble moves randomly between two states, a collapsing state $\mathcal{C}$ and a surviving state $\mathcal{S}$. Its expected value is given by

$$\mathbb{E}_t[B_{t+1}] = (1 - q) \cdot \mathbb{E}_t[B_{t+1}|\mathcal{C}] + q \cdot \mathbb{E}_t[B_{t+1}|\mathcal{S}], \quad (8)$$

where the notation $\mathbb{E}_t[\cdot|\mathcal{C}]$ (or $\mathbb{E}_t[\cdot|\mathcal{S}]$) is the expectation operator conditional on the state $\mathcal{C}$ (or $\mathcal{S}$) and q $(1 - q)$ is the probability of a bubble being in the surviving (collapsing) state.

In contrast to the original Blanchard model, the van Norden and Schaller (1993) specification allows a partial collapsing of a bubble in state $\mathcal{C}$. The expectation of the relative size of a bubble (defined as $b_t = B_t/P_t$) conditional on the state $\mathcal{C}$ depends on the relative size of the previous bubble, and thus is modelled as

$$\mathbb{E}_t[B_{t+1}|\mathcal{C}] = g(b_t) \cdot P_t, \quad (9)$$

where $g(\cdot)$ is a continuous function such that, $g(0) = 0$ and $0 \leq \partial g(b_t)/\partial b_t \leq 1$. This implies that the expected bubble size is expected to shrink in state $\mathcal{C}$.

Another unrealistic assumption in the Blanchard model is a constant probability of a bubble in collapsing state. As mentioned in Kindleberger (1978) and others, historical experiences show that the larger the size of a bubble becomes, the more likely that the bubble crashes. As a response, van Norden and Schaller (1993) propose a time-varying probability (denoted as q_{t+1}) of a bubble being in surviving regime for the next period and assume that it depends on the relative size of the previous bubble, thus

$$q_{t+1} \equiv m(b_t), \qquad \frac{\partial m(b_t)}{\partial |b_t|} < 0, \quad (10)$$

where $|b_t|$ is the absolute value of b_t, i.e., either positive or negative bubbles are possible. Using (8), (9), and (10) the expected size of the bubble in the surviving state can be written as

$$\mathbb{E}_t[B_{t+1}|\mathcal{S}] = \frac{(1 + R) \cdot b_t}{m(b_t)} - \left(\frac{1 - m(b_t)}{m(b_t)} \cdot g(b_t) \cdot P_t\right). \quad (11)$$

Moreover, one can express the expected gross returns R_{t+1} as the following non-linear regime switching system:

$$\mathbb{E}_t[R_{t+1}|\mathcal{S}] = \frac{1 - m(b_t)}{m(b_t)} \cdot [(1 + R) \cdot b_t - g(b_t)] \quad (12)$$

$$\mathbb{E}_t[R_{t+1}|\mathcal{C}] = g(b_t) - (1 + R) \cdot b_t. \quad (13)$$

The above equations can be linearized by taking a first-order Taylor expansion around an arbitrary point b_0:

$$\mathbb{E}_t[R_{t+1}|\mathcal{S}] = \beta_{\mathcal{S}0} + \beta_{\mathcal{S}1} \cdot b_t \quad (14)$$

$$\mathbb{E}_t[R_{t+1}|\mathcal{C}] = \beta_{\mathcal{C}0} + \beta_{\mathcal{C}1} \cdot b_t \quad (15)$$

with

$$\beta_{\mathcal{S}1} \equiv -\frac{1}{m(b_0)^2} \cdot \frac{\partial m(b_t)}{\partial b_t}|_{b_t=b_0} \cdot [(1+R) \cdot b_0 - g(b_0)] + \frac{1-m(b_0)}{m(b_0)} \cdot \left[1 + R - \frac{\partial g(b_t)}{\partial b_t}|_{b_t=b_0}\right] \quad (16)$$

$$\beta_{\mathcal{C}1} \equiv \frac{\partial g(b_t)}{\partial b_t}|_{b_t=b_0} - (1+R). \quad (17)$$

Recalling that $0 \leq \partial g(b_t)/\partial b_t \leq 1$, $\frac{\partial m(b_t)}{\partial |b_t|} < 0$ and $R \geq 0$ by assumption, one can derive some testable implications of the model: first, $\beta_{\mathcal{C}1}$ should be negative ($\beta_{\mathcal{C}1} < 0$), and second, $\beta_{\mathcal{S}1}$ should be positive ($\beta_{\mathcal{S}1} > 0$) or more general $\beta_{\mathcal{S}1} > \beta_{\mathcal{C}1}$. These two sign restrictions state that the expected returns in surviving (or collapsing) regime vary positively (or negatively) with the size of the bubble. Thus, the larger the relative size of the bubbles, the larger the difference between returns in these two regimes should be. A third testable restriction refers to the probability of being in the surviving state. To ensure that the value of q_{t+1} is bounded between 0 and 1, we follow van Norden and Schaller (1993) and impose a probit specification[2] for $m(\cdot)$:

$$q_{t+1} = \Phi(\beta_{q0} + \beta_{q1} \cdot |b_t|), \quad (18)$$

where Φ is the standard normal distribution function. $\Phi(\beta_{q0})$ denotes the probability of being in state $\mathcal{S}$ if the current bubble size is 0 and β_{q1} measures the sensitivity of the probability with respect to the bubbles size. It follows from the model derivation that β_{q1} must be negative $(\beta_{q1} < 0)$, i.e., the probability of a bubble being in the surviving state decreases if the absolute size of the bubble increases[3].

Replacing the expected returns in (14) and (15) by realized values plus an error term leads to the following two-regime switching regression model[4]:

$$\begin{aligned} R_{\mathcal{S},t+1} &= \beta_{\mathcal{S}0} + \beta_{\mathcal{S}1} \cdot b_t + \varepsilon_{\mathcal{S},t+1} \\ R_{\mathcal{C},t+1} &= \beta_{\mathcal{C}0} + \beta_{\mathcal{C}1} \cdot b_t + \varepsilon_{\mathcal{C},t+1} \\ P(\mathcal{S}) &= q_{t+1} = \Phi(\beta_{q0} + \beta_{q1} \cdot |b_t|), \end{aligned} \quad (19)$$

where $\varepsilon_{i,t+1} \sim N(0, \sigma_i)$, $i = \mathcal{S}, \mathcal{C}$.

[2] We tested the logit function as an alternative specification, but we did not get significantly different results than for the probit model.

[3] It is a property of switching regime models that their parameters cannot be unambiguously determined. Swapping the regime names $\mathcal{S}$ and $\mathcal{C}$ would result in the same value of the likelihood function. That means the finding $\beta_{\mathcal{S}1} \leq 0$, $\beta_{\mathcal{C}1} \geq 0$ and $\beta_{q1} > 0$ would be equivalent to the parameter restrictions implied by the bubble hypothesis (cf. van Norden and Vigfusson 1998).

[4] Note that the van Norden and Schaller model is a regime-switching regression model rather than a Hamilton-style Markov-switching model (Hamilton 1989), since the probability of being in a particular regime at time $t+1$ does not depend directly on the state at time t rather on the observed relative size of the bubble b_t.

Assuming normality of the unexpected gross returns $\varepsilon_{i,t+1}$, parameter estimates can be obtained by maximizing the log-likelihood function:

$$\mathcal{L} = \sum_{t=1}^{N} \ln \left\{ q_{t+1} \cdot \phi \left(\frac{R_{\mathcal{S},t+1} - \beta_{\mathcal{S}0} - \beta_{\mathcal{S}1} \cdot b_t}{\sigma_{\mathcal{S}}} \right) / \sigma_{\mathcal{S}} + (1 - q_{t+1}) \cdot \phi \left(\frac{R_{\mathcal{C},t+1} - \beta_{\mathcal{C}0} - \beta_{\mathcal{C}1} \cdot b_t}{\sigma_{\mathcal{C}}} \right) / \sigma_{\mathcal{C}} \right\}, \tag{20}$$

where $\sigma_{\mathcal{S}}$ and $\sigma_{\mathcal{C}}$ denote the standard deviations of the unexpected gross returns in the surviving and the collapsing states, respectively.

3.2. Adaptation to agricultural commodity prices

Though the present value model (4) is a rather simple and parsimonious approach to asset pricing, its application to agricultural commodity markets is not straightforward. At least two problems have to be tackled: First, what corresponds to dividend payments in the context of commodities? Second, how can one build expectations of future dividend payments? In what follows we briefly comment on these issues.

Pindyck (1993) points out that for storable commodities the notion of a convenience yield is very similar to the dividend accrued from holding a stock. Working (1949) defines convenience yield as a benefit that is obtained by the holder of the physical commodities. Holding physical commodities allows to smooth a firm's production and to minimize costs due to unexpected demand fluctuations. Therefore, we use the marginal net convenience yield (the convenience yield from holding a marginal unit of the commodity net of storage and insurance costs) as a substitute for dividend payments in (4).

The net convenience yield is a latent variable and cannot be observed directly. However, for commodities traded on a futures market the net convenience yield can be inferred from following the spot-futures relationship which holds under a no-arbitrage condition

$$F_t^T = P_t \cdot \exp[(i_t - \gamma_t) \cdot (T - t)], \tag{21}$$

where γ_t is the rate of net convenience yield at time t, F_t^T is a futures price with maturity T quoted at t and i_t is an interest rate. Direct application of (21) requires finding a spot price series that directly corresponds to the futures contract in terms of location and product grade, which is practically difficult. To circumvent this problem, we infer the spot price from futures price quotations. That means we determine γ_t and P_t simultaneously using two futures contracts with different maturities, for instance the nearest, $F_t^{T_1}$, and the second nearest, $F_t^{T_2}$. More formally,

$$\gamma_t = \ln \left(\frac{F_t^{T_2}}{F_t^{T_1}} \right) \cdot \frac{1}{T_1 - T_2} + i_t \tag{22}$$

$$P_t = F_t^{T_1} \Big/ \exp\left[(T_1 - t) \cdot ln\left(\frac{F_t^{T_2}}{F_t^{T_1}}\right) \cdot \frac{1}{T_2 - T_1}\right]. \quad (23)$$

These two equations can be solved for the two unknowns γ_t and P_t. The net convenience yield ψ_t is then

$$\psi_t = \gamma_t \cdot P_t. \quad (24)$$

Even after identifying convenience yields as an analog to dividend payments it is not straightforward to calculate fundamental price since this involves future dividends, which are not observable. Thus it is necessary to express future dividends in terms of observables. The simplest way to achieve this is to assume that dividends follow a stochastic process with a constant growth rate G. In that case the relation between prices and dividends is given by the classical Gordon model (Campbell and Shiller 1988)

$$P_t = \frac{\psi_t}{R - G}, \quad (25)$$

i.e., the price is a multiple of the current dividend. Schaller and van Norden (2002) suggest to approximate the multiple by the sample mean of the dividend-price-ratio $\left(\mathbb{E}\left[\frac{\psi_t}{P_t}\right]\right)$. This proposal, however, is not adequate in our case since net convenience yields may take negative values which, in turn, would lead to negative fundamental values. Therefore we pursue another approach. According to Campbell and Shiller (1988) and Pindyck (1993), the present value model implies a co-integration relationship between spot prices and convenience yields, i.e. their relation can be expressed as

$$P_t = c + \beta \cdot \psi_t + \varepsilon_t, \quad (26)$$

where c and β are parameters to be estimated. In the case of no bubbles, the error term ε_t is a stationary process. The basic idea is to consider the deterministic part of (26) as fundamental price, whereas the residual captures the bubble component (van Norden and Schaller 1993). In order to obtain a consistent estimator of $\hat{\beta}$, we run the following regression:

$$\Delta P_t = \alpha + \beta \cdot \Delta\psi_t + \epsilon_t. \quad (27)$$

Given an estimate $\hat{\beta}$, one can retrieve $\hat{c}$ by (cf. Liu and Tang 2010) :

$$\hat{c} = \mathbb{E}\big[P_t - \hat{\beta} \cdot \psi_t\big]. \quad (28)$$

The fundamental price is then $P_t^* = \hat{c} + \hat{\beta} \cdot \psi_t$.

A further alternative to define a fundamental price, that we do not pursue here, is based on an optimal linear forecast of future dividend changes using a vector autoregressive model which includes past prices and dividend changes (Campbell and Shiller 1987).

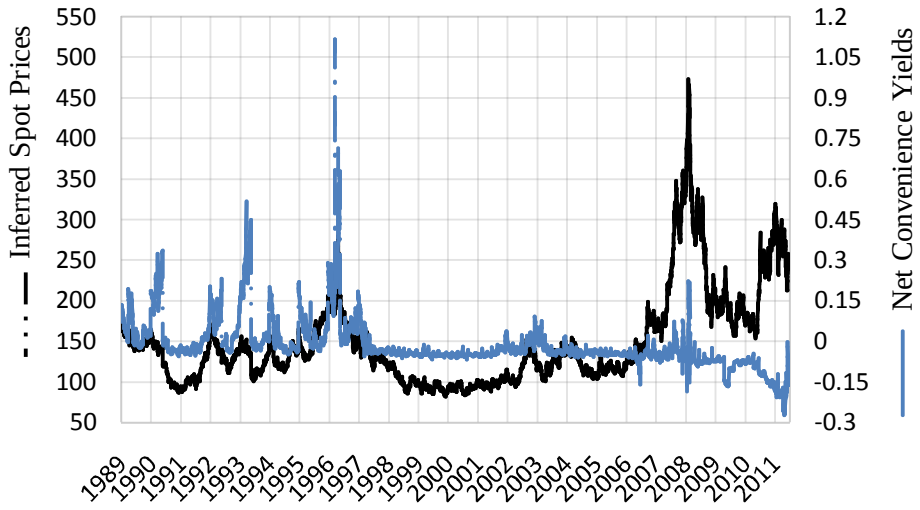
4. APPLICATION TO WHEAT PRICES

4.1. Data and derivation of model variables

The empirical analysis is conducted for soft red winter wheat quoted at the Chicago Board of Trade (CBOT). The daily settlement prices refer to the nearest and the second nearest soft red winter wheat futures contracts with five maturity months (March, May, July, September, and December). We use daily data since speculative activities may happen in rather short periods and thus low frequency data may cushion the effect of speculative behavior. Although price series start from 1960, we restrict the observation period from January 1989 to July 2011 since wheat prices prior to 1989 may be influenced by governmental interventions, such as price support and commodity storage programs (Koekebakker and Lien 2004). This leaves us with 5645 observations in total. We carry out the calculations with nominal prices, since the inflation rates (Consumer Price Indexes) are reported on a monthly basis and also prior to the time at which we obtain the flow of the net convenience yields so that deflating daily variables could cause measurement errors (Campbell and Shiller 1988). Daily Federal funds rates from the Federal Reserve Board are used as interest rate i_t.[5]

Based on these data we employ equations (22) (23) and (24) to obtain inferred spot prices and net convenience yields which are depicted in Figure 1.

Figure 1. Inferred spot prices and net convenience yields (US$/ton)



Source: own elaboration

The graph of the inferred wheat spot prices reflect the frequently mentioned price peaks in 2007 and 2010 as well as an increase in price volatility since 2006. The net convenience yield, however, exhibits a different behavior. Note, first of all, that the time series shows negative values, meaning that the cost of carry exceed the gross convenience yield. Negative net

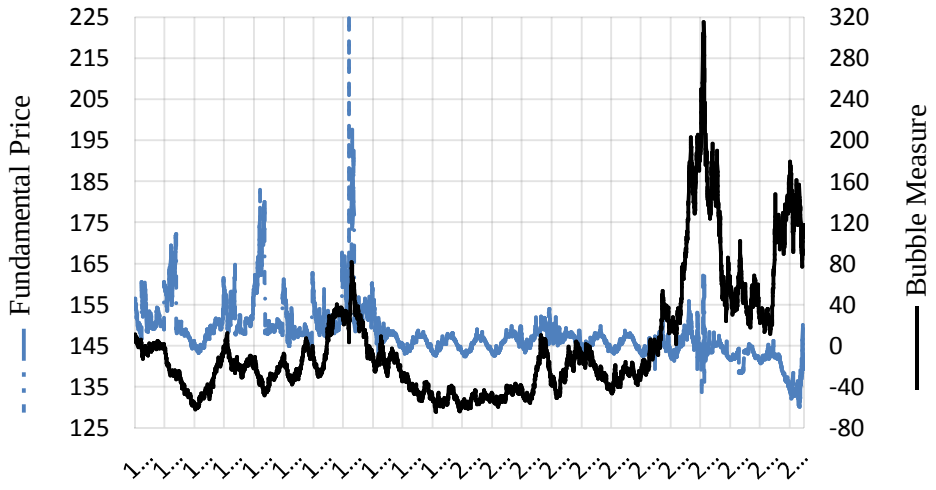
[5] The data available at http://www.federalreserve.gov/releases/h15/data.htm

convenience yields are not unusual for agricultural commodities and have also been reported by Pindyck (2001) and Sørensen (2002). The highest fluctuations of the net convenience yield occur in the period between 1989 and 1996 followed by a decade of rather stable values. From 2006 on net convenience yields become more volatile again, but fluctuations are still smaller compared to the beginning of the nineties. In contrast to spot prices there is a downward shift in the last decade. The conjecture that spot prices and net convenience yields drift apart in the recent past has been confirmed by Liu and Tang (2010) who conduct co-integration tests and find that wheat prices and convenience yields are not strongly co-integrated after 2004. As mentioned above, this finding has been interpreted as evidence for price bubbles.

Distinct from stocks, agricultural commodities exhibit seasonality due to harvest cycles (e.g. Sorensen 2002). Thus, prior to estimating fundamental prices of wheat, seasonal effects in both, the inferred spot price and the net convenience yields, are removed by using Fourier polynomials. More specifically, a first order trigonometric polynomial is chosen based on the Bayesian Information Criterion (BIC). The resulting estimates of the seasonal patterns are depicted in figure A1 in the appendix. Spot prices show their lowest level in July, increase after the harvest period and reach a seasonal peak in February. The seasonal price variation amounts to approximately 15 $ per ton. Net convenience yields are lagging about three weeks behind spot prices but follow a similar seasonal pattern.

Next, we calculate the fundamental prices P_t^* as described in the previous section using the seasonally adjusted P_t and ψ_t. The estimated slope coefficient $\hat{\beta}$ in eq. (27) is 69.67 and the estimated average daily spot price (constant $\hat{c}$) using equation (28) is 148.73 US $ per ton. Using these estimates we obtain fundamental prices by $P_t^* = \hat{c} + \hat{\beta} \cdot \psi_t$. Subtracting P_t^* from P_t, yields the absolute bubble measure B_t. The decomposition of the spot price is presented in Figure 2.

Figure 2. Fundamental prices and absolute bubble measure (US$/ton)



Source: own elaboration

The estimated fundamental wheat prices mimic the aforementioned pattern of net convenience yields by construction, which means that they show a relatively strong volatility in the first part of the observation period. A striking peak in fundamental values occurred in 1996. Schnepf (2008) points out government stock reductions followed by an unusual combination of global supply-reducing weather events and strong international demand as reasons for this exceptional increase of fundamental prices. Nevertheless, the volatility of the fundamental value is smaller than the volatility of the wheat price itself. This reflects the fact that only a small part of the variability in spot prices can be explained by a variation of convenience yields. Opposed to spot prices there is no obvious positive trend in fundamental values since 2006. As a result the bubble component becomes relatively large in the last five years of the observation period with a maximum value of 314.94 on 27.02.2008. Since the bubble term is defined as a residual in a regression model it is not surprising to see negative values of B_t. However, B_t does not fluctuate randomly around zero. One can rather observe consecutive periods of negative or positive bubble terms.

Finally, we calculate daily gross returns using $R_{t+1} \equiv \frac{P_{t+1}+D_{t+1}}{P_t}$ and the relative bubble term $b_t = B_t/P_t$ as inputs for the regime switching model (see figure A2 in the appendix). The log-likelihood function (eq. 20) is then maximized by using a combination of the MATLAB optimization algorithms "fminunc" and "fminsearch" which are based on the Quasi-Newton method and the Nelder-Mead simplex search method.

4.2. Results of the regime switching regression model

The upper part of Table 1 provides the estimated coefficients of the two-regime switching regression model together with their t-values and p-values.

Inspection of Table 1 reveals that some, but not all of the three coefficients (β_{q1}, $\beta_{\mathcal{S}1}$ and $\beta_{\mathcal{C}1}$) satisfy the restrictions implied by the model of periodically collapsing bubbles. More precisely, β_{q1} is negative and highly significant, saying that the probability of being in state $\mathcal{S}$ decreases as the (relative) bubble size increases as required by the theoretical model. Also, the estimated slope coefficient in the collapsing regime has the expected negative sign ($\beta_{\mathcal{C}1}$=-0.0018). However, this estimate is not statistically significant (p-value=0.7839). Moreover, the sign of the estimated slope parameter $\beta_{\mathcal{S}1}$ is negative and thus not in line with the model assumptions. A negative coefficient $\beta_{\mathcal{S}1}$ would imply that the return in the surviving state decreases with the bubble size, which is not plausible. Even the weaker requirement $\beta_{\mathcal{S}1} > \beta_{\mathcal{C}1}$ is statistically not significant according to a likelihood ratio test which is displayed in lower panel of Table 1. Although the two-regime model does not impose any precise restriction on the sign or magnitude of the intercepts $\beta_{\mathcal{S}0}$ and $\beta_{\mathcal{C}0}$, one would expect the former to be positive and the latter to be negative, because the return in the surviving state should be positive, whereas negative returns are expected when the bubble collapses. However, the estimated parameters suggest just the opposite: $\beta_{\mathcal{S}0}$ is negative while $\beta_{\mathcal{C}0}$ is positive. Also, the magnitude of $\beta_{\mathcal{C}0}$ is implausibly large (0.49% on a daily basis). Moreover, according to the LR test the estimated

intercepts β_{s0} and β_{c0} are not significantly different in the two regimes (p-value=0.1533) although both are different from zero.

Finally, the estimated volatilities of the error terms in the two return states, σ_S and σ_C, are 12.52% and 21.38% respectively. According to the likelihood ratio test their difference is significantly, which means that two volatility regimes exist in the US wheat prices. In addition, their ranking corresponds to the empirical observations that collapsing bubbles often cause extreme negative (or positive in case of negative bubbles) returns.

Table 1. Estimates of the two-regime switching regression model
(t-values in brackets)

Coefficient	Estimate	p-value
β_{q0}	1.6084 (14.8328)	0.0000
β_{q1}	-0.7207 (3.2104)	0.0013
β_{s0}	0.9996 (3390.2915)	0.0000
β_{s1}	-0.0011 (1.2093)	0.2266
β_{c0}	1.0049 (406.7050)	0.0000
β_{c1}	-0.0018 (0.2742)	0.7839
σ_s	0.1252 (112.9165)	0.0000
σ_c	0.2138 (33.0943)	0.0000

LR test for the restrictions
of the two-regime switching regression model

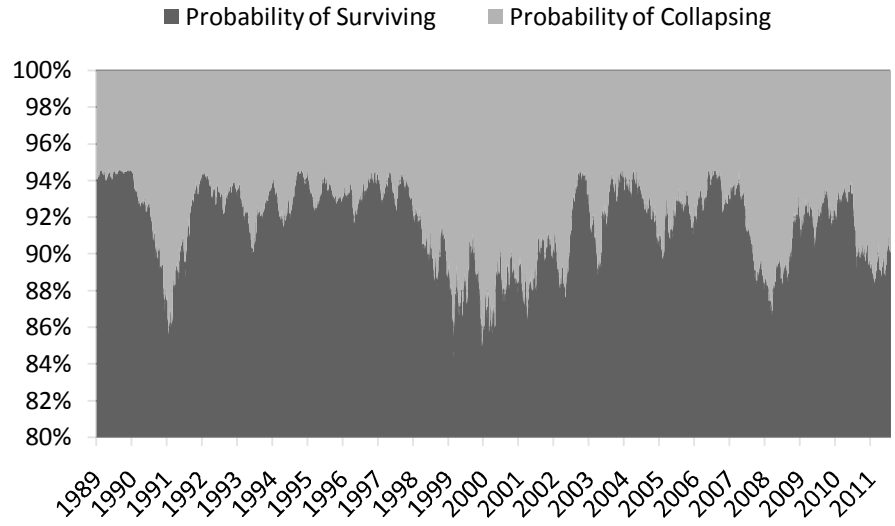
Restriction	LR Test Statistic	p-value
$\beta_{s0} \neq \beta_{c0}$	2.0392	0.1533
$\beta_{s1} > \beta_{c1}$	0.0057	0.9399
$\sigma_s \neq \sigma_c$	427.0993	0.0000

Source: own elaboration

The estimates of the parameters β_{q0} and β_{q1} can be used to calculate the probabilities of being in the surviving or in the collapsing bubble state (see Figure 3). The estimated value of β_{q0} is 1.6084 which implies that the probability of the surviving regime is $\Phi(1.6084) = 0.9461$ when the relative bubble size in the previous period equals zero and the probability of the collapsing regime is then $1 - \Phi(1.6084) = 0.0539$. These probabilities vary in accordance with the absolute value of the relative bubble size, $|b_t|$. We find that the variation of the probabilities is rather low which is due to the small value of the sensitivity measure β_{q1}. The

probability of the surviving regime falls in a range between 0.85 and 0.95. We cannot identify extreme values for either probability from Figure 3. This is particularly true for the period from 2006 on where speculative price bubbles were supposed to be present. In fact, the probability of a collapsing bubble increases in 2008, but similar values already occurred, for example, in 1991 and 1999.

Figure 3. Probabilities of surviving and collapsing states



Source: own elaboration

5. CONCLUSIONS

In this paper we investigated the presence of speculative bubbles in wheat futures prices. So far most contributions in the literature either use theoretical arguments for the (non)existence of bubbles or apply indirect tests which are plagued by low statistical reliability. In contrast, we apply a direct test which tests the hypotheses that a price bubble process can switch among two regimes, a surviving and a collapsing state. The implementation of this testing procedure is carried out by means of a regime-switching regression model. Using data for wheat futures from the CBOT we could not find evidence for the presence of periodically and partially collapsing speculative bubbles. The signs of the estimated coefficients are not entirely in line with the predictions of the theoretical model. This finding, however, should be carefully interpreted. Our results do neither imply that speculative activities do not have an impact on agricultural commodity prices nor that agricultural prices do not deviate from their fundamental value. Our results simply tell that there is no evidence for the particular bubble process under consideration. The rejection of the periodically-collapsing-bubbles-hypothesis might be explained by the fact that the wheat market (like other agricultural commodities) did never experience a price crash that is comparable to past stock market crashes, e.g. the dot.com bubble in March 2000 or the recent housing bubble. However, other bubble processes, as for example, deterministic bubbles and near random walk bubbles as well as other forms of market

inefficiencies, such as fads, might nonetheless exist. Actually, it turned out that the simple present value model of asset prices does not do a very good job in explaining wheat prices, at least if convenience yields are used as the sole explanatory factor. Convenience yields can only partly explain the observed variability in wheat prices and it seems that the explanatory power of this variable even decreases over time. This finding has also been reported by other studies (e.g. Liu and Tang 2010) and led the authors to the (indirect) conclusion that price bubbles exist.

There are several directions for extending the empirical analysis presented here. First of all, it would be worth to apply the proposed regime switching model to other agricultural commodities. For example, Robles et al. (2009) and Gilbert (2009) find that the speculative activities have different impact on wheat, corn and soybeans prices. Second, the assumptions of two regime model could be relaxed. Evans (1991) notes that the two-regime switching model does not reflect the typical feature that the bubble size has to exceed a certain threshold before entering either the explosive or the collapsing state. As a remedy, Brooks and Katsaris (2005) extend the van Norden and Schaller model to a three-regime switching regression by adding a dormant regime in which the bubble grows deterministically at a constant rate. Finally, we suggest examining alternative measures of fundamental prices. Actually, the specification of the fundamental value is the Achilles' heel of any empirical bubble test and it should be stressed that the null hypothesis of no bubbles is always a joint test of the hypothesis that there are no bubbles and the correct specification of the price fundamental (van Norden and Vigfusson 1998).

In view of the limitations of empirical bubble tests one may critically ask what we learnt in the end from the econometric exercise presented here. Our main message is that testing for speculative bubbles in agricultural commodity prices is a very sophisticated task and its treatment implies many degrees of freedom for the researcher. We conclude that our results do not provide the ultimate answer to the question whether bubbles are present or not and definite answers to this question should be treated with caution. Against this background we recommend that far reaching suggestions on the regulation of speculative activities in agricultural commodity markets that have been made in the aftermath of the price boom should be carefully reconsidered.

REFERENCES

Allen, F. and Gorton, G. (1993). Churning Bubbles. *Review of Economic Studies* 60 (4): 813-36.

Blanchard, O. J. (1979). Speculative bubbles, crashes and rational expectations. *Economics Letters* 3: 387-389.

Blanchard, O. J. and Watson, M. W. (1982). *Bubbles, Rational Expectations and Financial Markets*. in P. Wachtel (ed.). Crises in the Economic and Financial Structure: Lexington Books, Lexington, MA.

Brooks, C. and Katsaris, A. (2005). A Three-Regime Model of Speculative Behaviour: Modelling the Evolution of the S&P 500 Composite Index. *The Economic Journal* 115: 767-797.

Brunnermeier, M. K. (2001). *Asset Pricing Under Asymmetric Information: Bubbles, Crashes, Technical Analysis, and Herding*. Oxford Univ Pr, March 29.

Campbell, J. Y. and Shiller, R. J. (1987). Cointegration and Tests of Present Value Models. *Journal of Political Economy* 95: 1062-1088.

Campbell, J. Y., and Shiller, R. J. (1988). The Dividend-Price Ratio and Expectations of Future Dividends and Discount Factors. *Review of Financial Studies* 1: 195-228.

De Long, J B., Shleifer, A., Summers, L. H. and Waldmann, R. J. (1990). Noise Trader Risk in Financial Markets. *Journal of Political Economy* 98: 703-738.

Diba, B. T. and Grossman, H. I. (1988). Explosive Rational Bubbles in Stock Prices? *The American Economic Review* 78: 520-530.

Evans, G. W. (1991). Pitfalls in Testing for Explosive Bubbles in Asset Prices. *American Economic Review* 81: 922-930.

Flood, R. P. and Garber, P. M. (1980). Market Fundamentals versus Price-Level Bubbles: The First Tests. *Journal of Political Economy* 88: 745-770.

Gilbert, C. L. (2009). Speculative Influences on Commodity Futures Prices 2006-2008. Working Paper. Department of Economics, University of Trento. http://www.unctad.org/en/docs/osgdp20101_en.pdf.

Hamilton, J. D. (1989). A New Approach to the Economic Analysis of Nonstationary Time Series and the Business Cycle. *Econometrica* 57: 357-384.

Headey, D. and Fan, S. (2008). Anatomy of a crisis: the causes and consequences of surging food prices. *Agricultural Economics* 39: 375-391.

Irwin, S. H. and Sanders, D. R. (2011). Index Funds, Financialization, and Commodity Futures Markets. *Applied Economic Perspectives and Policy* 33: 1-31.

Kindleberger, C. P. (1978). *Manias, Panics, and Crashes: A History of Financial Crises*. New York: Basic Books.

Koekebakker, S. and Lien, G. (2004). Volatility and Price Jumps in Agricultural Futures Prices-Evidence from Wheat Options. *American Journal of Agricultural Economics* 86: 1018-1031.

LeRoy, S. F. (1989). Efficient Capital Markets and Martingales. *Journal of Economic Literature* 27: 1583-1621.

Liu, P. and Tang, K. (2010). Bubbles in the Commodity Asset Class: Detection and Sources. Working Paper. Center for Real Estate and Finance, Cornell University.

Liu, X.-L., Xu, W. and Odening, M. (2011). Can crop yield risk be globally diversified? SFB 649 Discussion Paper. Sonderforschungsbereich 649, Humboldt Universität zu Berlin, Germany.

Nagel, S. and Brunnermeier, M. K. (2003). Hedge Funds and the Technology Bubble. AFA 2004 San Diego Meetings; EFA 2003 Annual Conference Paper No. 446.

Pindyck, R. S. (1993). The Present Value Model of Rational Commodity Pricing. *Economic Journal* 103: 511-530.

Pindyck, R. J. (2001). The dynamics of commodity and futures markets: a primer. *Energy Journal* 22: 1-29.

Roberts, M. J. and Schlenker, W. (2009). World Supply and Demand of Food Commodity Calories. *American Journal of Agricultural Economics* 91: 1235-1242.

Robles, M., Torero, M. and Braun, J. von. (2009). *When Speculation Matters.* Issue Brief. Washington: IFPRI.

Salge, M. (1997). *Rational Bubbles: Theoretical Basis, Economic Relevance and Empirical Evidence with a Special Emphasis on the German Stock Market.* Berlin: Springer.

Sanders, D. R. and Irwin, S. H. (2010). A speculative bubble in commodity futures prices? Cross-sectional evidence. *Agricultural Economics* 41: 25-32.

Sanders, D. R., Irwin, S. H. and Merrin, R. P. (2010). The Adequacy of Speculation in Agricultural Futures Markets: Too Much of a Good Thing? *Applied Economic Perspectives and Policy* 32: 77-94.

Sarris, A. (2009). Factors Affecting Recent and Future Price Volatility of Food Commodities. in E. Berg et. al. (Eds), *Risiken in der Agrar und Ernahrungswirtschaft und ihre Bewaltingung.* Münster-Hiltrup: Landwirtschaftsverlag, 29-48.

Schaller, H. and van Norden, S. (2002). Fads or bubbles? *Empirical Economics* 27: 335-362.

Schnepf, R. (2008): *High Agricultural Commodity Prices: What Are the Issues?* Nova Science Publishers, New York.

Shiller, R.J. (1992). *Market Volatility*. Cambridge: MIT University Press.

Sørensen, C. (2002). Modeling seasonality in agricultural commodity futures. *Journal of Futures Markets* 22: 393-426.

Von Braun, J., Akhter A., Asenso-Okyere, K., Fan, S., Gulati, A., Hoddunott, J., Pandya-Lorch, R., Rosegrant, M. W. Ruel, M. Torero, M Rheenen, T. van and Grebmert, K. von. (2008). High Food Prices: The What, Who and How of Proposed Policy Actions. Washington: IFPRI.

Van Norden, S. and Shaller, H. (1993). The Predictability of Stock Market Regime: Evidence from the Toronto Stock Exchange. *The Review of Economics and Statistics* 75: 505-510.

Van Norden, S. (1996). Regime Switching as a Test for Exchange Rate Bubbles. *Journal of Applied Econometrics* 11: 219-251.

Van Norden, S. and Vigfusson, R. (1998). Avoiding the Pitfalls: Can Regime-Switching Tests Reliably Detect Bubbles? *Studies in Nonlinear Dynamics & Econometrics* 3:1-22.

Went, P., Jirasakuldech, B. and Emekter, R. (2009). Bubbles in Commodities Markets. SSRN Working Paper.

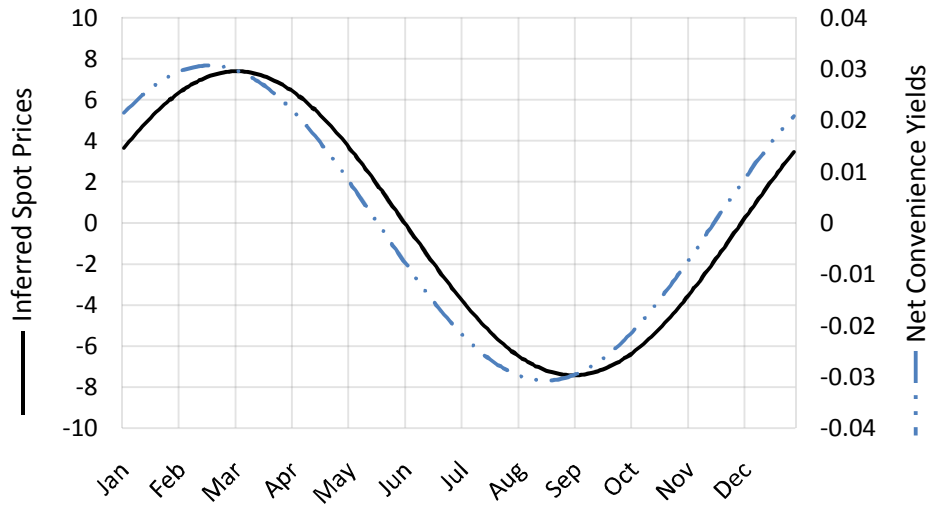
West, K. D. (1987). A Specification Test for Speculative Bubbles. *The Quarterly Journal of Economics* 102: 553-580.

West, K. D. (1988). Bubbles, Fads and Stock Price Volatility Tests: A Partial Evaluation. *Journal of Finance* 43: 639-656.

Working, H. (1949). The Theory of Price of Storage. *The American Economic Review* 39: 1254-1262.

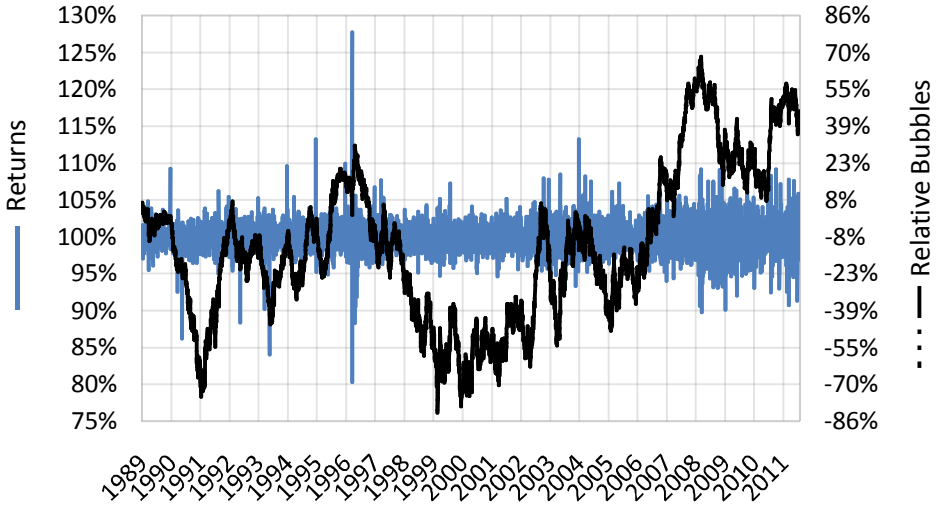
APPENDIX

Figure A1. Estimated seasonal patterns for inferred spot prices and net convenience yields



Source: own elaboration

Figure A2. Gross returns and relative bubble size (seasonality adjusted)



Source: own elaboration