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Asset Pricing Bubbles in Agricultural Commodities

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ASSET PRICING BUBBLES IN AGRICULTURAL COMMODITIES

SAMUEL RIFFLE

43 Pages

Recent asset pricing bubble bursts in some markets beg the question of whether bubbles exist in others. Determining whether they exist has been investigated for years, with various approaches. This paper combines the Engle-Granger technique with a GSADF test to test for bubbles in corn and soybean futures prices. I attempt to find measures for the market fundamentals of the futures, employing PPIs and costs of production for each commodity. My findings provide some evidence for the existence of bubbles, though the results are not definitive. Overall, the findings imply a possibility for bubbles but also a possibility of true increases in the underlying value of agricultural commodities.

KEYWORDS: agricultural commodities; bubbles; GSADF; macroeconomics; market fundamentals; unit-root tests

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CHAPTER I: INTRODUCTION

The past 25 years have seen more than one asset pricing bubble burst. Around the turn of the century, the Dot Com bubble, caused by an overvaluing of stocks for recently emerging internet-based companies, burst. Years later, the housing market crash was caused, in part, by a bubble burst in housing prices. Since the time of the COVID-19 pandemic, talk about the possibility of bubbles in different stock market indices has become a hot topic (Gayed, 2024; Smith, 2024; Fox, 2024). Whether or not bubbles exist in financial markets is thus, an important question. Should they exist, steps could be taken to deflate the bubbles and avoid the consequences of a burst. These consequences can be as severe as the fallout of the Great Recession after the housing bubble burst around 2007-2008. On the other hand, if they do not exist, there are implications for quickly rising values of assets. That is, in the absence of a bubble, explosive behavior in the price of an asset can imply high levels of return. Therefore, awareness of the presence of bubbles is important both for regulators to avoid potential fallouts and for investors to allow optimal use of capital.

Research into the existence of bubbles has taken place for nearly 50 years. Two of the most influential early studies, Blanchard, 1979 and Blanchard and Watson, 1982, laid the foundation of rational bubbles. The former argued that speculative bubble behavior agrees with rational expectations, while the latter developed a more formal theory for rational bubble development. The crux of this theory is that given existing information, if the price of an asset has been consistently increasing, it is rational to believe that it will continue to increase, at least for some time. Therefore, it is rational to purchase the asset with the expectation of selling it for a higher price at a later date, thus generating a return.

From here the “greater fool” idea takes place where an investor buys the asset, knowing its price is growing beyond its true value, with the intent to sell it at a higher price to a “greater fool.” The “greater fool,” using the same rational behavior, buys the asset with the intent of selling it to an “even greater fool.” The result of this strategy being used by successive investors is an over-inflated price, or rational bubble, of the asset. As the price cannot realistically grow forever, eventually there is a final buyer of the asset who cannot find anyone to sell it to at a higher price. Thus, the bubble bursts, and the asset price returns to its true value. Those who own the asset during the burst see its price go below the price at which they bought it, suffering a loss rather than a return.

Following these studies, Diba and Grossman, 1988a and Diba and Grossman, 1988b explore a class of bubbles called explosive rational bubbles and an empirical method for testing their existence. Their approach involves applying the method introduced by Engle and Granger, 1987 to prices and fundamentals (measures of the true value of the asset). However, Evans, 1991 notes that this test and the class of bubbles introduced by Diba and Grossman, 1988a and Diba and Grossman, 1988b fail to account for a class of bubbles he calls periodically collapsing rational bubbles (PCRB). These two classes are discussed further in Chapter 2. Following these studies, much attention began to be given to the development of bubble detection methods.

Multiple bubble detection methods have been used developed and used (Johansen and Sornette, 2000; Liu, Filler, and Odening, 2013; Enders and Granger, 1998), but the majority of these methods involve a version of the test developed by Dickey and Fuller, 1981. The Engle-Granger method used by Diba and Grossman, 1988a uses the Dickey-Fuller test and later methods use it or its derivatives (e.g., the Augmented Dickey-Fuller (ADF) Test). For example, Taylor and Peel, 1998 develop a test for PCRB which expands upon the Diba and Grossman, 1988a method by accounting for both the skewness and kurtosis of the error terms. Further, Phillips, Wu, and Yu, 2011 develop a more rigorous form of the Dickey-Fuller test which uses a recursive approach and focuses on a right-tailed alternate hypothesis, called the supremum Augmented Dickey-Fuller (SADF) test. Phillips, Shi, and Yu, 2015 then expand on this test to develop the generalized supremum Augmented Dickey-Fuller (GSADF) test.

Several studies have used the GSADF test to test for bubbles. For example, Ozgur, Yilanci, and Ozbugday, 2021 use the GSADF to show evidence of bubbles in the prices of several metals. Similarly, Li et al., 2020 and Khan et al., 2021 use it to show evidence for bubbles in the prices of natural gas and crude oil, respectively. Looking specifically, at agricultural markets, Zhang et al., 2019 and Wang et al., 2022, among others (Li et al., 2017; Mao, Ren, and Loy, 2021), use the GSADF method to show evidence for bubbles in Chinese markets. However, despite all showing positive results, each of these studies examines explosive behavior in the prices only. That is, none of them incorporate market fundamentals into their analysis. Despite the power of the GSADF test, evidence for bubbles without considering fundamentals should be subject to question. As explosive behavior in the prices could be accounted for by explosive behavior in the fundamentals, explosiveness in prices is not, on its own, evidence of a bubble.

Other studies have attempted to account for market fundamentals while using less powerful estimation methods. For example, Liu, Filler, and Odening, 2013 uses a regime-switching approach to test for bubbles in commodity markets. The fundamental used in this study is the convenience yield for the futures contracts used as price data. The logic behind the convenience yield is that it is similar to the dividend yield in stocks. However, as the convenience yield is not directly observable, the authors calculate the convenience yield series using the futures price series. This approach creates endogeneity issues as comparing the price series to this convenience yield is just comparing the price series to a transformation of itself. Brooks, Prokopczuk, and Wu, 2015 also acknowledge this issue with convenience yields and instead use macroeconomic measures that have been shown to impact commodity prices. However, even this approach is not perfect. If these measures are shown to impact prices, they must be closely correlated with the prices. If they are correlated they likely grow at similar rates and thus will show no evidence for bubbles. Therefore, if they do not accurately capture the market fundamentals, this approach could potentially miss bubbles that do exist.

This study uses price indices and production costs to act as fundamentals for futures prices of corn and soybeans. Applying the GSADF test to the

Engle-Granger method, I show mixed evidence for rational bubbles in these commodity futures. My findings imply a potential need for policy intervention on both bubble deflation and production cost reduction. The rest of the study proceeds as follows: Chapter II provides the conceptual framework, Chapter III the empirical strategy, Chapter IV covers the data, Chapter V the results, and Chapter VI concludes.

CHAPTER II: CONCEPTUAL FRAMEWORK

Discounted-Dividend Model

To test for the existence of bubbles, one must first define what a bubble is. Put simply, a bubble is a difference in the price of an asset from its true, or fundamental, value. Put more formally, let P_t be the price of an asset in period t where,

$$P_t = \frac{E_t(P_{t+1} + D_{t+1} + M_{t+1})}{1+r} \tag{1}$$

given dividend D, unobserved aspects of the market M and the interest rate r. This equation defines the price of an asset as the conditionally expected sum of the price, dividend, and unobserved market aspects of the asset in the next period, discounted by the interest rate. Solving this recursively by substituting for P_{t+1} eventually yields,

$$P_t = \sum_{k=1}^{\infty} \frac{E_t(D_{t+k} + M_{t+k})}{(1+r)^k} \tag{2}$$

that is, the price in period t is equal to the present value of the conditionally expected sum of the dividend stream and unobserved market aspects. Equation (2) can be understood as the price being determined by the present value of the rationally expected future stream of cash flows that holding the asset will generate, as well as market forces unobserved by the researcher but observed by market participants (for example, expectations of taxation or other "at the moment" aspects), and the interest rate. The interest rate can be understood as the return on a risk-free asset. That is, r represents the alternative return that the asset in question must be greater than to be worth investing in.

Let F be the solution to the expected stream of cash flows and market aspects, called the market fundamentals. Thus, in the absence of a bubble,

$$P_t = F_t = \sum_{k=1}^{\infty} \frac{E_t(D_{t+k} + M_{t+k})}{(1+r)^k}$$

implying that the price of an asset in the current period is equal to its market fundamentals. However, a difference in the price and fundamentals implies the presence of a bubble term, B, as defined above. The form of the price equation would then be,

$$P_t = F_t + B_t \tag{3}$$

which implies that the price of an asset is equal to the present value of all future market aspects (fundamentals) and a bubble term. If $B_t = 0$, the price is equal to the standard discounted dividend model.

Diba-Grossman Bubble

As mentioned previously, several models for the behavior of bubbles have been proposed. The differences in models come down to the structure of B_t. Different assumptions about the behavior of bubbles lead to differing forms of the term. Perhaps the most influential form is developed by Diba and Grossman, 1988a. This model follows the same discounted-dividend approach and reaches equation (3). In this case, B_t is the solution to the expectational difference equation

$$E_t B_{t+1} - (1 + r)B_t = 0 \tag{4}$$

where all terms are equivalent to those given by the authors and identical to those above. Here, $B_t \neq 0$ implies the existence of a bubble term. Further, any B_t which is a solution to the previous equation satisfies

$$B_{t+1} - (1 + r)B_t = z_t \tag{5}$$

where z_t is a stochastic variable such that $E_{t-j} z_{t+1} = 0$ for all $j \geq 0$.

The essence of this model is that the bubble term is a non-stationary process given $r \geq 0$. The explosiveness of the price in the presence of a bubble is the result of this non-stationary process. In fact, the authors show that given the dividends are I(1), in the absence of a bubble, the prices are also I(1). Further, they use this to show that in the absence of a bubble, the prices and dividends are cointegrated. This then implies that testing for cointegration can detect the presence of this class of bubbles.

Diba and Grossman, 1988b develop additional characteristics of this class of bubble. Specifically, they show that explosive rational bubbles are exclusively nonnegative and that the unobserved market aspect is stationary. From here they show that they also can only begin in the inception period for the asset (i.e., the IPO for equities) and thus, if a bubble pops, it cannot restart again. Additionally, the existence of these bubbles indicates that equity is overvalued from the day it is available. However, Evans, 1991 argues that this model cannot account for a class of bubbles he calls periodically collapsing rational bubbles.

Evans Bubble

Evans, 1991 notes that the Diba and Grossman, 1988a and Diba and Grossman, 1988b model limits bubbles by restricting them to start only in the first period, be nonnegative, and not reform once they burst. To account for this he presents a class of rational bubbles that are nonnegative and periodically collapsing. The generating process of these bubbles is given by

$$\begin{aligned} B_{t+1} &= (1+r)B_t u_{t+1} && \text{if } B_t \leq \alpha \\ B_{t+1} &= [\delta + \pi^{-1}(1+r)\theta_{t+1} \times (B_t - (1+r)^{-1}\delta)]u_{t+1} && \text{if } B_t > \alpha \end{aligned} \tag{6}$$

where δ and α satisfy $0 < \delta < (1+r)\alpha$, u_{t+1} is a stochastic variable such that $E_t u_{t+1} = 1$, and θ_{t+1} is a Bernoulli process with probability π that $\theta_{t+1} = 1$. Here, δ, α, and π determine the frequencies, lifespans, and magnitudes of the bubbles. Specifically, α represents the threshold at which a bubble will switch from growing at rate $(1+r)$ to the explosive rate of $(1+r)\pi^{-1}$ and collapses with probability $1-\pi$, that is, when $\theta_{t+1} = 0$. Collapsed bubbles then fall to an average value of δ at which they begin growing at rate $(1+r)$ again and the cycle repeats. He further notes that these bubbles would go undetected by the tests of Diba and Grossman, 1988a since they do not cause an absolute divergence of the price and fundamentals over time.

Phillips, Wu, & Yu Bubble

The model for the bubble term developed in Phillips, Wu, and Yu, 2011 begins by taking the log-linear transformation of (1) and solving to reach a version of (3) following Campbell and Shiller, 1989. The result is the price–fundamentals–bubble term equation:

$$p_t = p_t^f + b_t \tag{7}$$

where

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

,

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

,

$$E_t(b_{t+1}) = \frac{1}{\rho} b_t = (1 + exp(\overline{d-p}))b_t$$

, and

$$\kappa = -log(\rho) - (1-\rho)log(\frac{1}{\rho} - 1)$$

for $p_t = log(P_t)$, $d_t = log(D_t)$, $\gamma = log(1+r)\rho = 1/(1 + exp(\overline{d-p}))$, with P_t, D_t, and r being identical to those in (1) and ignoring the unseen market aspects M_t in (1). The key takeaway from this approach is that the price of the asset, p_t is the sum of the market fundamentals term, p_t^f, and a bubble term, b_t as in other models. Further, p_t^f is still a process determined by the future cash flows generated by owning the asset, or dividends, d_t as before. The key difference in this model is that the bubble term grows at a rate determined by the price–dividend ratio, $d - p$, rather than the discount rate, r. To be more specific, b_t is generated by the process:

$$b_t = \frac{1}{\rho} b_{t-1} + \epsilon_{b,t} \equiv (1+g) b_{t-1} + \epsilon_{b,t} \tag{8}$$

where $E_{t-1}(\epsilon_{b,t}) = 0$, $g = 1/\rho - 1 = exp(\overline{d-p}) > 0$, and $e_{b,t}$ is a martingale process. In sum, the generating process for the bubble term is made up of an autoregressive process with a stochastic term. The rate of growth of the process is determined by the price-dividend ratio of the asset and is an explosive growth rate.

From here we see that in the absence of a bubble, or $b_t = 0$, the price will be solely determined by the market fundamentals, that is the dividend series. This then implies,

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

meaning, the price-dividend ratio is determined by the sum of all expected future differences in the dividend series, or the ratio is determined by the expected change in dividends. Thus, in this case, if the price and dividend series are integrated of the same order, they will share a cointegrating vector. However, if a bubble exists, or $b_t \neq 0$, the explosive behavior in the bubble-generating process will lead to explosive behavior in the price series but not the dividend series. Thus, the price and dividend will no longer be integrated of the same order and therefore, cannot be cointegrated.

CHAPTER III: EMPIRICAL STRATEGY

From the conceptual framework, we can see that a bubble exists when the price of an asset differs from its market fundamentals and, more specifically when the order of integration of the price is greater than that of the fundamentals. That is all to say that there is evidence of a bubble when the price and fundamentals are not cointegrated. However, PCRB may cause a lack of cointegration in one window of time but not in the sample as a whole. To test this empirically, I apply the GSADF test to the Engle-Granger method. However, before using this method, I first test for cointegration of the series.

Cointegration Tests

I begin by determining the order of integration of each price and fundamentals series. This is done by running an ADF on the level of each series and then successive differences of each series until it is stationary. For example, if the level of the price is not stationary, but the first difference is, then the price is $I(1)$. Table 1 reports the results of these tests. The primary takeaway of these tests is that each series is not stationary in levels but is stationary in first differences. This implies that each series is I(0). Therefore, I can test each price-fundamental pairing for cointegration.

To test for cointegration, I run the test developed by Johansen, 1991 on the price and each measure of the fundamentals. Tables 2 and 3 present the results from the Johansen tests. These tests should yield results similar to those from using the exact checks used by Diba and Grossman, 1988a. That is, applying the Engle-Granger method with only an ADF test should show whether the price and fundamentals are cointegrated across the entire sample period. The Johansen tests show the same results. The lack of a cointegrating equation for the price and fundamentals shows the two diverging over time, implying a bubble in the entire sample. According to Diba and Grossman, 1988a the presence of a cointegrating equation shows that they do not diverge and is evidence against the presence of a bubble. However, as previously mentioned, these test fails to detect PCRBs as explained by Evans (1991). That is they do not capture subperiods in the sample where a bubble exists and then collapses as they look at the relationship across the entire period.

In this case, the Johansen tests indicate that corn futures prices are not cointegrated with either PPI used but are cointegrated with the production cost of corn per bushel. However, soybean futures prices are cointegrated with the PPI for agricultural commodities and the production cost, but are not cointegrated with the PPI for all commodities. As stated before, this is not definitive evidence for or against the presence of bubbles. Further, a lack of a cointegrating equation between the prices and the PPIs may speak more to the PPIs' weaknesses as measures of fundamentals than to the presence of a bubble. In contrast, the cointegration between the prices and the production cost does not rule out the PCRBs. Thus, to detect the presence of these bubbles, a more sophisticated test must be used.

GSADF Test

The main econometric method of this study is that developed by Phillips, Shi, and Yu, 2014 and Phillips, Shi, and Yu, 2015. This is a method of detecting bubbles that uses a right-tailed recursive Augmented Dickey-Fuller test. Following the bubble model in Phillips, Wu, and Yu, 2011, they continue by introducing an ADF test with an alternative hypothesis of an explosive root, that is $H1 : g > 1$, for g in equation (8) given by the specification:

$$x_t = \mu_x + \delta x_{t-1} + \sum_{j=1}^{J} \Phi_j \Delta x_{t-j} + \epsilon_{x,t} \tag{9}$$

for time series x_t and lag parameter J where $\epsilon_{x,t} \sim NID(0, \sigma_x^2)$ and NID indicates independent normal distribution. The authors indicate that J is determined by significance criteria as prescribed by Campbell and Perron, 1991.[1] This test is a standard ADF test that estimates the value of the autoregressive coefficient, δ, where δ is a stand-in for g, accounting for autocorrelation in x_t, with a null hypothesis of $H0 : \delta = 1$. The key difference with this test is that a standard ADF test has an alternate hypothesis of $H1 : \delta < 1$, whereas this version uses an alternate hypothesis of $H1 : \delta > 1$. This difference in $H1$ is what makes this test a

[1] In this study, a fixed lag length was used due to technical limitations. The availability and method by which I had access to statistical software prevented me from allowing the time needed to use an optimal number of lags.

right-tailed test.

For this method, equation (9) is then regressed recursively. That means that it is estimated in multiple regressions beginning with some subset of the data, τ_0, and increases by one observation in each successive estimation. τ_0 is defined as $\tau_0 = [nr_0]$ where n is the sample size, r_0 is some initial fractional multiplier, and [ ] is the greatest integer function. Thus, in successive estimations, τ_0 becomes $\tau = [nr]$ where r is a larger fractional multiplier than r_0 due to the addition of more observations. From here, the authors present that the t-statistic from the ADF test, ADF_r, has the following implication:

$$ADF_r \implies \frac{\int_0^r \tilde{W} dW}{(\int_0^r \tilde{W}^2)^{1/2}}$$

where W is standard Brownian motion and $\tilde{W}$ is demeaned Brownian motion. Put more simply, this says that the ADF statistic implies a stochastic process that develops with r. Further, this implies:

$$\sup_{r \in [r_0, 1]} ADF_r \implies \sup_{r \in [r_0, 1]} \frac{\int_0^r \tilde{W} dW}{(\int_0^r \tilde{W}^2)^{1/2}}$$

which means that a supremum of the ADF statistic implies a supremum of the stochastic process. They further note that this implication allows for the right-tailed approach but does not provide a way to date-stamp bubble periods.

To date stamp, estimates of the starting and ending dates of bubble periods are found. The estimate for the starting date is the observation that yields an r such that the greatest lower bound of the estimated ADF statistics is greater than the right-tailed critical value. That is, it is the observation in which the ADF statistic first becomes significant. Similarly, the estimate for the ending date is the observation that yields an r such that the greatest lower bound of the ADF statistics becomes less than the right-tailed critical value. Again, put more simply, it is the observation in which the ADF statistic becomes insignificant again. The authors state this formally as:

$$\hat{r_e} = \inf_{s \geq r_0} \{s : ADF_s > cv^{adf}_{\beta_n}(s)\}, \hat{r_f} = \inf_{s \geq \hat{r_e}} \{s : ADF_s < cv^{adf}_{\beta_n}(s)\} \tag{10}$$

where r_e is the observation where a bubble begins, r_f is the observation where the bubble ends, $cv^{adf}_{\beta_n}(s)$ is the right-tailed critical value, and β_n is the level of significance. They further note that as the sample size, n, goes to infinity, the level of significance must go to 0 and therefore, the critical value must go to infinity. They then prescribe setting the critical value as $cv^{adf}_{\beta_n}(s) = log(log(ns))/100$ when using the method. Thus, if the ADF statistics are significant, an estimate for the autoregressive root, δ can be found. They present a process for this estimation which builds upon Phillips and Magdalinos, 2007a and Phillips and Magdalinos, 2007b, but as finding an exact estimate for δ is beyond the scope of this study, I forgo reviewing this procedure.

Phillips, Shi, and Yu, 2015 take this procedure and adjust it to use a rolling window, as opposed to a fixed window. This simply means that the subsample used in each regression moves forward and adjusts in size each time rather than merely adding one observation at a time. They note that this improves on the supremum ADF (SADF) approach from Phillips, Shi, and Yu, 2014 as it is better suited for detecting multiple bubble periods than the SADF method. Thus, they define the GSADF statistic to be the largest ADF statistic under this new window procedure, given by:

$$GSADF(r_0) = \sup_{r_2 \in [r_0,1], r_1 \in [0, r_2 - r_0]} \{ADF_{r_1}^{r_2}\} \tag{11}$$

where r_2, r_1, and r_0 represent the new window parameters. They further propose and prove several theorems for this procedure. However, I will forgo any explanation of those theorems. The primary takeaway is that the GSADF procedure is powerful for detecting multiple bubbles in a sample period for several different classes of bubbles. Further, it is also able to date stamp those bubble periods.

For practical application of this procedure, I use the Eviews add-in developed by Caspi, 2017. I select the rolling window size to 6 for the base tests and 36 for the robustness checks[2] The sequence of critical values was estimated via Monte Carlo simulations. The number of simulations used for each test is 500[3].

Thus the procedure used in this study is the Engle-Granger method with a GSADF test. For each price-fundamental pair, I regress the price on the

[2]The window size of 6 was selected based on recommendations in Phillips, Shi, and Yu, 2015. In their application, they select a window that uses approximately 2 percent of the sample. For my sample, a window size of 6 covers this 2 percent margin. However, due to technical limitations, I used a window size of 36 for the robustness checks. This significantly reduces the power of the test in that case.

[3]The authors recommend a much higher number of simulations, but again due to technical limits, I had to reduce the number from 1000 to 500.

fundamental and a constant. Such a regression takes the form,

$$P_t = a + F_t + e_t$$

where P is the price, F is the fundamental, a is the constant, and e is the residual term. From Diba and Grossman, 1988a, we see that the residuals should capture any bubbles that exist. This applies both to the sample as a whole and to subsamples. The residuals capture the difference between the price and fundamentals. Thus, if there are no bubbles, the price and fundamentals should be cointegrated and the residuals should then be white noise. If a bubble is present, the explosive difference between the price and fundamentals will appear in the residuals. Thus, nonstationary residuals are evidence for the existence of bubbles. However, Diba and Grossman, 1988a use a standard ADF test that looks at the stationarity of the series as a whole. Again, as Evans, 1991 points out, this test cannot detect PCRB. However, the recursive nature of the GSADF test allows for the detection of PCRB and the Diba-Grossman class of bubbles.

CHAPTER IV: DATA

Prices

Data for the prices of commodities are taken from Investing.com. Series for US Corn (ZC) and US Soybean (ZS) monthly futures prices are used. The units for US agricultural futures are US cents per bushel. For cleaner data, both price series were converted to US dollars per bushel. This transformation has no impact on the bubble tests but does help with the consistency of units across different series. The selection of corn and soybeans as the commodities of focus is due to a few reasons. First, their position as the most produced agricultural commodities in the US according to the US Department of Agriculture[4]. Second, as well as being highly produced commodities, they are also highly traded commodities. This raises the susceptibility of these commodities to experience bubbles. Third, these two commodities are used in several sectors. While portions of the corn and soybean crop are used for food items, other portions are used for animal feed, ethanol, and biodiesel production, to name a few. Due to these factors, the presence of bubbles in corn or soybean prices could lead to bubbles, or at least price explosiveness, in products that use them as primary inputs.

[4]This information, as well as a chart of the most produced commodities, can be found on the USDA website at: https://www.ers.usda.gov/data-products/chart-gallery/gallery/chart-detail/?chartId=76955

The use of futures prices over spot prices is for a few reasons. First, data for futures prices are significantly easier to obtain than for spot prices. Further, as futures prices are standardized across regions, they are a more reliable measure of the "overall" prices of the commodities, whereas spot prices may vary by location. However, this is not a point of concern as what little spot price data are obtainable move almost completely with the futures prices data (Baldi, Peri, and Vandone, 2011).

Market Fundamentals

Perhaps the most contentious aspect of testing for bubbles in agricultural commodities is the identity of market fundamentals for the commodities. In the case of equities, either dividends or earnings per share are used as market fundamentals. For real estate, rent revenues are used. From these, it can be understood that the market fundamentals are essentially captured by any cash flows generated by owning the asset. This creates a problem not just for agricultural commodities, but all commodities. Owning a commodity, or a futures contract for a commodity, does not yield cash flows from owning it. The only cash flows are realized when the commodity (contract) is sold (sold or settled). The parallel to this with equities would be the cash received from selling the stock rather than from dividends. Thus, as discussed previously, each study on agricultural commodity bubbles has used only attempts to proxy for fundamentals, if they are considered at all.

In this study, several proxies for fundamentals were considered with a few ultimately being selected. I will review the considered options briefly. In an attempt to follow the same reasoning as using earnings per share with equities, net earnings per bushel were considered as a proxy. However, this runs into an endogeneity issue as the net earnings are dependent on the spot price received by farmers. Earlier I mentioned that spot prices and futures prices move together almost identically, therefore, net earnings derived from either spot or futures prices too would be nearly identical. As such, regressing the futures prices on a variable derived from the futures prices would give unreliable results, much the same issue with the convenience yield used in Brooks, Prokopczuk, and Wu, 2015. Ultimately, net earnings per bushel were not used.

Another option for market fundamentals would be to use the spot prices. At first appearance, spot price may seem to be immune from the financial market behavior which leads to bubbles. However, as setters for spot prices have access to all the same information as setters for futures prices, any significant difference in the prices would be caused by financial market speculation and trading. However, Etienne, Irwin, and Garcia, 2017, Stoll and Whaley, 2010, Irwin and Sanders, 2011all show evidence against the introduction of financial markets having any significant impact on prices.

Other options for a fundamental proxy are products that use the commodities of choice as major inputs. For corn and soybeans, the most likely candidates are ethanol and diesel fuel. The thinking behind these options was that since these are the primary use of corn and soybean crops, the underlying value of the commodities would be in their use as inputs. However, the primary issue with using these products is that any potential bubbles in the commodity prices would be seen in the product prices. Thus, explosive behavior in corn or soybeans would be matched by equally explosive behavior in ethanol or diesel and would potentially hide the existence of bubbles in the tests. For this reason, these two were not used as proxies.

The first potential proxy that was eventually used is the producer price index (PPI). The PPI is an index for the prices received by producers when selling their products. For example, there is a PPI specifically for corn. This PPI is an index for the typical revenue gained from farmers selling corn. This can be thought of as an index measuring the price of goods before the involvement of a "middle-man." However, the PPI specifically for either commodity was not used. This is because when focused on a single commodity, the PPI is essentially capturing an index of the spot prices for that commodity. This runs into the same issue as previously discussed concerning the use of spot prices. Instead, the PPI for all commodities and the PPI for all agricultural commodities were used. By using these, the prices of corn and soybeans are compared to prices of similar assets. Broadly, they are compared to all commodities, and more specifically, other agricultural commodities. Thus, it is plausible that an index of a comparable class of assets should move similarly to the market fundamentals of either commodity, as it is not likely that all commodities would experience a bubble at the same time.[5]

[5] A similar issue to using the specific PPI for either commodity could arise in the chosen PPIs if corn or soybeans had a large weight in the index. However, https://www.bls.gov/ppi/tables/ provides links to the makeup of the PPIs. Corn

A similar line of reasoning is used by Waters, 2019 who uses the price of gold as a proxy for the fundamentals of Bitcoin due to its role as a substitute store of value. Data for the PPIs were taken from the St. Louis Federal Reserve (FRED) database. The data that make up the PPI are collected by the Bureau of Labor Statistics.

The other potential proxy to be selected was the cost of production per bushel for each commodity. Since cash flows are not available for commodities, another possible way to value them is by examining input costs. Assuming agriculture is a perfectly competitive market, farmers will produce where average total cost equals average total revenue. Further, farmers must decide, at the time of planting, how much to produce. Therefore, it is plausible that they will choose to plant such an amount so that costs and revenues are equal at that time. Further assuming that planting does not occur during a bubble, this implies that the average cost of production for the commodity will be about the same as the average revenue, or true value since there is no bubble. If either of these assumptions fails, production costs may not be appropriate proxies for fundamentals. However, these assumptions are plausible, and in the absence of a better alternative, I opt to use production costs as a proxy.

The data for production costs were provided by the US Department of Agriculture Economic Research Service (ERS). The ERS provides different data sets for agricultural markets. In particular, they provide data sets for both current and historical costs and returns of various agricultural commodities. Datasets for corn and soybeans were used and the current and historical datasets were

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and soybeans have very small weights as specific commodities and do not contribute a large enough portion to the PPI to cause endogeneity issues.

appended. The series used in the bubble tests are the total cost per bushel for each commodity yearly, disaggregated into monthly series. Costs included in the total cost include both accounting costs (i.e., water, seed, labor, fertilizer) and economic costs (i.e., the opportunity cost of the land). Costs were provided in units of USD/acre. Using data provided by the ERS for the yield, in bushels/acre, for each commodity, the total cost series were converted to total cost per bushel. All series are monthly and cover the period 1999M01 to 2022M12[6]

Changing Interest Rates

A common pitfall of bubble models is the assumption of an unchanging interest rate (Diba and Grossman, 1988a; Evans, 1991). As a robustness test, I account for a changing interest rate by creating a capital-adjusted price/fundamental ratio (CAPE) in the vein of Shiller, 2018. To create this I made a ratio series of the price of each commodity and the PPI for all commodities. I then discounted this series by an interest rate series. This interest rate series is calculated from the average secondhand market discount rates of US Treasury Bills (T-bills) for all maturity lengths. This was done since US Treasuries are a go-to example of a risk-free interest rate or the rate of return that an investment would need to exceed to be worth investing in. Further, since agricultural commodities are short-term and perishable (as opposed to other commodities like metals),

[6] A longer sample period was originally considered. However, due to technical limitations, the number of observations was cut back. The final number for total observations was 276.

T-bills are a more suitable substitute than Treasury Bonds. The data for the T-bill discount rates were taken from FRED as monthly series. Altogether, this forms an approximate CAPE series for each commodity.

CHAPTER V: RESULTS

Table 4 provides results from GSADF tests for corn. The results show that there is no significant explosive behavior when using either PPI as a fundamental measure in the sample as a whole. However, when the cost of production of corn per bushel is used, there is evidence for explosive behavior with the GSADF statistic being significant at the 95 percent level. Similarly, accounting for a changing interest rate with the test on the CAPE series for corn having significant explosive behavior at the 90 percent level. That is, there is evidence for the Diba-Grossman class of bubbles in corn prices when the cost of production is used as a fundamental but not when either PPI is used. Further, there is also evidence for this class of bubble when a changing interest rate is accounted for.

It is important to note that for a significant portion of the sample, the interest rate was close to 0 due to quantitative easing done by the Federal Reserve. Thus, for this period, there should be no difference between tests that account for the interest rate and tests that do. Therefore, the significance of the test statistic for the CAPE series may speak more to an error in its construction than to the presence of bubbles.

Table 5 provides results for GSADF tests on soybeans. The same case for corn can be said about soybeans. Neither PPI fundamental shows evidence for the existence of Diba-Grossman class bubbles, while the cost per bushel to produce soybeans and the CAPE series do show this evidence. The tests on the PPIs are not statistically significant whereas the cost per bushel is significant at the 95 percent level and the CAPE at the 99 percent level. As before, the significance of the latter results may speak more to errors rather than the presence of bubbles. However, it is also possible that the lack of evidence for the PPIs speaks more to them being poor measures of market fundamentals than to a lack of bubbles.

To determine the existence of PCRBs, the date stamping procedure of the GSADF method was used. Figures 1 and 2 give the graphs for bubble dating from the GSADF tests. Each graph plots the corresponding residuals series, the sequence of estimated 95 percent critical values, and the backward sequence of GSADF statistics. Each graph corresponds to a different measure of the fundamentals. These graphs show whether or not there is explosive behavior for each fundamental. The first three graphs in each figure represent the residuals from the three fundamental regressions, while the fourth represents the CAPE regressions.

In every case, there were observations with t-statistics exceeding the critical value sequence. This is not inherent evidence of a bubble. Phillips, Shi, and Yu, 2015 suggest that bubble periods with lengths smaller than $ln(n)$ should not be counted as sufficient evidence. For this sample, $ln(n) \approx 6$ is the cutoff. Most of the explosive periods last for fewer than 6 observations. However, there are a few that meet or exceed it. For corn, the only sufficiently large period is from 2007M12-2008M05, for a total of 6 months, in the robustness check. For soy, the test with the cost of production as the fundamental has explosiveness from 2020M12-2021M05, for a total of 6 months. Then, the robustness check contains one marginal period from 2009M03-2009M07 for a total of 5 months, and two sure periods of 2007M12-2008M06 and 2020M08-2021M05, for a total of 7 and 10 months respectively. Despite none of the PPI tests showing sufficient periods of explosiveness, the cases that do have sufficient periods see them all line up at the same points in time. That is, they almost all occur in late 2007 to early 2008 and late 2020 to early 2021. The concurrence of these periods strengthens them as evidence for bubbles. Further, these periods also line up with times of financial upheaval, those being the housing market crash around 2007-2008 and the COVID-19 pandemic in 2020.

Overall, there is some evidence for the existence of Diba-Grossman class bubbles in both corn and soybeans. However, this evidence does not hold across every measure of the fundamentals. Further, there is minimal evidence for PCRBs in corn and fairly strong evidence for PCRBs in soybeans.

CHAPTER VI: CONCLUSION

Whether bubbles exist in agricultural commodity futures prices is an important question. Yet, despite much research into this question, it has not been sufficiently answered. The primary issue with these markets is a lack of an obvious measure for the market fundamentals of these assets. As such, studies into this must establish a sufficient measure for fundamentals and use sufficiently powerful tests to detect bubbles. Using PPIs and costs of production as fundamentals for corn and soybean futures prices, I show weak to moderate evidence for the existence of bubbles.

My results stand out as I combine the Engle-Granger technique with a GSADF test to detect the bubbles, whereas studies generally opt for one or the other. Further, I attempt to use accurate measures for fundamentals that avoid endogeneity issues. Results for corn shows little to no evidence for bubbles, while those for soybeans show some. Robustness checks, which account for a changing interest rate, support the existence of bubbles. The greatest takeaway is that my results give strong evidence against the constant interest rate assumption made in many bubble models. Of the five PCRBs detected, four of them were detected when accounting for a changing interest rate. Overall, the results may have implications for both policymakers and investors. Despite weakness of the results, if they are interpreted as establishing the existence of bubbles, this helps policymakers better able to take steps to deflate them. If not, they help investors better allocate available capital by implying high returns from exploding fundamental values.

REFERENCES

Baldi, Lucia, MassimoM Peri, and Daniela Vandone (2011). "Spot and Futures Prices of Agricultural Commodities: Fundamentals and Speculation". In: *Proceedings in Food System Dynamics*, pp. 110–125.

Blanchard, Olivier J and Mark W Watson (1982). *Bubbles, rational expectations and financial markets*.

Blanchard, Olivier Jean (1979). "Speculative bubbles, crashes and rational expectations". In: *Economics letters* 3.4, pp. 387–389.

Brooks, Chris, Marcel Prokopczuk, and Yingying Wu (2015). "Booms and busts in commodity markets: bubbles or fundamentals?" In: *Journal of Futures Markets* 35.10, pp. 916–938.

Campbell, John Y and Pierre Perron (1991). "Pitfalls and opportunities: what macroeconomists should know about unit roots". In: *NBER macroeconomics annual* 6, pp. 141–201.

Campbell, John Y and Robert J Shiller (1989). "The dividend ratio model and small sample bias: a Monte Carlo study". In: *Economics letters* 29.4, pp. 325–331.

Caspi, Itamar (2017). "Rtadf: Testing for bubbles with EViews". In: *Journal of Statistical Software* 81, pp. 1–16.

Diba, Behzad T and Herschel I Grossman (1988a). "Explosive rational bubbles in stock prices?" In: *The American Economic Review* 78.3, pp. 520–530.

Diba, Behzad T and Herschel I Grossman (1988b). “The theory of rational bubbles in stock prices”. In: *The Economic Journal* 98.392, pp. 746–754.

Dickey, David A and Wayne A Fuller (1981). “Likelihood ratio statistics for autoregressive time series with a unit root”. In: *Econometrica: journal of the Econometric Society*, pp. 1057–1072.

Enders, Walter and Clive William John Granger (1998). “Unit-root tests and asymmetric adjustment with an example using the term structure of interest rates”. In: *Journal of Business & Economic Statistics* 16.3, pp. 304–311.

Engle, Robert F and Clive WJ Granger (1987). “Co-integration and error correction: representation, estimation, and testing”. In: *Econometrica: journal of the Econometric Society*, pp. 251–276.

Etienne, Xiaoli L, Scott H Irwin, and Philip Garcia (2017). “New evidence that index traders did not drive bubbles in grain futures markets”. In: *Journal of Agricultural and Resource Economics*, pp. 45–67.

Evans, George W (1991). “Pitfalls in testing for explosive bubbles in asset prices”. In: *The American Economic Review* 81.4, pp. 922–930.

Fox, Matthew (2024). *Stocks are in a bubble that will keep inflating until 2025 and push the market 30% higher, research firm says.* `https://finance.yahoo.com/news/stocks-bubble-keep-inflating-until-233122429.html`.

Gayed, Michael (2024). *Are We in a Stock Market Bubble?* `https://www.nasdaq.com/articles/are-we-in-a-stock-market-bubble`.

Irwin, Scott H and Dwight R Sanders (2011). “Index funds, financialization, and commodity futures markets”. In: *Applied Economic Perspectives and Policy* 33.1, pp. 1–31.

Johansen, Anders and Didier Sornette (2000). “Evaluation of the quantitative prediction of a trend reversal on the Japanese stock market in 1999”. In: *International Journal of Modern Physics C* 11.02, pp. 359–364.

Johansen, Søren (1991). “Estimation and hypothesis testing of cointegration vectors in Gaussian vector autoregressive models”. In: *Econometrica: journal of the Econometric Society*, pp. 1551–1580.

Khan, Khalid et al. (2021). “Do crude oil price bubbles occur?” In: *Resources Policy* 71, p. 101936.

Li, Jian et al. (2017). “Commodity price bubbles and macroeconomics: evidence from the Chinese agricultural markets”. In: *Agricultural economics* 48.6, pp. 755–768.

Li, Yan et al. (2020). “Identifying price bubbles in the US, European and Asian natural gas market: Evidence from a GSADF test approach”. In: *Energy Economics* 87, p. 104740.

Liu, Xiaoliang, Guenther Filler, and Martin Odening (2013). “Testing for speculative bubbles in agricultural commodity prices: a regime switching approach”. In: *Agricultural Finance Review* 73.1, pp. 179–200.

Mao, Qianqian, Yanjun Ren, and Jens-Peter Loy (2021). “Price bubbles in agricultural commodity markets and contributing factors: evidence for corn and soybeans in China”. In: *China Agricultural Economic Review* 13.1, pp. 22–53.

Ozgur, Onder, Veli Yilanci, and Fatih Cemil Ozbugday (2021). “Detecting speculative bubbles in metal prices: Evidence from GSADF test and machine learning approaches”. In: *Resources Policy* 74, p. 102306.

Phillips, Peter CB and Tassos Magdalinos (2007a). “Limit theory for moderate deviations from a unit root”. In: *Journal of Econometrics* 136.1, pp. 115–130.

Phillips, Peter C.B. and Tassos Magdalinos (2007b). “Limit Theory for Moderate Deviations From a Unit Root Under Weak Dependence”. In: *The Refinement of Econometric Estimation and Test Procedures: Finite Sample and Asymptotic Analysis*. Ed. by Garry D. A. Phillips and EliasEditors Tzavalis. Cambridge University Press, 123–162.

Phillips, Peter CB, Shuping Shi, and Jun Yu (2014). “Specification sensitivity in right-tailed unit root testing for explosive behaviour”. In: *Oxford Bulletin of Economics and Statistics* 76.3, pp. 315–333.

— (2015). “Testing for multiple bubbles: Historical episodes of exuberance and collapse in the S&P 500”. In: *International economic review* 56.4, pp. 1043–1078.

Phillips, Peter CB, Yangru Wu, and Jun Yu (2011). “Explosive behavior in the 1990s Nasdaq: When did exuberance escalate asset values?” In: *International economic review* 52.1, pp. 201–226.

Shiller, Robert (2018). *Online data - Robert Shiller*. `http://www.econ.yale.edu/~shiller/data.htm`.

Smith, Elliot (2024). *Stock market bubble? Analysts explain why they're not worried*. https://www.cnbc.com/2024/03/07/stock-market-bubble-analysts-explain-why-theyre-not-worried.html.

Stoll, Hans R and Robert Whaley (2010). "Commodity index investing and commodity futures prices". In: *Journal of Applied Finance (Formerly Financial Practice and Education)* 20.1.

Taylor, Mark P and David A Peel (1998). "Periodically collapsing stock price bubbles: a robust test". In: *Economics Letters* 61.2, pp. 221–228.

Wang, Jiayue et al. (2022). "Study on Price Bubbles of China's Agricultural Commodity against the Background of Big Data". In: *Electronics* 11.24, p. 4067.

Waters, George A (2019). "Bubbles and rationality in bitcoin". In: *Economic Notes: Review of Banking, Finance and Monetary Economics* 48.2, e12133.

Zhang, Xi-Xi et al. (2019). "Bubbles in agricultural commodity markets of China". In: *Complexity* 2019, pp. 1–7.

Table 1: Unit Root Tests

Series	Level		First Difference	
	Test stat	p-val	Test stat	p-val
Corn	-2.249	0.190	-10.601	0.000
Soybeans	-2.223	0.198	-17.307	0.000
PPI All	-0.779	0.823	-10.337	0.000
PPI Ag.	-1.419	0.5731	-14.424	0.000
Corn cost per bu	-1.067	0.729	-16.610	0.000
Soy cost per bu	-0.384	0.909	-16.942	0.000

Table 1 gives results from Augmented Dickey-Fuller tests on the prices of corn and soybean futures in USD and different proxies for market fundamentals. The proxies are the PPI for all commodities, the PPI for agricultural commodities only, and the cost of production for both corn and soybeans per bushel.

Table 2: Johansen Cointegration Test–Corn

Fundamental		Trace Test			Eigenvalue Test		
	No. of CEs	Trace Stat	Crit Val	Prob	Eigen Stat	Crit Val	Prob
PPI All	None	9.405	15.495	0.329	9.006	14.265	0.286
	At most 1	0.399	3.841	0.528	0.399	3.841	0.528
PPI Ag.	None	13.948	15.495	0.0844	12.044	14.265	0.109
	At most 1	1.904	3.841	0.168	1.904	3.841	0.168
Cost per bu	None	22.570	15.495	0.004	21.436	14.265	0.003
	At most 1	1.134	3.841	0.287	1.134	3.841	0.287

Table 2 gives results from Johansen cointegration tests on the price of corn futures in USD and different proxies for market fundamentals. The three proxies are the PPI for all commodities, the PPI for agricultural commodities only, and the cost of production for corn per bushel. CE stands for cointegrating equation and the critical values are at the 0.05 level.

Table 3: Johansen Cointegration Test–Soybeans

Fundamental		Trace Test			Eigenvalue Test		
	No. of CEs	Trace Stat	Crit Val	Prob	Eigen Stat	Crit Val	Prob
PPI All	None	10.393	15.495	0.252	9.735	14.265	0.230
	At most 1	0.6658	3.841	0.417	0.658	3.841	0.417
PPI Ag.	None	18.232	15.495	0.019	16.077	14.265	0.026
	At most 1	2.156	3.841	0.142	2.156	3.841	0.142
Cost per bu	None	17.734	15.495	0.023	17.27	14.265	0.016
	At most 1	0.463	3.841	0.496	0.463	3.841	0.496

Table 3 gives results from Johansen cointegration tests on the price of soybean futures in USD and different proxies for market fundamentals. The three proxies are the PPI for all commodities, the PPI for agricultural commodities only, and the cost of production for soybeans per bushel. CE stands for cointegrating equation and the critical values are at the 0.05 level.

Table 4: GSADF Test–Corn

Fundamental	t-statistic	0.10 Critical Value	0.05 Critical Value	0.01 Critical Value	Prob
PPI All	2.375	2.450	2.704	3.545	0.114
PPI Ag	1.795	2.450	2.704	3.545	0.330
Cost per bu	2.195	1.846	2.081	2.555	0.028
CAPE	1.992	1.916	2.137	2.859	0.086

Table 4 gives results from GSADF tests on the price of corn futures in USD and different proxies for market fundamentals. The three proxies are the PPI for all commodities, the PPI for agricultural commodities only, and the cost of production for corn per bushel. Row four gives results for a GSADF test on a capital-adjusted price/fundamental ratio created using the future price of corn, the PPI for all commodities, and the average secondhand market discount rate of US Treasury Bills.

Table 5: GSADF Test–Soybeans

Fundamental	t-statistic	0.10 Critical Value	0.05 Critical Value	0.01 Critical Value	Prob
PPI All	3.526	5.661	7.683	11.812	0.366
PPI Ag	3.336	5.661	7.683	11.812	0.406
Cost per bu	2.100	1.887	2.081	2.468	0.040
CAPE	5.974	1.829	2.087	2.679	0.000

Table 5 gives results from GSADF tests on the price of soybean futures in USD and different proxies for market fundamentals. The three proxies are the PPI for all commodities, the PPI for agricultural commodities only, and the cost of production for soybeans per bushel. Row four gives results for a GSADF test on a capital-adjusted price/fundamental ratio created using the future price of soybeans, the PPI for all commodities, and the average secondhand market discount rate of US Treasury Bills.

Figure 1: GSADF Test Graphs–Corn

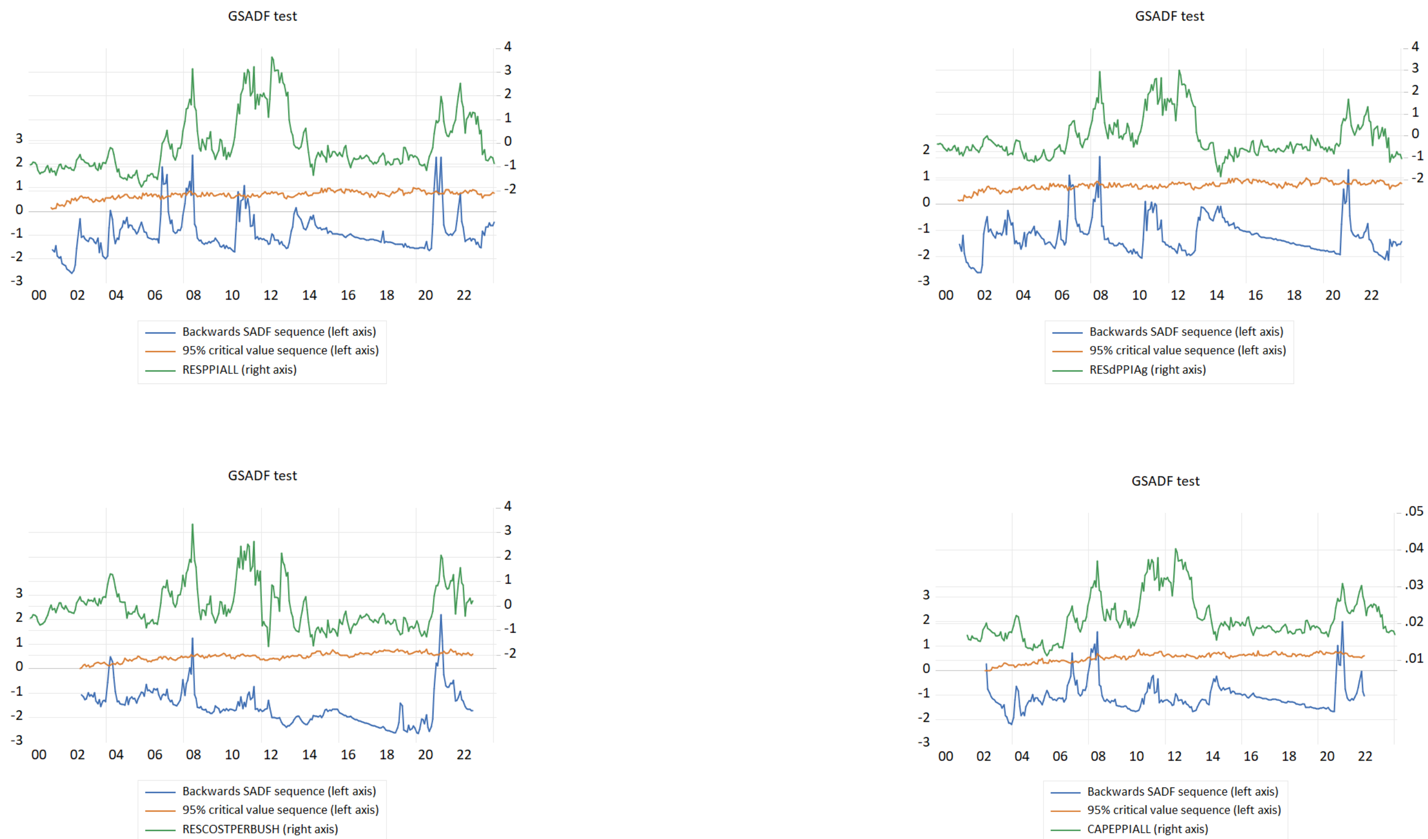

Figure 1 depicts graphs of the results for a GSADF test run on the Engle-Granger method residuals for prices and market fundamentals of corn. Each graph corresponds to a fundamental. Going clockwise from the top left, the fundamentals are the PPI for all commodities, the PPI for agricultural commodities, a capital-adjusted price/fundamentals ratio, and the production cost of soybeans per bushel. Periods where the blue line crosses the orange line represent bubble periods.

Figure 2: GSADF Test Graphs–Soybeans

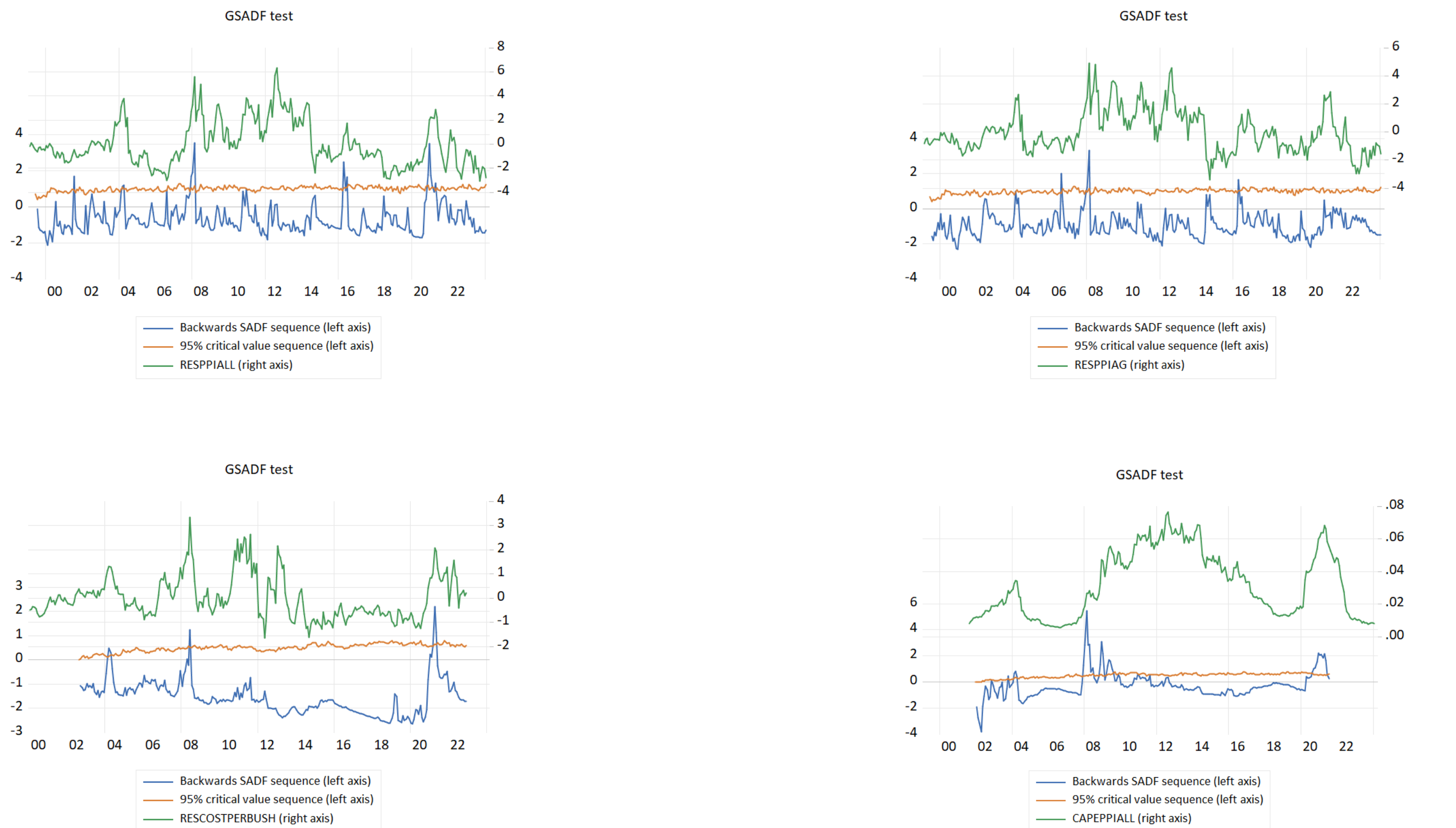

Figure 2 depicts graphs of the results for a GSADF test run on the Engle-Granger method residuals for prices and market fundamentals of soybeans. Each graph corresponds to a fundamental. Going clockwise from the top left, the fundamentals are the PPI for all commodities,the PPI for agricultural commodities, a capital-adjusted price/fundamentals ratio, and the production cost of soybeans per bushel. Periods where the blue line crosses the orange line represent bubble periods.