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Testing for bubbles in agriculture commodity markets

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ABSTRACT: We apply the recent generalized sup augmented Dickey-Fuller (GSADF) test for explosive bubbles (Phillips *et al*., 2012) to monthly time-series for food, beverages, agricultural raw material, cereals, dairy, meat, oils and sugar indices and a total of 28 agricultural commodities between 1980-2012. We found price bubbles occurred for 6 out of the 10 indices studied and for 6 out of the 28 commodities within food markets. Results from the tests can help implementing policies aimed at mitigating effects of future price bubbles to targeted food commodity markets that may require special attention.

KEYWORDS: Generalized SUP augmented Dickey Fuller, food prices, price bubbles.

JEL classification: C1.

DOI: 10.7201/earn.2016.01.04.

Detectando burbujas en los mercados de productos agrícolas

RESUMEN: Aquí aplicamos un test estadístico recientemente desarrollado para la identificación de burbujas explosivas, generalized sup augmented Dickey-Fuller (GSADF) test (Phillips et al., 2012) a series temporales mensuales de indicadores de precios de alimentos, bebidas, materias primas agrícolas, cereales, productos lácteos, productos cárnicos, aceites y azúcar así como para un total de 28 productos agrícolas durante el período 1980-2012. Se han encontrado burbujas en los precios para 6 de los 10 índices y para 6 de los 28 productos alimenticios estudiados. Los resultados de estos tests pueden ayudar a llevar a cabo políticas que tengan como objetivo mitigar los efectos de futuras burbujas explosivas en mercados de productos agrícolas identificados como aquellos puedan requerir una atención especial.

PALABRAS CLAVE: Burbujas de precios, generalized SUP augmented Dickey Fuller, precios alimentarios.

Clasificación JEL: C1.

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1. Introduction

Since 2007 the world experienced dramatic swings in internationally traded food commodity prices. In June 2008, December 2010 and more recently in the autumn of 2012, food prices increased sharply and subsequently declined from their peak, only to remain at relatively high levels, as compared with the 2005-2006 average.

Food prices are inherently volatile and addressing the consequences of such volatility is one of the most challenging issues facing policy makers, especially in developing countries[1]. Since Gustafson's (1958) price behavior model for a storable staple, over 50 years of empirical analysis have added a lot to our knowledge on the behavior of commodity and food prices. We know that unrelated commodity prices move together (Pindyck and Rotemberg, 1990); they are highly autocorrelated and significantly volatile (Deaton and Laroque, 1992); their long run downward trend (Grilli and Yang, 1988) is subject to violent upward spikes which are not matched by the few, or no downward spikes (Deaton and Laroque, 1992); the shocks that generate these spikes tend to have a persistence effect on prices over the years (Cashin *et al.*, 2000); and regarding causes of commodity prices following cyclical patterns, there is little evidence that such cyclical patterns are determined by business cycles (Cashin *et al.*, 2002).

In spite of what we have learned about commodity price behavior during the last 50 years, the 2008 commodities price episode revealed a gap in our knowledge on the drivers that determine commodity, and especially food prices. Since 2005 real food prices have exhibited an upward trend, and in mid-2008 they increased in a violent surge by more than 60 percent, as compared to the 2007 levels. Since then food prices have remained at a level significantly higher than the average of the 2000-2005 period and exhibited large fluctuations, with slums followed closely by booms in 2009, 2010 and 2012 as shown in Figure 1. Indeed, the evidence so far suggests that volatility is both persistent and increasing (FAO, 2011; Rapsomanikis, 2011) with the macroeconomic environment and climatic shocks generating wide price movements.

Persistent food price volatility can have significant economic and social effects, especially on developing countries. In the short run, for net food importing developing countries price shocks can negatively affect the balance of payments, foreign currency reserves and worsen the ability to implement social safety programmes. In the longer run, the diversification of activities to minimize exposure to price risk inhibits efficiency gains from specialization in production and hinders the development of the agricultural sector (Kurosaki and Fafchamps, 2002). Income risks may also blunt the adoption of technologies necessary for agricultural production efficiency, as producers may decide to apply less productive technologies in exchange for greater stability (Larson and Plessman, 2002).

[1] Recently, the EU has funded a FP7-project on understanding and coping with food markets volatility towards more Stable World and EU food systems (ULYSSES). In this project macroeconomic models (e.g. Aglink-Cosimo, CAPRI) to analysis medium and long term analysis of agricultural markets (Araujo-Enciso *et al.*, 2014).

FIGURE 1

FAO Food price index

Source: FAO statistics.

The volatility in world food prices strengthened the attention of policy makers to agriculture and fuelled the debate about the future reliability of world markets as a source for food. They have also generated a wide array of opinions concerning their nature and drivers, and have led to an equally wide array of policy proposals among policy makers.

The debate on whether the drivers of food price volatility go beyond market fundamentals is reflected on the wide range of the policies proposed. Investing to accelerate agricultural productivity growth to meet increasingly stronger demand for food and ease the pressure on prices (FAO, 2011) is a proposal founded on the understanding that supply, demand and stocks are the relevant drivers of volatility. Proposals such as the establishment of 'virtual funds' to intervene in the food futures markets by executing a number of progressive short sales are based on the surmise that changes in supply and demand fundamentals cannot fully explain volatility and speculation, especially in the futures markets (Von Braun and Torero, 2009). There is no consensus between economists on the nature and drivers of food price volatility and, unsurprisingly, between policy makers on the policies to mitigate it.

A number of tests and dating algorithms have been developed and used to identify rapid increases in prices followed by a collapse, also known as explosive bubbles (Phillips *et al.*, 2011; Phillips *et al.*, 2012; Gilbert, 2010; Gutierrez, 2013). Previous analyses on agriculture commodities by Gilbert (2010) and Gutierrez (2013) applied the tests developed by Phillips *et al.* (2011) and focused on four agricultural commodities (maize, soybeans, wheat and rice). In contrast, we apply the more recent generalized sup augmented Dickey-Fuller (GSADF) test for explosive bubbles (Phillips *et al.*, 2012) to monthly time-series for food, beverages, agricultural raw material, cereals, dairy, meat, oils and sugar indices and a total of 28 agricultural commodities between 1980-2012[2]. We found price bubbles occurred for some commodities within food markets.

2. The Debate

Assessing the extent to which prices reflect fundamental values or not is difficult. It entails testing the validity of the present value model. If this fails, the question whether one can separate bubble behaviour for the possibility that the model itself is misspecified. With such difficulties, examining the evidence in an indirect manner, such as exploring both fundamental and non-fundamental factors and reconciling their movements with price variation, consists of an approach often encountered in the agricultural economics literature.

A number of authors underline the importance of the fundamental forces of supply and demand in explaining the food prices surges of 2008 and 2010. Growing population and income in emerging and developing countries adds significantly to the demand for food, while the rate of growth of agricultural production has not kept pace with demand (Alston *et al.*, 2010; Bioversity *et al.*, 2012). This alone is sufficient to exert pressure on commodity prices. The growing demand for food and feed crops for the production of biofuels is another significant factor, resulting in food and energy markets being integrated (Serra *et al.*, 2010; Balcombe and Rapsomanikis, 2008). Very inelastic derived demand for maize by the biofuel sector contributes to both higher prices and greater price volatility (Abbott, 2013). A response to the strong demand for grains due to high income growth and biofuel mandates is the decline of aggregate grain stocks relative to utilization. Indeed, the global grain market stocks-to-utilization ratio has been fluctuating at a low point since 2005-06, signifying a reduction in the buffer capacity of the global market. Even small supply and demand shocks as well as trade policies can generate wide price variations. Wright (2010) encapsulates the above strand of literature based on the competitive storage model, and concludes that the balance between consumption, available supply and stocks is sufficient to justify the recent wide grain price movements. Balcombe (2011) found that crude oil prices volatility, exchange rate volatility were determinant factors in many of the commodities studied (e.g. maize, rice, soya oil, rapeseed, poultry and pork).

Beyond market fundamentals, dramatic increases in commodity futures investments by financial institutions as well as commercial traders coincided with the 2008 food price surge, giving rise to questions on whether the forces of demand and supply

[2] These GSADF tests may identify other forms of behaviour (e.g. regime switching, trends or structural breaks) as bubbles.

alone are sufficient to explain such price developments. While most of the speculative capital is invested in non-agricultural, especially energy futures, investments in agricultural futures, reflected by market open interest[3], marked a significant increase from 2007 to 2008, a period with rapid increases in food prices, especially for maize, soybeans and wheat. Once again in 2010, although increases in the global market price of wheat were triggered by market fundamentals – reduced supply from Russia and the Fine Sea region due to drought and export restrictions, open market interest in commodity exchanges increased significantly.

Robles *et al.* (2009) stress that, along with market fundamentals, trend-following behavior such as rising expectations, speculation, hoarding, and hysteria played a significant role in the increasing level and volatility of food prices, attributing the 2008 food price episode partly to 'speculative bubbles'. UNCTAD (2011), in the similar line, lay emphasis on the fact that some aspects of 'financialization' of commodities[4], may imply that some activities of 'non-commercial' financial participants may drive commodity prices away from levels justified by market fundamentals. Non-commercial investors do not engage in physical markets, as commercial investors do. The latter include producers and processors who hedge price risks, while the former view commodity futures as assets exhibiting relatively high returns which are negatively correlated with those from other assets, such as equities and bonds, providing effective portfolio diversification. However, these non-commercial investors are far from homogeneous and their behavior in the market differs. Commodity index funds form the majority of financial investors on commodity futures and follow a passive futures position. They take long positions and hold these positions by rolling them forward (automatically participating in price movements that are also reflected in the index price movement). They reduce or increase their overall long positions based on investors demand for their shares.

Hedge funds invest on behalf of rich individuals following discretionary trading strategies: they adjust their investments in commodity futures in line with changes in asset prices to stabilize and diversify their portfolio (Gilbert, 2010; UNCTAD, 2011). The concern is whether these non-commercial investors and their trend following behavior feed price bubbles, thus detaching both prices from their market fundamental values. Such an impact may also be reflected in the physical markets, as the information flow runs from futures to local spot markets (Hernández and Torero, 2010), thus distorting price signals.

Friedman's (1953) theory on efficient markets underlines that, given rational behavior and rational expectations, the price of an asset will always reflect market fundamentals. Any divergence of the price from its market fundamental value, caused by non informed traders, can be eliminated as it provides an opportunity to informed

[3] Open interest is a calculation of the number of active trades for a particular market calculated using futures and options contracts. More specifically, as defined by the US Commodity Futures Trading Commission (CFTC), it is the total of all futures and/or option contracts entered into and not yet offset by a transaction, by delivery, by exercise, etc.

[4] Financialization refers to an increased presence of financial traders, an increase in derivative trading and increased availability of commodity investment products.

traders to trade against non-informed ones, make profit, and bring the price back to its fundamental value. Nevertheless, divergences may occur and although short-lived, can be frequent. There are many empirical exceptions to the theory of efficient markets. For example, informed traders may choose to follow positive-feedback trading strategies. If they expected prices to continue rising, they will chase the trend in the short run, thus feeding the bubble, instead of alleviating it (De Long *et al.*, 1990). DeMarzo *et al.* (2008) point out that even rational and informed traders may choose to join trend-chasing due to the risk underlying trading against the majority of participants. Dass *et al.* (2008) focus on the incentives fund managers have to trend-chase, as they are assessed against the performance of other fund managers. This provides strong incentives for herding and accentuating a bubble.

In the debate of whether agricultural and food commodity prices are unjustifiably volatile and detached from market fundamentals, the agricultural economics literature has mainly centred on analyzing whether the 2008 dramatic food price increases were induced by speculative purchases of futures contracts by non-commercial institutional investors on prices. These analyses do not constitute tests for the detection of a bubble, but focus on identifying the possible avenues through which positive-feedback strategies in commodity exchanges contributed towards price increases that could not be explained by market fundamentals. Nevertheless, in these analyses the term 'bubble' is used liberally.

Irwin *et al.* (2009) assess the impact of speculative purchases of food commodity futures by index funds on futures prices by means of Granger causality tests and conclude that the argument that speculators caused the food price bubble does not hold. Sanders and Irwin (2010) investigate the effect of index funds' positions on the prices of a number of agricultural and food commodities, finding no impact when quarterly and monthly data were used, and only weak evidence when weekly data was analysed. They concluded that, overall, the evidence that non-commercial investors with passive strategies affect agricultural futures prices is scant. Sanders and Irwin (2011a,b) find little evidence of an index-induced food price bubble for a number of markets with the exception of soybeans.

Gilbert (2010) assesses the impact of an index of futures positions in twelve major agricultural futures markets on the International Monetary Fund (IMF) Food Price Index, in addition to the impact of other variables such as the price of oil, money supply and the US exchange rate. He concludes that index fund investment is sufficiently large to influence food prices. Gilbert (2010) formally tests for a bubble in three food commodities, maize, wheat and soybean, using futures prices and applying the methodology of Phillips *et al.* (2011). He finds clear evidence for a bubble in soybean prices in December 2009 and in January 2009, but no evidence for explosive behavior in the wheat and maize prices. Gilbert (2010) finding concurs with that of Sanders and Irwin (2011a) on the role of index funds in this market, but the interpretation of such results is not easy. First, the question relates to the avenue through which non commercial investment behavior would generate a price surge. Gilbert (2010) notes that an increase in the demand for futures contracts will tend to raise long-dated futures prices and increase inventory demand, which in the short term will result to an increase in the cash price. Recently, Gutierrez (2013) found speculative bubbles for wheat corn and rough rice prices and minor evidence for soya bean prices. Such differences, as pointed out by Gutierrez (2013), may be due to differences in the bootstrap method used and differences in the method used and differences in the method used to define the critical values.

3. Theory

As part of the discussion regarding the potential analytical frameworks for explosive price behaviour it is important to explain the distinction between rational and irrational bubbles. Rational bubbles are those that have the 'sub-martingale' property, which essentially means that there are only normal expected returns to holding a given asset. One can also divide models according to whether they are intrinsic or extrinsic. Extrinsic models posit that the actual price is equal to a fundamental price plus a bubble component which is not a function of dividends (such as Blanchard and Watson, 1982; Evans, 1991; Van Norden and Schaller, 1999; Brooks and Katsaris, 2005). Intrinsic models either specify the bubble component but make it a function of dividends (such as in Froot and Obstfeld, 1991) or posit that the bubble is itself within the fundamental price (such as Phillips and Yu, 2011). The particular rationalisation developed by Phillips and Yu (2011) depends on the idea that the discount rates can be subject to structural change, however the work of Homm and Breitung (2012) demonstrate that the this class of tests also has power to detect other forms of bubbles.

Earlier tests such as in Diba and Grossman (1988) tested both stock prices and dividends for nonstationarity. Evidence of stationarity after differencing was taken as providing no support for the existence of a bubble, while, cointegration between stock and dividends would support the conclusion that stock prices did not diverge from their fundamental values. Evans (1991) criticised this integration-based approach, stressing that unit root and non cointegration tests are not effective in making a distinction between a unit root or a stationary autoregression and a process which exhibits periodically collapsing bubble behaviour.

The recursive tests proposed by Phillips *et al.* (2011) are not subject to this criticism, being effective in distinguishing unit root processes from periodically collapsing bubbles and date-stamping their origin and collapse. Their methodology is based on a repeated application of the augmented Dickey-Fuller test (ADF), estimating through a recursive regression the specification:

$$\Delta y_t = \alpha_{r_w} + \beta_{r_w} y_{t-1} + \sum_{i=1}^{k} \varphi_{r_w}^{i} \Delta y_{t-i} + \varepsilon_t, \quad \varepsilon_t \sim N\left(0, \sigma_{r_w}^2\right) \qquad [1]$$

where y_t is the logged price of the commodity studies at time t; α, β, φ are parameters to be estimated; r_w is the sample window size; and, k is the lag order. The recursive regression involves the estimation of [1] by least squares starting with $r_w = r_0$ fraction of the sample, and repeatedly expanding the sample forward, with the last regression utilising the full sample T. For example, the first regression utilises a subsample $\tau_0 = [T\, r_0]$ from the first observation of the sample to the k^{th} observation, selected to ensure estimation efficiency. This produces an ADF statistic denoted ADF_{r0}. The second regression expands the sample by one observation to the $(k + 1)^{th}$ observation, utilising a subsample $\tau_1 = [T\, r_1]$ and producing an ADF statistic denoted by ADF_{r1}. Subsequent regressions expand the sample window size r_w, from r_0 to 1, with 1 being the whole sample and ADF_1 corresponding to the whole sample ADF statistic. Phillips *et al.* (2011) by expanding the sample forward, generate a sample of ADF statistics and test the null hypothesis of a unit root against the right-tailed alternative of explosive behaviour with the supremum ADF, $\underset{r_w \in [r_0,1]}{sup} ADF_{r_w}$, utilising the critical values. Although the *sup* ADF detects periodically collapsing bubbles, date stamping its origination and subsequent collapse, Phillips *et al.* (2012) underlined its weakness when there are multiple bubble episodes within the same sample period.

Econometric analysis of explosive processes using *sup* ADF has been conducted mainly in financial research (Phillips *et al.*, 2011; Phillips and Yu, 2011). *sup* ADF differs from the GSADF in that the former uses a fixed initialisation window whereas the latter uses a moving window, which avoids results being sensitive to sample start data. Also, the GSADF does allow for the possibility of periodically collapsing bubbles (Phillips *et al.*, 2011).

We use the generalised version of the sup augmented Dickey-Fuller (GSADF) test recently developed by Phillips *et al.* (2012), which has been applied to 12 agricultural prices previously (Etienne *et al.*, 2014)[5], to test for bubble phenomena. The test developed by Phillips *et al.* (2012) is characterised by its ability to deal with multiple bubbles. The first order Augmented Dickey-Fuller regression model used by Phillips *et al.* (2012) is

$$\Delta y_t = \alpha_{r1,r2} + \beta_{r1,r2} y_{t-1} + \sum_{i=1}^{k} \varphi_{r1,r2}^{i} \Delta y_{t-i} + \varepsilon_t \qquad [2]$$

In related work, Phillips (e.g. Phillips and Magdalinos, 2007) outlines the asymptotic theory behind this class of tests demonstrating its power under some 'mildly' explosive alternatives. In practice, however, the GSADF tests will detect bubbles that might be characterised as highly explosive also.

Following the GSADF approach by Phillips *et al.* (2011) we allow for variable window widths in the recursive regressions. This allows the starting points r_1 to change within a feasible range. The standard Augmented Dickey-Fuller (ADF) tests the null hypothesis of non-stationarity H_0: $\beta_{r1,r2} = 0$ against the alternative hypothesis H_1: $\beta_{r1,r2} > 0$ which implies explosive behaviour. Significant ADF test statistics indicate a bubble episode. The estimated parameters α, β, φ of model [2] are obtained through recursive ordinary least squares (OLS)[6]. The idea behind is that if an explosive behaviour exists this will be present over a subsample [$r1$, $r2$] of the entire sample [1, T].

[5] Price bubbles in six agricultural commodities have also been analysed using regime switching (Liu *et al.*, 2013).

[6] We use 10 % of the total sample as the starting sample.

Phillips *et al.* (2011) provide critical values of GSADF tests against an explosive behaviour. These critical values were obtained setting the lag order to be zero (i.e. zero lags). We obtained the finite 90, 95 and 99 % critical values for lag orders set from 0 to 12 by numerical simulations, where, as in Phillips *et al.* (2012), the Wiener process is approximated by partial sums of 2,000 independent variates and the number of replications is 2,000. For our empirical application we set the smallest sample window $r_0 = 0.4$. The asymptotic critical values obtained are shown in the Appendix.

Homm and Breitung (2012) investigate a number of methods that have the power to reject the no-bubble hypothesis including the SADF test. They demonstrate that the SADF test has maximum (and good) power. This paper also demonstrates that the tests employed here have power to detect alternative forms of bubbles including that of Evans (1991). Thus the theoretical Bubble models elucidated by out by Phillips and Yu (2011) need not be the only structural rationalisation for these tests.

4. Data

We use price indexes for food and beverage and agricultural raw materials as well as 28 individual agriculture commodity prices (see Appendix for a list of price definitions).

We use monthly price indices data from the Food and Agriculture Organisation of the United Nations (FAO), as well as from International Monetary Fund (IMF). The FAO indices include the food price index, as well as indices for meat, dairy, cereals, oils and sugar from January 1990 to August 2012 comprising 271 observations for each index. We examine the IMF indices which include the food and beverage index, and indices for food, beverages and agricultural raw materials from January 1980 and February 2012 comprising 386 observations.

Data on the 28 individual agricultural commodity prices are collected from the International Financial Statistics of the IMF from January 1980 and February 2012 and deflated using the US monthly CPI obtained from the US Department of Labour. Previous work by Etienne *et al.* (2014) using the same approach considered 12 agricultural future contracts included in the CFTC supplemental commitment of traders report that includes maize, soybeans, soybean oil, wheat[7], feeder cattle, live cattle, and lean pigs, cocoa, coffee, cotton, and sugar.

5. Results and discussion

We estimate equation [1] allowing for variable window widths in the recursive regressions. Phillips *et al.* (2012) provide critical values of GSADF tests against an explosive behaviour using Monte Carlo simulations, setting the lag order to be zero (i.e. zero lags). We obtained the finite 90, 95 and 99 % critical values for lag orders set from 0 to 12. As in Phillips *et al.* (2012), the Wiener process is approximated by partial sums of 2,000 independent N(0,1) variates and the number of replications is 2,000. For our empirical application we use 10 % of the sample, as our initial start-

[7] Etienne *et al.* (2014) include maize traded in both the Chicago Board of Trade and the Kansas City Board of Trade.

up sample, $r_0 = 0.1$, and set the smallest sample window, $r_w = 0.4$. The finite critical values obtained are shown in the Appendix.

Table 1 shows the maximum ADF test obtained from estimating the GSADF model [2] repeatedly over the feasible ranges r_1 and r_2. Maximum values greater than the critical values reported show evidence of bubble behaviour in the particular index or price as the tests reject the null hypothesis $H_0\colon \beta_{r_1}^{r_2} = 0$ in favour of the right tailed alternative hypothesis $H_1\colon \beta_{r_1}^{r_2} > 0$. The tests provide evidence for bubble behaviour at the 10 % significance level for the both FAO and IMF food price indices, the IMF food and average price index, the FAO cereals, dairy and oils indices, and the prices of wheat, rice, soybean oil, rapeseed oil, sugar and coffee.

In order to date-stamp the origin and conclusion of the explosive behaviour in the series we plot the relevant recursive $ADF_{r_1}^{r_2}$ statistics (Figure 2).

Our results show bubble behaviour during the end of 2007 and the first months of 2008 in six out of the ten indices examined. Our recursive regressions suggest that the price surge of 2007-08 is of a different nature than that of 2010 and 2011, as no evidence is found of explosive behaviour in indices and prices outside the period August 2007 to July 2008. The analysis suggests that price bubbles are relatively short lived. With the exception of the FAO food price index, explosive behaviour in food prices lasted for a limited period of time amounting to two, three or, at most four months, before collapsing.

For the FAO food price index, the evidence suggests persistent explosive behaviour from August 2007 until June 2008, while the IMF food and beverages price indices bubble behaviour is found during January, February and March 2008[8]. It is possible that the food component is the factor behind the bubble behaviour in the latter since no explosive behaviour is attributable neither to the beverage index nor to any of the individual beverages analysed during the period 2007- 2008. For the FAO cereals and oil indices, there is evidence for bubble behaviour from December 2007 to April 2008, and for the FAO oils index during February and March 2008.

[8] Not entirely synchronised explosive behaviour of indices may be attributable to the different aggregation and weighting methods. The FAO food price index is trade-weighted and as trade increased at a fast rate during the 2007-08 period, the results show persistent bubble behaviour.

TABLE 1

GSADF model results for agricultural commodities

Commodities	Max	90 % critical value	Lags	n
Index				
Food and beverage index	2.00	1.87	1	254
Food Index	2.09	1.87	1	254
Beverage Index	0.88	2.11	1	386
Agricultural Raw Material Index	1.41	2.11	1	386
Food Price Index – FAO	3.10	1.93	1	271
Cereals Price Index – FAO	2.98	1.93	1	271
Meat Price Index – FAO	-0.04	1.93	1	271
Dairy Price Index – FAO	1.97	1.93	1	271
Oil Price Index – FAO	2.28	1.93	1	271
Sugar Price Index – FAO	1.06	1.93	1	271
Cereals				
Wheat	2.24	2.11	1	386
Maize	1.13	2.11	1	386
Rice	4.09	2.29	2	386
Barley	0.85	2.11	1	386
Vegetable oils and protein meal				
Soybean	1.28	2.11	1	386
Soybean meal	0.68	2.11	1	386
Soybean oil	2.60	2.11	1	386
Palm oil	1.90	2.53	4	386
Fishmeal	2.01	2.11	1	386
Sunflower oil	1.11	2.29	2	386
Olive oil	1.89	2.29	2	386
Groundnuts (peanuts)	0.80	2.11	1	386
Rapeseed oil	2.09	1.96	0	386
Meat				
Beef	1.36	2.29	2	386
Lamb	0.34	2.29	2	386
Swine (pork)	1.51	1.96	0	386
Poultry (chicken)	0.89	2.11	1	386
Seafood				
Fish (salmon)	0.80	2.71	6	386
Shrimp	0.00	2.29	2	386

TABLE 1 (CONT.)

GSADF model results for agricultural commodities

Sugar				
Sugar, free market	1.56	2.11	1	386
Sugar, European import price	1.53	1.87	1	254
Sugar, U.S. import price	3.50	2.11	1	386
Fruit				
Bananas	-1.44	1.96	0	386
Oranges	-0.61	2.11	1	386
Beverages				
Cocoa beans	2.07	2.29	2	386
Coffee, other mild arabicas	1.70	2.11	1	386
Coffee, Robusta	2.15	2.11	1	386
Tea	0.38	2.11	1	386

Source: Own calculations.

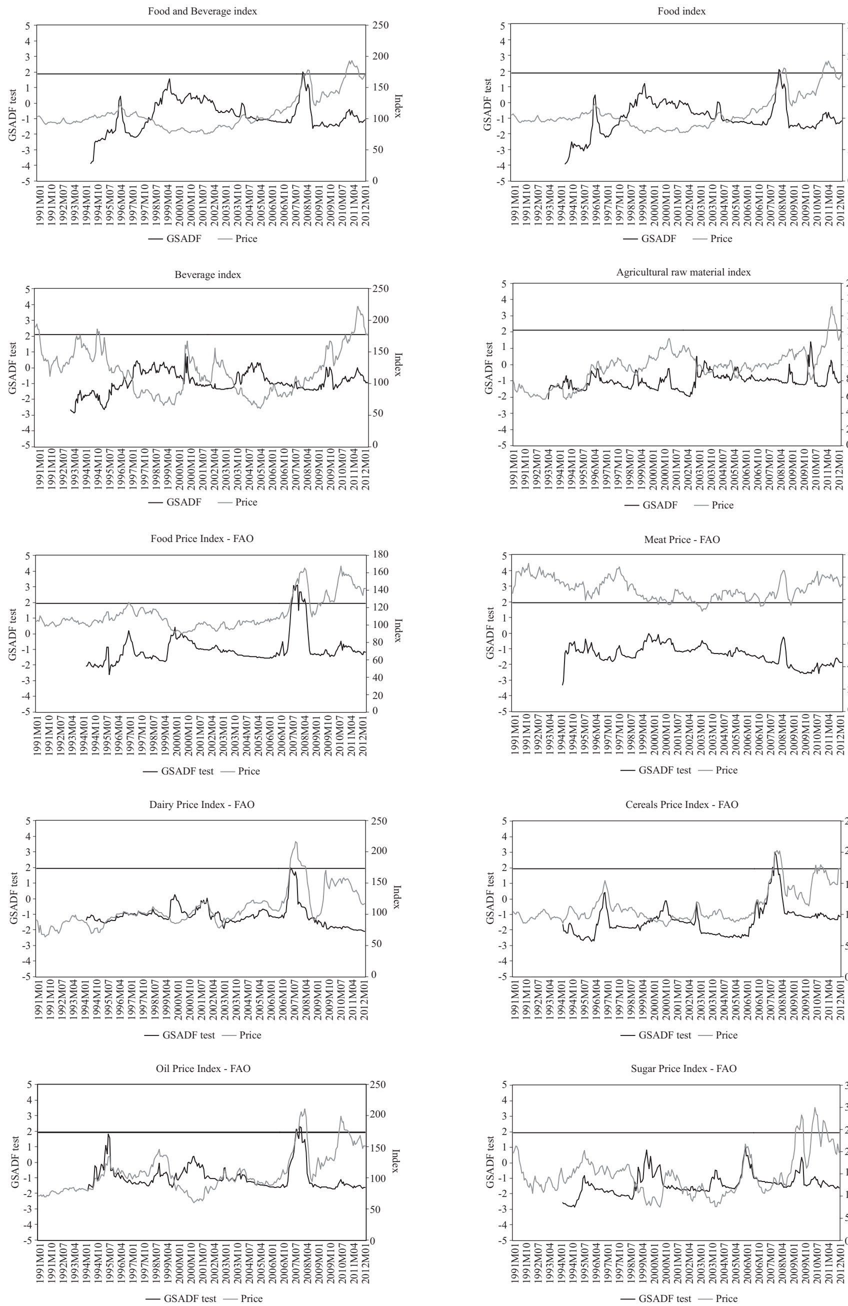
For the individual commodity prices, the tests provide evidence for bubble behaviour in the wheat, rice, soybean oil and rapeseed oil price series all of which have exhibited record increases during the first months of 2008 relative to other commodities. In their peak, wheat and rice prices were 350 and 530 percent higher, as compared to January 2002 levels which could mark the beginning of an upward trend in food prices. Prices of wheat, soybean oil and rapeseed oil show bubble behaviour during February and March 2008. Although in 2010 and 2011, wheat prices surged as a result of climatic factors and trade policies, such as the export ban by Russia in 2010, there is no evidence that prices exceeded their fundamental value. Our results are in line with Adämmer and Bohl (2015) who analysed speculative bubbles in three agricultural commodities (maize, wheat and soybean) using a momentum threshold autoregressive approach. Our results regarding wheat, rice and soybeans coincide with Gutierrez (2013) who also found bubble behaviour for wheat and rice and did not find evidence of bubbles for soybeans. However, Gutierrez (2013) found evidence of bubble behaviour for maize which we did not find here. Some of our results (e.g. soybean oil, wheat) coincide with findings by Etienne *et al*. (2014). However, while Etienne *et al*. (2014) found bubbles for maize and soybeans this has not been the case for our analysis.

Amongst food commodities the strongest evidence for a price bubble occurring is for rice, for which the explosive behaviour lasted for three months, from February 2008 to April 2008, and again in July 2008.

In sum, we do not detect multiple bubbles in the food price series after the summer of 2008, a finding that suggests that since that time, food prices respond to the fundamental forces of demand and supply.

FIGURE 2

Price trends and GSDAF test statistics



Source: Own calculations.

Although our analysis provides answers as to if, and when food prices exhibited bubble behaviour, the results raise a number of important questions related to the drivers of explosive

behaviour. As far as the price of rice is concerned, the results concur with the panic –driven trade policy reactions of countries in Asia. Export restrictions, in the form of both taxes and bans, started during late 2007. In late September 2007, Vietnam, the second largest exporter in rice, announced a ban on commercial sales. In October 2007, India, the third largest rice exporter, imposed an export tax on non-basmati rice and in March 2008 imposed a complete ban in March. These export bans, in conjunction with aggressive and panic-driven buying by Philippines, the world's leading importer, during March and April 2008 at prices over US$ 1,100 per tonne, as compared to an average of US$ 326 per tonne in 2007, contributed towards the price of rice being over-valued, detaching from market fundamentals.

The results for bubbles in the wheat and vegetable oil prices are more difficult to be interpreted, especially because no explosive behaviour was detected in the prices of maize and oilseeds. At their peak in 2008, soybean oil prices increased by 410 percent as compared to their January 2002 values, proportionally more than those of soybeans which increased by 350 percent. Maize prices also registered a significant increase at their peak in 2008 from their January 2002 level by about 300 percent, a rate lower than that of wheat prices. For all four commodities, markets were tight in 2007-08: oilseeds and oils markets suffered from poor growth and low stocks; in the wheat market, stagnant production in conjunction with very low carryover stocks resulted in an extremely tight global market; and, maize prices also faced pressure from strong demand from the biofuels industry, although the 2007 record crop relatively lessened the strain on the market.

Beyond fundamentals, even if the GSDAF detects price bubbles, it cannot provide evidence that these bubbles are the result of trend-following behaviour in the futures markets[9]. Nevertheless, the lack of evidence on explosive behaviour in maize and oilseeds prices questions the conjecture that trend-following behaviour in futures markets has been the driver of food price increases. Maize and oilseeds futures are traded in commodity exchanges and, like wheat, their contracts are included in commodity indices. There are some differences in index investments movements across these commodities, but these do not correspond with our findings on explosive behaviour. Between December 2007 and June 2008, the index funds' net positions on wheat increased from 38.2 % to 41.9 % of the total open interest. During the same six months period, for maize the share of the index funds net positions was not as substantial as that of wheat, but also increased from 25.8 % to 27.4 % of the total (Gilbert, 2010). With such a high share of the wheat open interest held by non-commercial traders, in an already tight market, the possibility that the demand for long (buy-side) position over a prolonged period of time may have affected prices and generated bubbles through strengthening inventory demand, should not be ignored. The size of index funds' wheat net positions come second only to the share of open interest they held

[9] The rationalisation of GSDAF by Phillips *et al.* (2012) does not include explaining sources of price bubbles.

on live cattle and lean hogs, which amounted to over 40 percent during 2007-08. In spite of this high share, no bubble is detected in beef and pork prices. Nevertheless, it is the view of the authors that it is doubtful that index fund investments would have a direct impact on meat markets, through strengthening the demand for inventories (herds) in a period of high feed prices. The specificities of each food market, in conjunction with the wide diversity of traders, both non commercial and commercial, and their complex trading behaviour over a short period of time, makes the analysis of the role of futures markets in the 2007-08 price episode difficult and beyond the scope of this article.

5.1 Public policy implications

As pointed out in the introductory section persistent food price volatility can have significant economic and social effects. Addressing these effects (i.e. forecasting food price volatility and/or preventing the result of food price volatility) is a challenge for policy makers. Tests as the one used in this paper serve to spot price situations of a rapid increase in price followed by a collapse (i.e. explosive bubbles). However, we need to bear in mind that what these tests identify is whether food prices have departed from their fundamental value or not. They are not a crystal ball, they cannot predict whether a price bubble will occur, but they can serve to evaluate whether one has occurred, and it consequently can help prioritising which food commodity markets require attention by identifying commodity prices that have shown a bubble behaviour. Hence, policies aiming at mitigating the pressure on prices such as the investment on enhancing productivity growth could use this type of information to focus on those markets that have shown certain tendency toward bubble behaviour in the first place. The use of results from these tests in combination with other information such as potential factors behind bubble behaviour may also be beneficial to prevent future price bubble episodes. Based on our results on a number of commodities (wheat, rice, soybean oil and rapeseed oil) that have shown bubble behaviour in the recent years we recommend that close attention should be paid to their price evolution and possible factors behind such behaviour should be investigated. On the other hand, since fruits, meat, seafood and to a large extent beverages have not shown evidence of bubble behaviour, they present low relative risk of bubble behaviour (i.e. these commodities are not considered to be a priority regarding spending resources on policies aiming at prevent or lessen the effects of commodity price bubbles).

6. Conclusions

We apply the GSADF test for explosive bubbles to monthly time-series for food, beverages, agricultural raw material, cereals, dairy, meat, oils and sugar indices and a total of 28 agricultural commodities between 1980-2012. We found price bubbles in 6 out of 10 indices (food and beverage index, food index, FAO´s food price index, FAO´s cereals price index, FAO´s dairy price index, FAO´s oil price index). For cereal markets we found price bubbles in wheat and rice markets.

Such rapid changes in agricultural commodity prices may have important immediate effects on the income and welfare of producers, agents along the food change and consumers as well as the trading positions of countries (Balcombe, 2009). Two important related questions arise. Are the price bubbles found in food commodities of speculative origin? And, are some commodities more prone to suffer price bubbles than others? Looking forward, on the first question, while appreciating that most of previous analyses do not support such relationship between index fund investing and price bubbles (Gilbert, 2010; Sanders and Irwin, 2011a, 2011b; Aulerich *et al.*, 2014), there is need for further analysis of trading positions of commercial and non commercial participants in the futures markets. A price bubble was identified in the wheat market, where the share of open interest was held by non-commercial traders. However, maize, as well as other commodities are traded in futures markets and further research based on disaggregated data on the composition of both commercial and non commercial positions and their behaviour during price surges is necessary to unravel their potential role in determining price movements.

With regard to the second question we conclude that a number of agriculture commodities are prone to suffer price bubbles and therefore efforts in both identifying and tackling price bubbles should focus on those commodities that have shown bubble behaviour in the past. For example, the global rice market is quite thin, with major producers and exporters managing domestic markets through export controls combined with buffer stocks. Our results show that export restrictions can exacerbate or even cause severe disruption and a collapse in confidence on international markets. Increased international trade policy coordination in times of crisis can also reduce volatility and ensure that global markets can be still a reliable source of food. Enhanced trade policy harmonization through more predictable and less discretionary policies would convey clearer information and render panic and hoarding less likely, resulting in less uncertainty. Therefore, our results are suitable to discern commodity markets where explosive bubbles exist facilitating the prioritisation of what markets may need intervention or what countries may be at risk regarding the consequences of rapid increase in food prices.

From the methodological point of view, an important issue also highlighted by Gilbert (2010) and Tothova (2011) is the data frequency (e.g. daily, monthly) used in the analysis may be important in detecting bubbles. The fact that we have not found more price bubbles may be precisely because of the data frequency used (i.e. using higher frequency data such as daily data may have detected bubbles that are disguised under lower frequency data). Therefore, high frequency data of agricultural prices, particularly data of commodities that have shown bubble behaviour in the past, should be used to detect emerging trends of price spikes.

References

Adämmer, P. and Bohl, M.T. (2015). "Speculative bubbles in agricultural prices". *The Quarterly Review of Economics and Finance*, 55: 67-76. http://doi.org/bdmd.

Abbott, P. (2013). "Biofuels, Binding Constraints and Agricultural Commodity Price Volatility". In Chavas, J.P., Hummels D. and Wright, B. (Eds.): *The Economics of Food Price Volatility.* National Bureau of Economic Research, Massachusetts.

Alston, J.M., Beddow, J.M. and Pardey, P.G. (2010). "Global Patterns of Crop Yields and Other Partial Productivity Measures and Prices". In Alston, J.M., Babcock, B.A. and Pardey, P.G. (Eds.): *The Shifting Patterns of Agricultural Production and Productivity Worldwide.* Iowa State University, Ames.

Araujo-Enciso, S.R., Blanco, M., Artavia, M., Ramos, F., Fernández, F.J., Van Doorslaer, B., Fumagalli, D. and Ceglar, A. (2014). *Volatility modelling: long term challenges and policy implications*. Scientific Paper No. 5, ULYSSES "Understanding and coping with food markets voLatilitY towards more Stable World and EU food SystEmS".

Aulerich, N.M., Irwin, S.H. and Garcia, P. (2014). "Bubbles, Food Prices and Speculation". In Chavas, J.P., Hummels, D. and Wright, B.D. (Eds.): *The economics of Food Price Volatility*. The University of Chicago Press, Chicago.

Balcombe, K. (2011). "The nature and determinants of volatility in agricultural prices: an empirical study". In Prakash, A. (Ed.): *Safeguarding food security in volatile global market*. FAO, Rome.

Balcombe, K. (2009). "The nature and determinants of volatility in agricultural prices: an empirical study from 1962-2008". In Sarris A. and Morrison, J. (Eds.): *The evolving structure of world agricultural trade*. FAO, Rome: 109-136.

Balcombe, K. and Rapsomanikis, G. (2008). "Bayesian estimation and selection of nonlinear vector error correction models: The case of sugar-ethanol-oil nexus in Brazil". *American Journal of Agricultural Economics*, 90(3): 658-668.

Bioversity, CGIAR Consortium, FAO, IFAD, IFPRI, IICA, OECD, UNCTAD, Coordination Team of UN High Level Task Force on the Food Security Crisis, WFP, World Bank, and WTO. (2012). *Sustainable Agricultural Productivity Growth and Bridging the Gap for Small Family Farms: Interagency Report to the Mexican G20 Presidency, FAO and the OECD.*

Blanchard, O.J. and Watson, M.W. (1982). "Bubbles, Rational Expectations, and Financial Markets". In Wachtel, P (Ed.): *Crisis in the Economic and Financial Structure*. D.C. Heathand Company, Lexington, M.A.: 295-315. http://doi.org/fs45hj.

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(505): 763-793. http://doi.org/fn748w.

Cashin, P., Liang, H. and McDermott, C.J. (2000). "How persistent are shocks to world commodity prices?" *IMF Staff Papers*, 47: 177-217.

Cashin, P., McDermott, C.J. and Scott, A. (2002). "Booms and Slumps in World Commodity Prices". Journal of Development Economics, 69: 277-296.

Dass, N., Massa, M. and Patgiri, R. (2008). “Mutual Funds and Bubbles: The Surprising Role of Contractual Incentives”. *Review of Financial Studies*, 21(1): 51-99. http://doi.org/dzv9wd.

Deaton, A. and Laroque, G. (1992). “On the Behaviour of Commodity Prices”. *Review of Economic Studies*, 59(1): 1-23. http://doi.org/c728s8.

De Long, B., Shleifer, A., Summers, L. and Waldmann, R. (1990). “Noise Trader Risk in Financial Markets”. *Journal of Political Economy*, 98(4): 703-38.

DeMarzo, P., Kaniel, R. and Kremer, I. (2007). “Relative Wealth Concerns and Financial Bubbles”. *Review of Financial Studies*, 21(1): 19-50. http://doi.org/fpgc4f.

Diba, B.T. and Grossman, H.I. (1988). “The theory of rational bubbles in stock prices”. *The Economic Journal*, 98(392): 746-754.

Etienne, X.L., Irwin, S.H. and Garcia, P. (2014). “Bubbles in food commodity markets: Four decades of evidence”. *Journal of International Money and Finance*, 42: 129-155. http://doi.org/bdmf.

Evans, G.W. (1991). “Pitfalls in testing for explosive bubbles in asset prices”. *American Economic Review*, 81(4): 922-930.

FAO. (2011). *Safeguarding food security in volatile global markets*. FAO, Rome.

Friedman, M. (1953). *Essays in Positive Economics*, University of Chicago Press, Chicago.

Froot, K. and Obstfeld, M. (1991). “Intrinsic Bubbles: The Case of Stock Prices”. *American Economic Review*, 81(5): 1189-1214. http://doi.org/br4vfc.

Gilbert, C.L. (2010). “Speculative influences on commodity prices 2006-2008”. *United Nations Conference of Trade and Development,* 197. Geneva, Switzerland.

Grilli, E.R. and Yang, M.C. (1988). “Primary Commodity Prices, Manufactured Goods Prices, and the Terms of Trade of Developing Countries: What the Long Run Shows”. *The World Bank Economic Review*, 2(1): 1-47.

Gutierrez, L. (2013). “Speculative bubbles in agricultural commodity markets”. *European Review of Agricultural Economics*, 40(2): 217-238. http://doi.org/bdmg.

Gustafson, R.L. (1958). “Carryover Levels for Grains: A Method for Determining Amounts that are Optimal under Specified Conditions”. *USDA Technical Bulletin*, 1178. Available at: http://purl.umn.edu/157231. Last access: February, 2015.

Hernández, M. and Torero, M. (2010). “Examining the dynamic relationship between spot and futures prices of agricultural commodities”. *Commodity Market Review* 2009-2010: 47-87.

Homm, U. and Breitung, J. (2012) “Testing for Speculative Bubbles in Stock Markets: A Comparison of Alternative Methods”. *Journal of Financial Econometrics*, 10(1): 198-231. http://doi.org/fzdstq.

Irwin, S., Sanders, D.R. and Merrin, R.P. (2009). “Devil or Angel? The Role of Speculation in the Recent Commodity Price Boom (and Bust)”. *Journal of Agricultural and Applied Economics*, 41(2): 377-391.

Kurosaki, T. and Fafchamps, M. (2002). "Insurance Market Efficiency and Crop Choices in Pakistan". *Journal of Development Economics,* 67(2): 419-53. http://doi.org/cgwj7j.

Larson, D. and Plessman, F. (2002). "Do farmers choose to be inefficient? Evidence from Bicol Philippines". *Policy Research Working Paper,* 2787. The World Bank, Washington, D.C. http://doi.org/b5w9v9.

Liu, X., Filler, G., and Odening, M. (2013). Testing for speculative bubbles in agricultural commodity prices: A regime switching approach. *Agricultural Finance Review*, 73(1): 179-200.

Phillips, P.C.B. and Magdalinos, T. (2007) "Limit theory for moderate deviations from a unit root". *Journal of Econometrics*, 136(1): 115-130. http://doi.org/cv7bpq.

Phillips, P.C.B., Shi, S. and Yu, J. (2012). "Testing for multiple bubbles". *Cowles Foundation Discussion Paper,* 1843. Yale University.

Phillips, P.C.B., Wu, Y. and Yu, J. (2011). "Explosive behaviour in the 1990s NASQAD: When did exuberance escalate asset values?" *International Economic Review*, 52: 201-226.

Phillips, P.C.B. and Yu, J. (2011). "Dating the timeline of financial bubbles during the subprime crisis". *Quantitative Economics*, 2(3): 455-491. http://doi.org/d77th5.

Pindyck, R.S. and Rotemberg, J.J. (1990). "The excess co-movement of commodity prices". *The Economic Journal*, 100: 1173-1189. http://doi..org/d2hgdw.

Rapsomanikins, G. (2011). "Price transmission and volatility spillovers in food markets". In: Prakash, A. (Ed.): *Safeguarding food security in volatile global markets, Food and Agriculture*. Organization of the United Nations, Rome.

Robles, M., Torero, M. and Von Braun, J. (2009). "When Speculation Matters". *Issue Brief,* 57, International Food Policy Research Institute. Washington DC. Available at: http://www.ifpri.org/pubs/ib/ib57.asp. Last access: November, 2014.

Sanders, D.R. and Irwin, S.H. (2010). "A speculative bubble in commodity futures prices? Cross-sectional evidence". *Agricultural Economics*, 41(1): 25-32.

Sanders, D.R. and Irwin, S.H. (2011a). "New Evidence on the Impact of Index Funds in U.S. Grain Futures Markets". *Canadian Journal of Agricultural Economics*, 59(4): 519-32. http://doi.org/b93j6b.

Sanders, D.R. and Irwin, S.H. (2011b). "The Impact of Index Funds in Commodity Futures Markets: A Systems Approach". *Journal of Alternative Investments*, 14: 40-49.

Serra, T, Zilberman, D., Gil, J.M. and Goodwin, B.K. (2010). "Price Transmission in the US Ethanol Market". In Khanna, M., Scheffran, J., Zilberman, D. (Eds.): *Handbook of Bioenergy Economics and Policy Natural Resource Management and Policy*. *Natural Resource Management and Policy*, 33. Springer, New York: 55-72.

Tothova, M. (2011). "Main challenges in price volatility in agricultural commodity markets". In Piot-Lepetit, I. and M'Barek, R. (Eds.). *Methods to Analyse Agricultural Commodity Price Volatility*. Springer, New York: 13-29.

UNCTAD. (2011). *Price Formation in Financialized Commodity Markets: The Role of Information*. Study prepared by the secretariat of the United Nations Conference on Trade and Development.

Van Norden, S. and Schaller, H. (1999). "Speculative behaviour, regime switching, and stock market crashes". In Rothman, P. (Eds.): *Nonlinear Time Series Analysis of Economic and Financial Data*, Dordrecht Kluwer: 321-256.

Von Braun, J. and Torero, M. (2009). "Implementing physical and virtual food reserves to protect the poor and prevent market failure". *Policy Briefs,* 10. International Food Policy Research Institute (IFPRI).

Wright, B. (2010). "International Grain Reserves and Other Instruments to Address Volatility in Grain Markets". *Policy Research Working Paper*, 5028. The World Bank. http://doi.org/bdmj.

Appendix

Tables A.1, A.2 and A.3 show the critical values at 90, 95 and 99 % level, respectively. Tables show the critical value by lags (0 to 12) and number of observations (100 to 500).

TABLE A.1

Critical values at 90 % level by lags and number of observations

Number of lags	Number of observations								
	100	150	200	250	300	350	400	450	500
0	1.145	1.449	1.593	1.723	1.814	1.892	1.957	2.009	2.045
1	1.267	1.567	1.753	1.868	1.970	2.028	2.111	2.160	2.208
2	1.415	1.748	1.926	2.056	2.153	2.236	2.289	2.343	2.384
3	1.462	1.775	2.004	2.154	2.239	2.331	2.396	2.451	2.501
4	4.607	1.987	2.159	2.311	2.397	2.473	2.534	2.577	2.631
5	1.628	1.988	2.210	2.335	2.435	2.539	2.620	2.688	2.728
6	1.691	2.089	2.317	2.457	2.571	2.678	2.750	2.785	2.841
7	1.768	2.162	2.382	2.514	2.639	2.733	2.800	1.875	2.930
8	1.834	2.258	2.502	2.639	2.733	2.834	2.891	2.961	3.024
9	1.838	2.263	2.465	2.659	2.763	2.855	2.925	2.988	3.051
10	1.953	2.389	2.613	2.763	2.877	2.962	3.037	3.126	3.182
11	1.985	2.439	2.671	2.806	2.930	3.046	3.092	3.161	3.220
12	2.093	2.477	2.749	2.916	3.039	3.132	3.215	3.273	3.325

Source: Own calculations.

TABLE A.2

Critical values at 95 % level by lags and number of observations

Number of lags	Number of observations								
	100	150	200	250	300	350	400	450	500
0	1.455	1.709	1.863	1.992	2.061	2.140	2.203	2.266	2.308
1	1.589	1.836	2.039	2.163	2.251	2.310	2.374	2.423	2.458
2	1.780	2.061	2.209	2.347	2.426	2.520	2.567	2.618	2.662
3	1.783	2.131	2.331	2.474	2.566	2.649	2.715	2.759	2.789
4	2.015	2.335	2.496	2.605	2.695	2.765	2.836	2.873	2.923
5	2.000	2.334	2.517	2.659	2.759	2.852	2.923	2.974	3.003
6	2.083	2.484	2.664	2.806	2.896	2.992	3.037	3.097	3.138
7	2.168	2.492	2.735	2.881	2.985	3.058	3.109	3.157	3.185
8	2.280	2.645	2.874	2.990	3.061	3.144	3.212	3.260	3.317
9	2.235	2.659	2.869	3.007	3.127	3.218	3.305	3.359	3.418
10	2.350	2.761	2.970	3.127	3.239	3.311	3.378	3.438	3.490
11	2.418	2.821	3.008	3.122	3.250	3.349	3.424	3.476	3.514
12	2.452	2.870	3.103	3.259	3.358	3.445	3.564	3.601	3.654

Source: Own calculations.

TABLE A.3

Critical values at 99 % level by lags and number of observations

Number of lags	Number of observations								
	100	150	200	250	300	350	400	450	500
0	2.048	2.229	2.381	2.493	2.639	2.716	2.766	2.791	2.803
1	2.160	2.440	2.641	2.738	2.848	2.917	2.968	2.994	3.033
2	2.484	2.667	2.787	2.916	2.993	3.093	3.173	3.222	3.232
3	2.488	2.849	3.003	3.059	3.159	3.241	3.281	3.330	3.346
4	2.751	3.072	3.216	3.254	3.325	3.352	3.431	3.472	3.517
5	2.778	2.977	3.144	3.281	3.377	3.498	3.539	3.576	3.629
6	2.885	3.179	3.296	3.424	3.529	3.589	3.660	3.688	3.736
7	2.972	3.272	3.411	3.539	3.663	3.712	3.786	3.825	3.835
8	3.061	3.325	3.441	3.559	3.684	3.815	3.829	3.864	3.977
9	3.084	3.508	3.678	3.788	3.842	3.890	3.994	4.065	4.086
10	3.225	3.452	3.621	3.752	3.864	3.937	4.025	4.078	4.105
11	3.088	3.545	3.692	3.811	3.893	3.934	3.957	4.017	4.063
12	3.253	3.575	3.792	3.937	4.054	4.162	4.243	4.243	4.307

Source: Own calculations.