Commodity Price Bubbles and Macroeconomics: Evidence from Chinese Agricultural Markets*

Jian Li[a]

Jean-Paul Chavas[b]

Xiaoli L. Etienne[c]

Chongguang Li[a]

a. College of Economics and Management,

Huazhong Agricultural University

b. Department of Agricultural and Applied Economics,

University of Wisconsin-Madison

c. Division of Resource Management,

West Virginia University

Abstract: This paper investigates the linkages between commodity price bubbles and macroeconomic factors, with an application to agricultural commodity markets in China from 2006 to 2014. Price bubbles are identified using a newly-developed recursive right-tailed unit root test. A Zero-inflated Poisson Model is used to analyze the factors contributing to bubbles. Results show that a) there were speculative bubbles in most of the Chinese agricultural commodities during the sample period, though their presences are rather infrequent; b) economic growth, money supply and inflation have positive effects on bubble occurrences, while interest rate has a negative effect; c) among all macroeconomic factors considered, economic growth and money supply have the greatest effects on bubble occurrences. Our findings shed new light on the nature and formation of bubble behavior in the Chinese agricultural commodity markets.

Keywords: price bubbles; macroeconomic factors; agricultural commodity; right-tailed unit root test; Zero-inflated Poisson model; China

---

* Jian Li is a PhD candidate in College of Economics and Management, Huazhong Agricultural University; Jean-Paul Chavas is Anderson-Bascom professor in Department of Agricultural and Applied Economics, University of Wisconsin-Madison; Chongguang Li is a professor in College of Economics and Management, Huazhong Agricultural University; Xiaoli L. Etienne is an assistant professor in the Division of Resource Management, West Virginia University. Chongguang Li is the corresponding author.

Commodity Price Bubbles and Macroeconomics: Evidence from Chinese Agricultural Markets

1. Introduction

From the 17th century Dutch tulip mania, to the Dot-com bubble in 2000, to the US housing bubble in the mid-2000s, speculative activities and the resulting price bubbles have generated significant interest among the general public and academic researchers. Price bubbles and associated dramatic price volatility not only lead to turmoil in regional markets but may also act to destabilize the global economy and have significant welfare effects among market participants (Akerlof and Shiller, 2009). A sharp decline in economic activity occurred across the globe following the 2008 sub-prime financial crisis, a period often considered the largest recession since the Great Depression in 1930s. The last decade has also witnessed periods of dramatic booms and busts in commodity prices. Some market analysts argue that the 2008 financial crisis along with soaring institutional trading may have affected world commodity pricing due to excess speculative activities in commodity markets (Masters, 2008; Gilbert, 2010; Tang and Xiong, 2012).

Many studies have examined whether bubbles existed in commodity markets during the massive price run-ups and collapses between 2006 and 2009, with some concluding that speculative activities were at least partially responsible for the dramatic commodity price behavior during that period (Gutierrez, 2013; Esposti and Listorti, 2013; Etienne et al., 2014, 2015). If these conclusions hold true, then a more fundamental question arises: why did bubbles occur? More specifically, what market conditions are more prone to price bubbles?

While numerous previous studies have investigated the causes of the 2006-2008 *price spike*, few studies have directly investigated the driving forces behind commodity *price bubbles*. The objective of this paper is to fill this gap in the literature by linking macroeconomic factors with commodity price bubbles, with an application to agricultural markets in China.

This paper proposes a new analytical framework to detect bubbles and uncover their causes by incorporating a newly-developed right-tailed unit root test and a Zero-inflated Poisson regression model. Significant breakthroughs have been made over the past decade in detecting and date-stamping price bubbles (Phillips and Magdalinos, 2007; Magdalinos and Phillips, 2009; Phillips et al., 2011; Phillips et al., 2015). Based on these new tools, the analysis in this paper consists of two parts. First, we test for the existence of price bubbles in selected agricultural commodities using the right-tailed unit root test procedure of Phillips et al. (2015), and date-stamp their specific origination and collapse dates. A measure of "bubble count" across these markets is constructed based on the bubble testing results. We rely on bubble count across markets for two reasons: (1) bubbles tend to occur rather infrequently in a given market, making statistical analysis of bubble occurrence impractical when analyzing an individual market; and (2) we focus on the macroeconomic determinants of bubbles that are common across all commodity markets—a feature that makes it appropriate to pool bubble occurrences across all markets. In the second part of the empirical analysis, the determinants of bubble counts are evaluated using a Zero-inflated Poisson model. The analysis provides a basis to investigate the linkages between commodity price bubbles and macroeconomic policy.

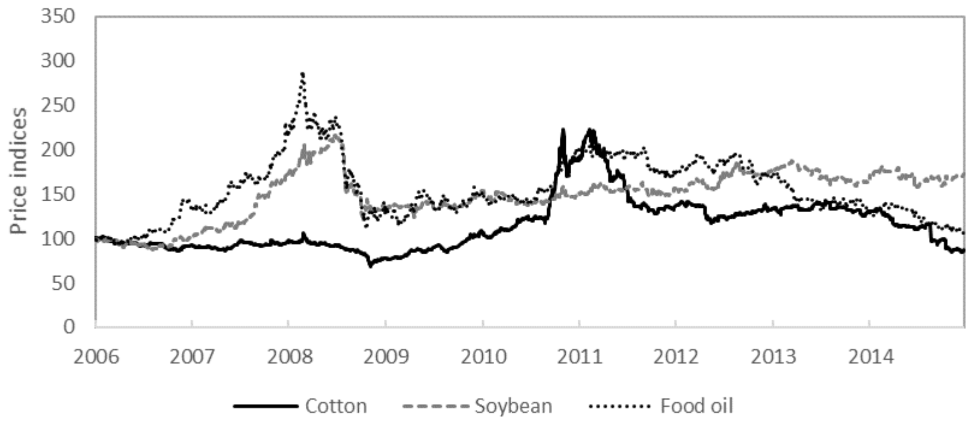

Figure 1. Selected Chinese agricultural commodity prices, 2006 to 2014

Source: the price indices are calculated using futures prices in commodity exchanges in China

We apply the framework outlined above to the Chinese agricultural commodity markets over the period of 2006-2014. Like many other countries, the Chinese economy experienced a dramatic downturn in the aftermath of 2008 financial crisis. In response, the Chinese government significantly revised its domestic macroeconomic policy in an attempt to sustain domestic economic growth. Meanwhile, agricultural prices in China experienced several dramatic booms and busts during the 2008 economic crisis (see Figure 1). The coincidence of these events raises several intriguing questions: (1) Did bubbles occur in the Chinese agricultural commodity market during the 2008 financial crisis? (2) If bubbles indeed existed in the Chinese agricultural market, how have policy changes affected their behavior? Further, what is the relative importance of each contributing factor? Our empirical analysis on Chinese agricultural markets suggests that bubbles indeed existed in these markets between 2006 and 2014. However, bubbles only account for a small portion of the price behavior in these markets. We show that economic growth, money supply, and inflation all have a positive impact on the occurrence of price bubbles, while the effect of interest rates is negative. By contrast, exchange rate does not significantly affect the likelihood of bubbles. Regarding the magnitude of these impacts, we find that economic growth and money supply have the strongest effects on price bubbles than other factors. Our findings provide useful information on the nature and formation of bubble behavior, and shed new light on the impacts of macroeconomic policy on commodity markets.

The rest of this paper is organized as follows. The economics of bubbles is discussed in section 2. The econometric methodology is presented in section 3. Section 4 describes the data, and section 5 reports the bubble detection results for Chinese agricultural commodity markets. Section 6 investigates the relationship between agricultural price bubbles and macroeconomic factors. Concluding remarks are presented in Section 7.

2. Economics of Bubbles

Economic bubbles are often associated with market situations exhibiting large price increases followed by sudden price drops. Examples of large price bubbles include the Dutch tulip mania of 1637, the British South Sea Bubble of 1711-1720, the US Real Estate market of 2000-2007 and the food price crisis of 2008 (e.g., Kindlenberger and Aliber 2005; Carter et al. 2011; Jacks 2013; Shiller, 2014, 2015), just to name a few. In each case, significant price increases were followed by sharp price declines. Periods of massive price volatility are often associated with negative welfare implications for at least some groups of market participants. Carter and Janzen (2009) report that the dramatic price movements in cotton markets in 2008 posed significant hedging costs for cotton farmers, resulting in the demise of a number of the US cotton merchants. World Bank (2008) reports that the food price spike in 2008 pushed at least 130 million people into extreme poverty.

These negative welfare implications suggest that there is an acute need to understand the driving forces behind price bubbles. To date, little consensus has been reached in the literature regarding the root causes of price bubbles. Some economists argue that bubbles do not exist, pointing out that observed fluctuations in market prices (even large fluctuations) can be explained entirely by changes in market conditions and the rational behavior of market participants responding to such changes (e.g., Garber, 1989, 1990). For instance, inventory holders of storable commodities have the incentive to buy when the price is low and to sell when the price is high. As long as stocks are positive, this can smooth price fluctuations over time (Deaton and Laroque, 1992, 1995). This scarcity argument indicates that price volatility of storable commodities will be high when the inventory is low. However, others contend that bubbles can occur in the presence of poorly informed or "noise" traders (e.g., De Long et al., 1990).

The controversies surrounding the existence of bubbles and their root causes pose several challenges to our analysis. First, as illustrated in Figure 1, the historical price data indicate that commodity prices are often characterized by frequent booms and sharp drops. Which episodes should be considered bubble periods? On a related note, how can the normal and bubble patterns of commodity prices be quantified mathematically? These issues are addressed in section 3 by incorporating a newly-developed bubble testing procedure of Phillips et al. (2015).

Second, if bubbles do exist, what are the factors driving market bubbles? Which factors play a larger role? One strand of literature relates bubbles to the way market participants obtain and process information about market conditions (Akerlof and Shiller, 2009; Shiller, 2014, 2015). Akerlof and Shiller (2009) argue the behavior of market participants and the dynamics of markets are largely driven by “animal spirits” involving noneconomic motivations of human behavior. Levine and Zajac (2007) argued that bubbles are caused by herd behavior and social norms as individuals observe and adopt the behavior of others. Another strand of related literature discusses the role of macroeconomic factors on commodity prices (Frankel, 1986, 2006; Akram, 2009; Gilbert, 2010). For instance, monetary liquidity associated with expansionary monetary policy or easy credit have often been related to the commodity price booms and bursts (e.g. Frankel, 1986). Other macroeconomic factors commonly considered in the literature include monetary, fiscal policy and trade policies (e.g. Pindyck and Rotemberg, 1990; Akram, 2009). However, previous studies focused on the relationship between commodity prices (not price bubbles) and macroeconomic factors. A frequent conclusion of the research is finding “overshooting effects” of commodity prices to changes in macroeconomic factors, i.e. commodity price moves more than proportionately to the changes in monetary supply (Frankel, 1986; Akram, 2006). But bubbles are somewhat rare and extreme forms of overshooting. Our analysis below provides evidence how the occurrence of bubbles can be triggered by macroeconomic policies.

As far as the authors are concerned, there has been no comprehensive study in the literature that directly examines the linkage between price bubbles in commodity markets and macroeconomic variables. In this article, we seek to fill in this gap by relating our bubble testing results to various macroeconomic factors, empirically identifying how changes in overall economic variables can contribute to the occurrence of bubbles in the Chinese agricultural commodity markets.

3. Econometric Methodology

In this section, we propose an analytical framework to identify price bubbles and to investigate links between bubbles and macroeconomic factors. The investigation proceeds in two steps. First, we detect and date-stamp the price bubbles in six Chinese agricultural commodity price sequences by using the right-tail unit root test of Phillips et al. (2015). We then use the bubble detection results to measure the extent of bubbles occurring across markets. This generates a "bubble count" that can be used to investigate the factors contributing to the price bubbles. Second, we specify and estimate a Zero-inflated Poisson model to investigate the effects of macroeconomic factors on the formation of agricultural commodity bubbles.

3.1. Detecting and date-stamping price bubbles

Detecting price bubbles has been historically a challenging issue in the literature. Conventional methods are often criticized for being unable to effectively detect bubbles due to their low discriminatory power in distinguishing an explosive process from a unit root process (Evans 1991, Gürkaynak 2008). Theoretically, bubble detection in time series data may be viewed as testing for a change from unit root to explosiveness. A series of right-tailed unit root bubble detecting procedures have been recently developed and used in the literature (Philips et al., 2011; Philips et al., 2015). These methods rely on the notion of mildly explosiveness that works to capture the explosive process with good asymptotic distributional property (Phillips and Magdalinos 2007, Magdalinos and Phillips 2009, Phillips et al. 2010).

Based on the concept of mild explosiveness and a double-recursive procedure, Philips, Shi and Yu (2015, PSY hereafter) proposed a generalized sup Augmented Dickey-Fuller (GSADF) test to detect and date-stamp price bubbles. The null hypothesis in PSY model is that the price P_t follows a random walk with a negligible drift:

$$P_t = dT^{-\eta} + \theta P_{t-1} + \varepsilon_t, \theta = 1 \tag{1}$$

where d is a constant, T is the sample size, η > 1/2,[1] t is the t-th time period and ε_t is an $i.i.d.$ error term. Under the alternative hypothesis where $\theta > 1$, there are price bubbles in the time series. Next, denoting r_1 and r_2 as the sample starting and ending points, consider the recursive regression model:

$$\Delta P_t = \alpha_{r_1,r_2} + \beta_{r_1,r_2} P_{t-1} + \sum_{i=1}^{k} \gamma_{r_1,r_2} \Delta P_{t-1} + \varepsilon_t,\ \varepsilon_t \sim i.i.d.(0, {\sigma_{r_1,r_2}}^2) \tag{2}$$

where $\Delta P_t = P_t - P_{t-1}$, and k is the lag length. Then, the standard augmented Dickey-Fuller statistic can be calculated as:

$$ADF_{r_1,r_2} = \beta_{r_1,r_2} / se(\beta_{r_1,r_2}). \tag{3}$$

Based on the recursive implementation of right-tail ADF test, the PSY detecting procedure can be divided into 2 steps: (1) detect price bubbles using the GSADF test statistic; and (2) date-stamp the starting and ending points of the bubble period using the backward sup ADF (BSADF) statistic.

First, the GSADF statistic is calculated after varying the starting point of the regression r_1 from 0 to $r_2 - r_0$ and varying the end point r_2 from r_0 to 1. In this context, the GSADF statistic is:

[1] The parameter η is defined as a localizing coefficient that controls the magnitude of the intercept and drift as $T \rightarrow \infty$. See details in Phillips et al. (2015).

$$GSADF(r_0) = sup_{r_1 \in [0, r_2 - r_0]}^{r_2 \in [r_0, 1]} \{ADF_{r_1, r_2}\} \tag{4}$$

The existence of bubbles in a sample sequence can be determined by comparing the GSADF statistic with the asymptotic critical values calculated from a Monte Carlo simulation[2].

Second, the BSADF statistic sequence is obtained by implementing the right-tail ADF test on backward expanding sample sequences, and comparing the BSADF statistic sequence with critical values calculated from a Monte Carlo simulation. Define the minimum window size of the estimated model as $r_{w_0} = r_2 - r_1 + 1$. Moving from the first sample observation to the observation $r_2 - r_{w_0} + 1$, and denoting $BSADF_{r_2}$ as the supremum of the ADF statistics with respect to $r_1 \in [1, r_2 - r_{w_0} + 1]$ with the fixed end point at r_2, we then have:

$$BSADF_{r_2} = sup_{r_1 \in [1, r_2 - r_{w_0} + 1]} \ ADF_{r_1, r_2} \tag{5}$$

Allowing the end point to vary from r_{w_0} to the last sample observation, we obtain the BSADF statistic sequence. In this context, the criteria to date the bubble origination and termination dates are:

$$\widetilde{r_{1e}} = inf_{r_2 \in [r_{w_0}, T]} \{r_2 : BSADF_{r_2} > cv_{r_2}^{\beta}\} \tag{6}$$

$$\widetilde{r_{1f}} = inf_{r_2 \in [\widetilde{r_{1e}} + h, T]} \{r_2 : BSADF_{r_2} < cv_{r_2}^{\beta}\} \tag{7}$$

where $cv_{r_2}^{\beta}$ is the $\beta\%$ critical values of the BSADF statistic based on the r_2 observations from the simulations. In practice, we set $\mathrm{h} = \delta \ log(T)$ to be the minimum length of the bubble period, where δ depends on data frequency.

[2] The critical values are obtained from Monte Carlo simulations where the Wiener process is approximated by partial sums of independent N(0, 1) variates and the number of replications is 2000.

3.2. Measuring the extent of bubbles

In the previous step, we date-stamp the bubbles by comparing the BSADF sequence ($\mathrm{BSADF}_{\mathrm{r}_2}$) and 99% critical value sequence ($cv_{r_2}^{\beta}$). The analysis identifies bubbles and the timing of their occurrences in each market. Next, we consider applying this approach to m agricultural commodity markets.[3] Using the $BSAFD$ test, define a variable Z_{it} to represent the bubble detection result for i-th commodity on t-th date:

$$Z_{it} = \begin{cases} 0, & \text{when } BSADF_{r_2,i,t} < cv_{r_2,i,t}^{\beta} \\ 1, & \text{when } BSADF_{r_2,i,t} > cv_{r_2,i,t}^{\beta} \end{cases} \tag{8}$$

$i = 1, 2, \dots, m;\ \ t = 1, 2, \dots, T$. For i-th commodity, Z_{it} is equal to 1 when a bubble is detected on the t-th date, and is equal to 0 otherwise. Next, we create a "bubble count" variable, Y_t, defined as

$$Y_t = \sum_{i=1}^{m} Z_{it} \tag{9}$$

From (9), the variable Y_t measures the extent of bubble behavior at time *t* across all m commodity markets. The aggregation across markets has two motivations. First, bubbles are typically rare events, meaning that few bubbles are observed in a given market. This makes is very difficult to analyze bubbles one market at a time. Second, our investigation of the driving factors behind bubbles focuses on the role of macroeconomic factors that are common across all markets in a given country. As such, pooling bubble counts across all markets as in equation (9) appears appropriate. On a given date *t*, the bubble count variable Y_t in equation (9) takes discrete values $\{0,1,2,\dots,m\}$ as it measures the number of markets simultaneously experienced a bubble. If no bubbles were detected in any of the markets Y_t would be equal to 0. On the other hand, Y_t takes the value of m if bubbles are detected in

[3] The application presented below will involve six agricultural markets in China.

all m markets.

3.3. Investigating the linkage between price bubbles and macroeconomic factors

Using the bubble count variable Y_t in equation (9) as the dependent variable, we next investigate the effect of macroeconomic factors on bubble occurrences in the commodity markets. Since Y_t is a count variable that ranges from 0 to m, we assume it follows a Poisson distribution, leading to a Poisson Regression Model (PRM). However, classic Poisson models may generate biased estimation results if the count data has an excess of zero counts (Lambert, 1992). Previous studies (as well as our results in section 5) show that bubbles are likely to be rare events, indicating the possibility of excess zeros in the dependent variable Y_t even after pooling bubbles across all markets. To address the "excess zeros" problem of PRM, we consider a Zero-inflated Poisson (ZIP) model proposed by Lambert (1992) to allow additional flexibility in the modeling of zeros.

In the ZIP model, the dependent variable (bubble count, denoted as Y_t) is assumed to come from a mixture of two data generating processes, one that only generates zeros and the other follows the usual Poisson distribution. The probability distribution of Y_t may be written as in (10):

$$Y_t \sim \begin{cases} 0, & \text{with the probability of } p_t \\ \text{Poisson } (\mu_t), & \text{with the probability of } 1 - p_t \end{cases} \tag{10}$$

The probability density function of the ZIP model therefore is:

$$\Pr(Y_t \mid \boldsymbol{X_t}, p_t) \sim \begin{cases} p_t + (1 - p_t)e^{-\mu_t}, & Y_i = 0 \\ (1 - p_t)\dfrac{e^{-\mu_t}{\mu_t}^{Y_t}}{Y_t\ !}, & Y_i = 1,2, \dots \end{cases} \tag{11}$$

By adding the following link functions, we obtain the ZIP model used in our analysis

$$\ln(\mu_t) = \boldsymbol{X_t}' \boldsymbol{\beta}$$

$$\mathrm{logit}(p_t) = \ln\frac{p_t}{1-\ p_t} = \boldsymbol{X}_{\boldsymbol{t}}^{'}\ \ \boldsymbol{\gamma} \tag{12}$$

where $\boldsymbol{X_t}$ is the vector of contributing factors, and $\boldsymbol{\beta}$ and $\boldsymbol{\gamma}$ are the coefficient vectors of the covariates. In this context, the coefficient vector $\boldsymbol{\beta}$ measures the effects of $\boldsymbol{X_t}$ on the log of μ_t, and the coefficient vector γ measures the effects of $\boldsymbol{X_t}$ on the logit function of probability p_t.

The joint log-likelihood function for the ZIP regression model is:

$$\ln \mathrm{L}(\boldsymbol{\beta},\boldsymbol{\gamma}|Y_t,\boldsymbol{X_t}) \ \ = \sum_{t=1}^{n} h(Y_t = 0)\ln\left(\exp\left(\boldsymbol{X}_{\boldsymbol{t}}^{'}\ \ \boldsymbol{\gamma}\right) + \exp\left(-\exp\left(\boldsymbol{X}_{\boldsymbol{t}}^{'}\ \ \boldsymbol{\beta}\right)\right)\right)$$

$$+\sum_{t=1}^{n}\big(1-h(Y_t=0)\big)\left(Y_t\ \boldsymbol{X}_{\boldsymbol{t}}^{'}\ \ \boldsymbol{\beta} - \exp\left(\boldsymbol{X}_{\boldsymbol{t}}^{'}\ \ \boldsymbol{\beta}\right)\right) - \sum_{t=1}^{n}\ln\left(1+\exp\left(\boldsymbol{X}_{\boldsymbol{t}}^{'}\ \ \boldsymbol{\gamma}\right)\right), \tag{13}$$

where the function $h(Y_t)$ takes a value of 1 when $Y_t = 0$, and 0 otherwise. Using Newton-Raphson optimization algorithm, the log-likelihood function can be maximized. The Vuong test can be used to assess whether the ZIP model is preferred over PRM, with large positive values providing evidence in favor of the ZIP model.

4. Data description

The empirical application proposed in this study uses two types of time series data over the period of 2006-2014. First, we collected data on the main agricultural commodity prices in China, including wheat, corn, soybeans, cotton, sugar and food oil. Second, we collected data on key macroeconomic variables, including economic growth, money supply, interest rate, exchange rate and inflation.

4.1. Agricultural commodity price data

The above approach is applied to six key agricultural commodities in China, including wheat, corn, soybeans, cotton, sugar, and food oil. Over the last decade, these six commodities covered over 60 percent of commodity trading volume in Chinese agricultural futures markets.[4] As can be seen in Figure 1, these markets have experienced several large price swings during the sample period.

We use daily futures settlement prices for these six commodities. Compared with monthly and weekly data, daily price data provide detailed information about short-term price movements that are of keen interest to investors and other market participants in the commodity markets. Futures price data are collected from Zhengzhou Commodity Exchange (ZCE) and Dalian Commodity Exchange (DCE) for January 2006 - December 2014, yielding 2183 daily observations for each commodity. The sample period considered covers most recent booms and subsequent busts (including the world food crisis period of 2008). To create continuous price sequences, we use the adjusted front-month method that rolls nearby contracts at the end of the month prior to contract expiration. Due to the relatively low trading volumes and open interests in the maturity month, we switch contracts before the delivery month to avoid "delivery period problems" (Karali and Power 2013).

Table 1 presents summary statistics on the price data. Among these 6 commodities, soybean and cotton prices tend to be more volatile than other commodities. The prices of soybean and cotton peaked approximately at the same time with world price spikes. In contrast, Chinese grain (wheat and corn) prices followed different patterns. Wheat and corn prices increased consistently over time since 2006, even during the 2008 world price booms and busts.

[4] Source: data are calculated by the authors using official datasets from China Futures Association. Available at: http://www.cfachina.org/.

Table 1: Summary statistics of Chinese agricultural commodity prices in 2006-2014, Yuan/ton

Commodity	Mean	S.D.	Max.	Date(max)	Min.	Date(min)
Wheat	2208	387	2933	30 Apr, 2014	1413	19 Oct, 2006
Corn	1944	394	2614	29 Aug, 2014	1245	12 Jan, 2006
Soybean	4028	752	5821	2 Jul, 2008	2370	28 Jul, 2006
Cotton	17244	4464	33545	17 Feb, 2011	10310	12 Nov, 2008
Sugar	4870	1247	7892	24 Aug, 2011	2564	7 Oct, 2008
Food oil	7861	1751	14614	29 Feb, 2008	4660	17 Apr, 2006

4.2. Macroeconomic data

To investigate the links between agricultural price bubbles and macroeconomic factors in the Chinese commodity markets, we consider several macroeconomic factors, including economic growth, money supply, interest rate, exchange rate and inflation. Below we briefly describe each variable.

Economic growth. Rapid economic growth can possibly trigger global and domestic commodity price booms (Caballero et al., 2008). A number of recent studies have highlighted the role of economic growth on the behavior of commodity prices (Kilian, 2009; Gilbert 2010; Baffes and Etienne 2016). Gilbert (2010) find that economic growth is an important determinant of changes in world agricultural prices over a 38-year period from 1970 to 2008. Baffes and Etienne (2016) show that in the short-run, economic expansion as represented by income growth can positively affect both the real and nominal commodity prices. Hence, we use Chinese official macroeconomic indicator, Economic Climate Index (ECI), to investigate the impact of economic growth on price bubbles, and convert it from monthly data to daily data assuming a constant rate throughout the month.[5]

[5] Some direct indicators for economic growth (e.g., GDP) are not suitable in our analysis due to their low frequency. ECI is an official macroeconomic indicator in China published by Economic Monitoring & Analysis Centre, China National Bureau of Statistics. The sources of the macroeconomic variables are listed in Table 2.

Money Supply. China has exhibited a rapid growth in its money supply during the last decade, especially in the period after 2008 economic crisis.[6] Previous studies show that increasing money supply may result in appreciation in commodity prices (Frankel, 1986; Saghaian et al., 2002; Kang et al., 2016). For instance, Frankel (1986) developed carry-trade models to discuss the overshooting effect of money supply on commodity prices. Saghaian et al. (2002) further found that a 1 percent increase in money supply leads to a 0.43 percent increase in agricultural prices. Hence, to explore the impact of expansionary monetary policy on Chinese commodity price bubbles, we use the year-over-year growth rate of broad money (M2) converted from monthly data into daily data by constant rate.

Interest Rate. Interest rate affects the cost of borrowing and is expected to influence the behavior of commodity market investors. Many existing studies found that interest rates contribute to the historical commodity price booms. For instance, Pindyck and Rotemberg (1990) showed that interest rates are negatively related to the commodity price booms in 1970's and 1980's. Similarly, Akram (2009) argues that a decline in real interest rate contributed to higher commodity prices in 2006-2008. Thus, it is expected that interest rate is negatively associated with the presence of commodity bubbles. Note that the Chinese official interest rate may not be an accurate indicator due to government controls. We measure the interest rate in China using a more market-oriented interest rate indicator, the daily Shanghai interbank overnight rate.

Exchange Rate. In an increasingly inter-linked global market, booms in the domestic

[6] According to data from China Bureau of Statistics, the supply of broad money (M2) increased from 30.4 trillion Yuan in January 2006 to 122.8 trillion Yuan in December 2014. Especially, the monthly year-over-year growth rate of money supply kept over 25% during the period of 2008-2009.

market may be due to rising international trade. Exchange rate thus could play a role on commodity price volatility (e.g. Akram, 2009; Gilbert, 2010). Exports and agricultural prices are found to be sensitive to movements in the exchange rate (Chambers and Just, 1982). Here, we explore whether the exchange rate is a contributing factor to bubbles by including the effective exchange rate (ERR) of Chinese Yuan from Bank for International Settlements (BIS). Calculated as geometric weighted averages of bilateral exchange rates, ERR is an effective index that shows the real exchange rate over time and is more appropriate than the official exchange rate heavily controlled by the Chinese government.

Inflation. Commodity price boom-and-bust cycle is likely to be highly associated with domestic inflation. Many studies have found commodity price booms are more likely to occur when inflation rate is high, as high inflation puts upward pressure to commodity prices (Pindyck and Rotemberg, 1990; Kyrtsoua and Labysb, 2006). For instance, Kyrtsoua and Labysb (2006) showed that increase in domestic inflation contribute to commodity price booms by constructing a noisy chaotic multivariate model. To explore the impact of inflation on commodity price bubbles, we use Producer Price Index (PPI) as a proxy variable for Chinese domestic inflation and convert it from monthly data to daily data by constant rate.

Table 2 provides the summary statistics of the macroeconomic factors used in the study. The Chinese economy experienced a dramatic downturn in the aftermath of 2008 financial crisis (minimum value of ECI reached in June 2009), and began to recover in 2010 (maximum value of ECI reached in July 2011). In response, the Chinese government significantly revised its domestic macroeconomic policies in an attempt to sustain domestic economic growth, including accelerating the growth rate of money supply (peaked in

November 2009), decreasing interest rate (bottomed in March 2009) and lowering domestic inflation (bottomed at July 2009). By contrast, Chinese exchange rate appreciated smoothly during the period of 2006-2014.

Table 2: Summary statistics of the macroeconomic factors

Factors	Proxy variable	Mean	S.D.	Max	Date (Max)	Min	Date (min)
Economic Growth	Economic climate index (ECI)	3.26	0.12	3.43	2011.7.1	2.98	2009.6.1
Money Supply	Broad money (M2) year-on-year growth rate (%)	0.57	0.15	0.99	2009.11.1	0.40	2014.3.3
Interest Rate	Shanghai interbank offered rate (O/N) (%)	2.39	1.06	13.44	2013.6.20	0.80	2009.3.4
Exchange Rate	BIS nominal effective exchange rate	3.29	0.28	4.05	2014.12.1	2.96	2006.6.16
Inflation	PPI (%)	0.05	0.15	0.34	2008.2.1	-0.27	2009.7.1

Source: Economic Growth, Money Supply and Inflation are collected from China National Bureau of Statistics; Interest Rate is collected from National Interbank Funding Center, the People's Bank of China; Exchange Rate is collected from Bank of International Settlement (BIS).

5. Bubble detection results

In this section, we present the bubble detection and date-stamping results in each of the six commodity markets considered in the paper.

5.1. Bubble detection in Chinese agricultural commodity markets

The trajectories of the BSADF sequences and corresponding critical values are graphed in Figure 2. Almost all observed price spikes (e.g., soybean price in 2008 and cotton price in 2010) trigger escalations in BSADF sequences, indicating that the PSY model provides a good basis to evaluate bubbles in agricultural commodity markets. The correspondence between detected bubbles and large price movements rules out the possibility of detecting "pseudo bubbles" caused by "splicing bias".[7]

Our bubble detection procedure proceeds in two steps. In the first step, to identify the presence of bubbles, we compare the sample GSADF statistic in each commodity market with the 99% critical value obtained from 2000 Monte Carlo simulations. As reported in Table 3, the GSADF statistics are 1.11, 1.78, 4.38, 11.14, 8.52 and 4.40, for wheat, corn, soybeans, cotton, sugar, and food oil, respectively. With the exception of wheat, the sample GSADF statistics are all greater than the 99% critical values of 1.55, providing strong evidence that price explosiveness does arise in the Chinese agricultural commodity markets. In the second step, we compare the BSADF sequence in each commodity market with the 99% critical value sequence obtained from 2000 Monte Carlo simulations to locate the timing of a bubble (origination and termination). Following Etienne et al. (2015), the minimum bubble length is set to 3 days as price bubbles are likely to be short-lived in competitive markets.

[7] "Splicing bias" is a problem that needs special attention in futures price research. It refers to the potential overlapping switch price from one nearby contract to the next one, and causes price variation unrelated to true volatility or "pseudo bubbles" at the splicing date.

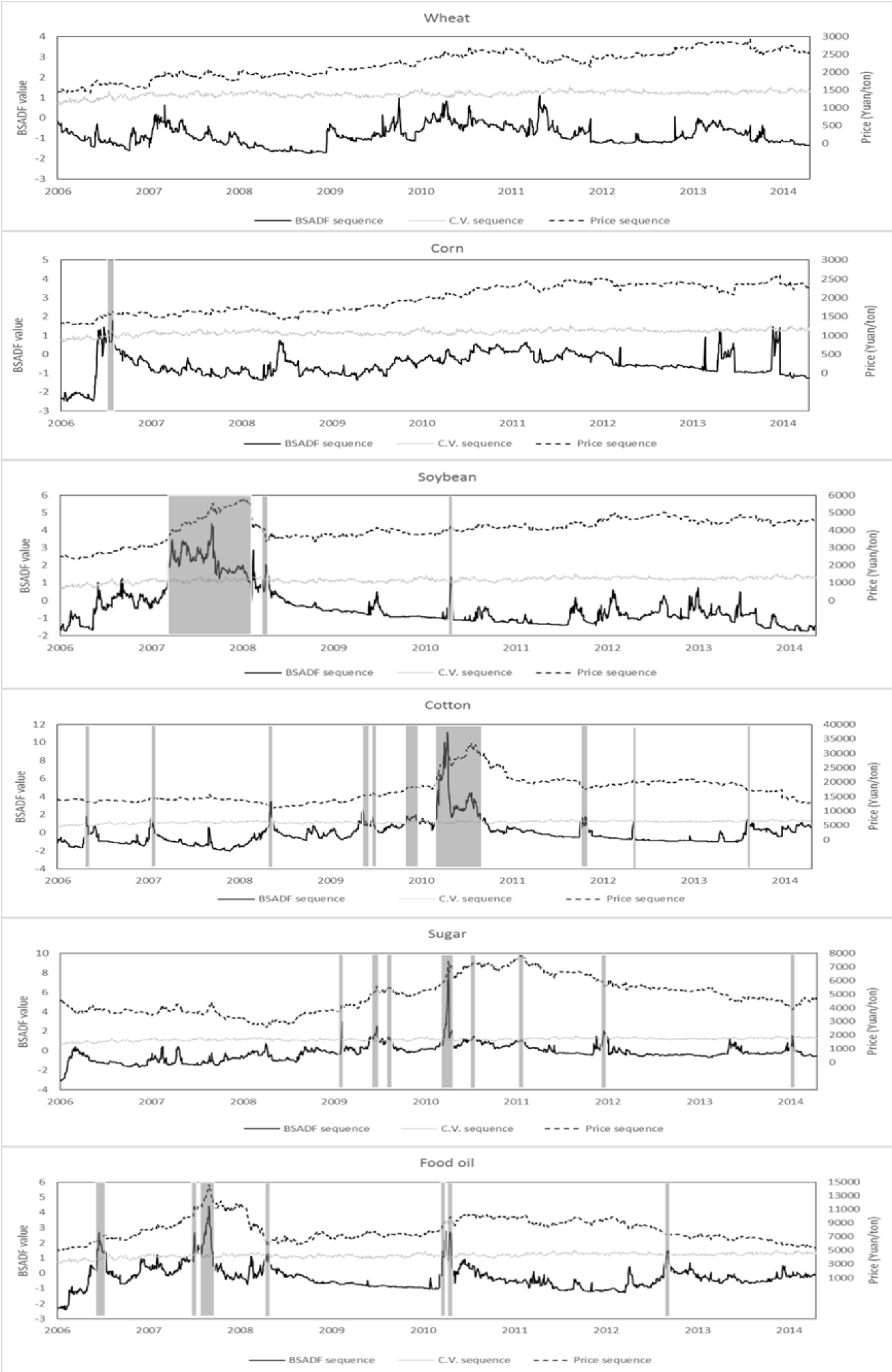

Figure 2. Detected explosive episodes in Chinese agricultural commodity prices: 2006-2014

Note: BSADF sequences and 99% Critical Value (C.V.) sequences are labeled using left axis, and price sequences are labeled using right axis.

Table 3: Bubble detection results in Chinese agricultural commodity markets

Commodity	GSADF	C.V.	Existence of bubble	Total bubble days	Number of distinct bubble periods	Longest bubble duration	Price change in longest bubble
Wheat	1.11	1.55	No	0	0	0	0
Corn	1.78	1.55	Yes	3	1	3	0.4%
Soybean	4.38	1.55	Yes	229	3	216	63.7%
Cotton	11.14	1.55	Yes	216	10	138	73.9%
Sugar	8.52	1.55	Yes	90	8	26	13.6%
Food oil	4.40	1.55	Yes	101	7	14	17.7%

Note: 1. results are calculated using the 99% critical value (C.V.) sequence and minimum bubble period of 3 days.

The last four columns of Table 3 report the summary of bubble date-stamping results for the six commodity prices. We evaluate several aspects of bubble behavior, including the total number of days when bubbles are detected (total bubble days), the number of distinct bubble periods, and bubble magnitudes measured by the longest bubble duration and by the price change in the longest bubble.

First, as shown in the fifth column in Table 3, there are 229, 216, 101, 90, 3 and 0 days identified with bubbles for soybean, cotton, food oil, sugar, corn and wheat in Chinese markets, respectively. During the sample period, soybean and cotton markets appear to have experienced the most number of bubble days compared to the other four commodities, indicating the presence of greater instability in those two markets. Given that soybean and cotton are China's largest import commodities (Yang et al., 2008), this result suggests that significant price instability tends to develop in markets with close linkages to international markets. Our results are consistent with Etienne et al. (2014) who find significant bubbles in the US cotton and soybean markets between 2006 and 2011. By contract, we find that bubbles were almost non-existent in the Chinese grain markets during the sample period (0 days for wheat, and 3 days for corn), a result in sharp contrast with Gutierrez (2013) and Etienne et al. (2014, 2015) who find strong evidence of price explosiveness in the corn and wheat futures markets in the US. The differences in the results found for these markets may reflect the fact that the Chinese wheat and corn markets are subject to significant government interventions compared to their counterparts in the US. Previous studies indicate that government policy may dampen short-term price volatility and reduce the likelihoods of bubbles (Li et al., 2016).

Second, it appears that bubbles in different markets have distinct characteristics. The sixth column in Table 3 shows the number of distinct bubble periods detected in the six agricultural commodity markets. Cotton and sugar show the largest number of bubble periods, 10 and 8 respectively, corresponding to nearly one bubble per year during the sample period. By contrast, there is only one bubble episode in corn and zero in the wheat market. It is interesting to note that despite having the most bubble days among the six markets, the soybean market only experienced three distinct bubble episodes, a number much smaller compared to cotton, sugar, and food oil. Combined with the BSADF testing results in Figure 2, it can be seen that most of the Chinese commodity bubbles occurred in either 2008 or 2010, periods when commodity prices international markets also experienced dramatic price volatility.

Third, the last two columns in Table 3 report the longest bubble duration and the price change during the longest bubble episode in each commodity market. Such information is necessary in order to examine the magnitude of bubbles and the extent to which prices may have deviated from their fundamental values. The longest bubble episodes are found in the soybean and cotton markets, lasting 216 and 138 days, respectively. These two large price bubbles occurred during periods of dramatic volatility in the international market: during the 2008 world food price spike for soybeans and during the 2010 cotton price spike for cotton. This indicates that market participants may find it difficult to obtain and process information on shocks originated in world markets, reflecting poor "Market Intelligence" in the Chinese soybean and cotton markets and generating possible overreactions to such shocks.[8] Given China's large soybean and cotton imports, these findings should not be surprising as volatility could be transmitted into the domestic markets through international trading. Finally, the last column in Table 3 shows the rate of price change during the longest bubbles in each commodity market. Consistent with the results on bubble length, the rates of price change are highest for soybean and cotton, reaching 63.7 percent and 73.9 percent, respectively. The rates for the other commodities are relatively low, averaging less than 20 percent.

In summary, we find strong evidence of price bubbles for most Chinese agricultural commodities (with the exception of wheat) between 2006 and 2014.[9] However, notice that bubbles only comprise a small portion of the price behavior during the sample periods. Out of the 2183 daily prices for each commodity, we find only 10.5% of the days experienced bubbles for soybean, the highest ratio among all commodities. For wheat, corn, sugar, and food oil, the ratio of bubble days are all smaller than 5%. Our results are highly consistent with Etienne et al. (2014) who find that bubbles tend to occur infrequently in the US

[8] The term of "market intelligence" in this paper is used to characterize the ability of market participants in obtaining and processing market information in a timely manner.

[9] To evaluate the quality of our empirical findings, we conducted robustness checks by altering the starting point of the sample and dividing the sample into two subsamples. Our main conclusions were found to be invariant to these changes.

commodity market. Additionally, we find that the nature and distribution of price bubbles vary across different commodities in China. Soybean and cotton markets exhibited most bubbles during the sample period, while the grain markets (wheat and corn) experienced almost no bubbles. A possible explanation for the price behavior in the grain market is that the Chinese government implemented price support and trade policies that contributed to stabilizing domestic grain markets (e.g., Li et al., 2016). Such policies can help explain some of the differences in bubble occurrence we found across markets.

5.2. Creating "bubble count" for Chinese agricultural commodity markets

In order to identify the factors contributing to bubble occurrence in Chinese agricultural markets, we next construct a variable that measures the existence and strength of bubbles across markets. Following equations (8) and (9), a bubble count Y_t is defined as the total number of markets experienced bubbles on date *t* across all six Chinese agricultural markets. As such, Y_t measures not only whether a bubble existed, but how many markets simultaneously experienced a bubble on a given date. Specifically, $Y_t = 0$ when no bubble was detected on date t in any of the six markets, and $Y_t \geq 1$ when at least one market experienced a bubble on date *t*. A larger number of Y_t indicates a stronger presence of bubbles as more markets experienced bubbles on the same date. Figures 3 and 4 plot the histogram of our bubble count variable Y_t and its distribution over time, respectively.

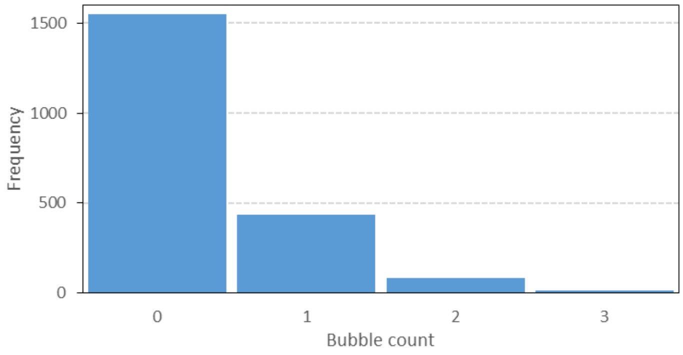

Figure 3. Histogram of bubble count Y_t across Chinese agricultural commodity markets.

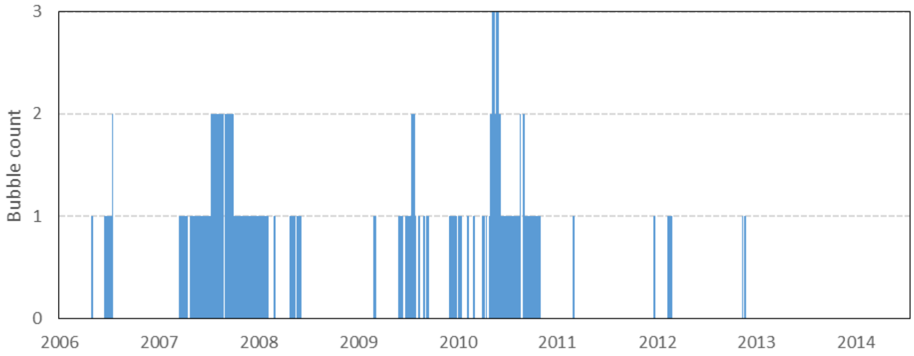

Figure 4. The temporal distribution of bubble count Y_t across Chinese agricultural commodity markets

As illustrated in Figure 3, the bubble count shows values ranging from 0 to 3. The largest bubble count is "3", meaning that bubbles occurred in 3 out of 6 commodity markets on a given date. A larger bubble count would likely reflect some "irrational exuberance" across markets. The overall low number of markets simultaneously experiencing bubble possibly indicating that "irrational exuberance" was unlikely to be at play in Chinese agricultural markets between 2006 and 2014. In our sample period, the proportion of time with no bubble (when $Y_t = 0$) is 74.5 percent, again reflecting that bubble occurrences were not very common in Chinese agricultural markets. A positive bubble count (when $Y_t \geq 1$) occurred only 25.5 percent of the time. The proportions of bubble count of "1", "2" and "3" are 20.9%, 3.9% and 0.6%, respectively.

Figure 4 plots the temporal distribution of bubble count Y_t between 2006 and 2014. It appears that days with a bubble count greater than one mostly occurred in 2007-2008 and 2009-2010, periods of world price spikes. The 2007-2008 bubbles seem to last longer, while the 2009-2010 bubbles are stronger in magnitude when measured by the number of markets experiencing bubbles simultaneously. Interestingly, bubbles are less frequent and of lower magnitude after 2011, possibly due to stronger government intervention in the Chinese agricultural markets after 2011.

Next, we explore factors that may have contributed to bubble occurrences in the Chinese agricultural commodity market. As discussed above, due to the high proportion of zeros in the bubble count Y_t, we use a Zero-inflated Poisson (ZIP) model as opposed to a simple Poisson Regression Model (PRM). For comparison and robustness checks, we report both the ZIP and PRM model estimation results in the next section.

6. Linking agricultural commodity bubbles to macroeconomic factors

Taking the bubble count Y_t as the dependent variable, we investigate the macroeconomic determinants of commodity bubbles in Chinese agricultural markets using both ZIP and PRM models. In Section 6.1, we discuss the estimation results based on the marginal effects to show the statistical significance of macroeconomic factors. In Section 6.2, we further compare the magnitude of the impacts of each macroeconomic factor by simulating predicted changes in bubble formation (occurrence and magnitude) under alternative scenarios.

6.1. Estimation results

Table 4 reports the estimation results from both ZIP and PRM. The Vuong test is positive and statistically significant at 1 percent level, indicating that the ZIP model is strongly preferred over the PRM. As can be seen in Table 4, with the exception of exchange rate, all other factors are significant at the 1 percent level in both models. Below we discuss the effects of each variable in detail.

Table 4. PRM and ZIP model estimation results

Variable	Estimation result			
	PRM		ZIP	
	Coefficient	Marginal effect	Coefficient	Marginal effect
Intercept	-32.69 ***		-33.76 ***	
	(4.10)		(4.10)	
Economic growth	8.21 ***	0.97***	8.93 ***	1.27***
	(0.95)	(0.12)	(0.96)	(0.16)
Money supply	6.85 ***	0.81***	6.40 ***	0.91***
	(0.59)	(0.07)	(0.59)	(0.09)
Interest rate	-0.26 ***	-0.03***	-0.37 ***	-0.05***
	(0.06)	(0.01)	(0.07)	(-0.01)
Exchange rate	0.09	0.01	-0.06	-0.01
	(0.33)	(0.04)	(0.32)	(0.05)
Inflation	4.44 ***	0.52 ***	2.92 ***	0.41***
	(0.50)	(0.06)	(0.55)	(0.07)
Vuong statistic	-		5.54 ***	

Notes: 1. Vuong test is used to test the appropriateness of the ZIP model. A statistic value greater than 1.96 favors the ZIP model.

2. Marginal effects ($\partial Y/\partial X$) are calculated as the change in expected count for unit increase in X.

3. Asterisks indicate the significance level: * at the 10 percent level, ** at the 5 percent level, and *** at the 1 percent level.

Economic growth. In the ZIP model, the marginal effect of economic growth is positive and statistically significant (at 1 percent level). It suggests that economic growth contributes significantly to bubble occurrence. A stronger Chinese economy is associated with a higher likelihood of price bubbles in commodity markets. Rapid economic growth presumably leads to more income and increased demand, putting upward pressure on commodity prices, a result consistent with previous research about the role of economic growth on commodity prices (e.g. Gilbert, 2010; Baffes and Etienne, 2016).

Money supply. Money supply is directly related to monetary policy. We find that the supply of money contributes positively to bubble count as the marginal effect is positive and statistically significant. An increase in the growth rate of the money supply raises the likelihood of presence of price bubbles. Results found in this study complement similar evidences obtained in asset markets (e.g., Okina et al. 2001), as well as other studies in commodity markets (e.g., Frankel 1986, 2006). Frankel (1986) further discussed the "overshooting" effect of money supply on commodity prices: commodity price moves more than proportionately to the change in the growth rate of money supply. Our results further provide evidence that extends the "overshooting" effects to "overreaction" results (occurrence of price bubbles) in commodity markets. In the last decade, Chinese government increased money supply rapidly[10]. Our analysis indicates that such policy contributed to the occurrence of bubbles in Chinese agricultural markets significantly.

Interest rate. Interest rates affect the cost of investment, with higher (lower) rate providing disincentives (incentives) to invest. The results presented in Table 4 show a negative and significant marginal effect of interest rates on price bubbles. More price bubbles tend to occur when market interest rates are low. Again, it is as expected and consistent with the literature (e.g., Pindyck and Rotemberg, 1990; Akram, 2009). Akram (2009) also found that commodity prices increased significantly in response to reductions

[10] According to data from China Bureau of Statistics, the supply of broad money (M2) increased from 30.4 trillion Yuan in January 2006 to 122.8 trillion Yuan in December 2014, with an average annual growth rate of 16.8%.

in real interest rates and displayed overshooting behavior in response to such interest rate changes. This is a scenario where a low interest rate stimulates investment, contributing to increased demand, upward pressure on prices and a higher likelihood of bubbles.

Exchange rate. From Table 4, the marginal effects of exchange rate have different signs in the ZIP model and PRM. However, the effects are not statistically significant in either model, indicating that the links between agricultural price bubbles and exchange rate are weak. This is a result in direct contrast with findings focusing on large export countries such as the US and the EU. The insignificant role of exchange rate may reflect the fact that the Chinese agriculture market is not export-oriented. In addition, the domestic and trade policies in China may have dampened the linkages between domestic markets and world markets. It remains unclear whether the insignificance comes from the high self-sufficiency of the Chinese agricultural industry or the strong interventions by the Chinese government. Our analysis highlights the need to reevaluate the role of exchange rate in emerging countries with high self-sufficiency and limited export in agriculture. It would be also interesting to investigate how this linkage may evolve if Chinese agricultural markets were to become more integrated with the world economy.

Inflation. Inflation rate is found to have a positive and significant marginal effect on bubble count. This indicates that commodity price bubbles are more likely to occur when inflation rate is high. Our findings for the Chinese markets are consistent with existing studies in the US markets (Pindyck and Rotemberg, 1990; Kyrtsoua and Labysb, 2006). It suggests that market participants are more likely to seek opportunities to invest or hedge against inflation when the inflation rate is high. This may stimulate investments in commodity markets, thus contributing to the occurrence of price bubbles.

In summary, our analysis shows that macroeconomic factors can significantly affect the occurrence of commodity bubbles. Specifically, we find that economic growth, money supply and inflation have positive effects on the occurrence of price bubbles in Chinese agricultural commodity markets, while interest rates have a negative effect. The effect of exchange rate, on the other hand, is not significant, highlighting the necessity to reevaluate the role of exchange rate in emerging economies when the domestic market is subject to heavy government regulations.

In addition, the relationship between macroeconomic factors and commodity prices (not price bubbles) are frequently discussed in literature. Those studies often end up with the discussion of "overshooting" response of commodity prices to changes in macroeconomic factors (e.g., Frankel, 1986; Akram, 2009). Our finding further shows evidence that the "overshooting" response can lead to more extreme situations: price bubbles. These results contribute to literature by showing the possible consequences from "overshooting" to "overreaction" (occurrence of bubbles) triggered by macroeconomic policies.

6.2. Evaluating the Determinants of Bubbles

In this section, we use our estimated ZIP model to further quantify the effects of macroeconomic variables on price bubbles. We simulate the ZIP model to generate predicted changes in bubble formation (occurrence and magnitude) under alternative scenarios. To obtain meaningful comparisons of effects across macroeconomic variables, our simulated changes involve one standard deviation (SD) change of each variable while holding other variables constant.[11] This provides a basis to assess the relative magnitude of the effects of each factor. We consider three sets of scenarios. The first is a base scenario where all variables are evaluated at sample means. The second involves a one SD increase in each factor with the remaining variables holding constant. The third involves a one SD decrease in each factor. Comparing scenario 2 (or 3) with scenario 1 shows the relative magnitude of the effects of each macroeconomic variable. Additionally, comparing the changes between scenarios 1 and 2 and between scenarios 1 and 3 can shed light on the possible presence of asymmetric responses where the response to an increase differs from the response to an equivalent decrease.

The simulations generated the predicted probability of no bubble, 1 bubble, 2 bubbles, etc. under each scenario. We calculated the predicted number of bubbles (with bubble count of "0", "1", "2", …) by multiplying the associated probability by the sample size. We also evaluated the predicted total bubble days (as the sum of days of positive bubble counts) across scenarios. The simulations provided detailed information on changes in total bubble days (bubble occurrence) as well as changes in the presence of high bubble count (bubble magnitude) triggered by a one SD change in the macroeconomic factors. The results are reported in Table 5.

[11] Note that evaluating the effects of one SD change in each variable allows us to compare the magnitude of the impacts of each variable in a meaningful way. This is information that cannot be obtained from the marginal effects reported in Table 4 since such marginal effects can be sensitive to the scaling of each variable.

Table 5 Policy simulation results

Predicted bubble count	Base scenario	(a) Policy adjustment (one SD increase in X)				
		Economic growth	Money supply	Interest rate	Exchange rate	Inflation
0	1894	1468	1515	1983	1899	1750
1	269	583	553	190	265	387
2	19	116	101	9	19	43
3	1	15	12	0	1	3
4	0	2	1	0	0	0
Total bubble days	289	716	668	200	284	433
Change	-	427	379	-89	-5	144
Predicted bubble count	**Base scenario**	**(b) Policy adjustment (1 SD decrease in X)**				
		Economic growth	Money supply	Interest rate	Exchange rate	Inflation
0	1894	2075	2066	1798	1890	1994
1	269	105	114	346	273	180
2	19	3	3	36	20	8
3	1	0	0	3	1	0
Total bubble days	289	108	117	386	293	189
Change	-	-181	-172	97	4	-100

Notes: 1. Predicted bubble counts in base scenario are calculated at sample means; predicted bubble counts in policy adjustment scenarios are calculated using one standard-deviation (SD) change of each macroeconomic variable while keeping other variables at sample means.

2. Numbers in this table are calculated using the probability of predicted counts multiplied by the number of observations (2183). Total bubble days are calculated as the sum of the third to fifth row in each column.

Comparing scenarios 2 and 3 with the base scenario, Table 5 shows that economic growth has the largest impact on bubble formation: a one SD deviation increase (decrease) in its value generated the largest increase of 427 days (decrease of 181 days) in the total number of predicted bubble days. The variable with the second largest impact is money supply: a one SD increase (decrease) in its value is associated with an increase of 379 (decrease of 172) bubble days. The impacts of inflation and interest rate are as well important but of a much smaller magnitude. For inflation, a one SD increase (decrease) results in an increase of 144 (decrease of 100) bubble days. For interest rate, a one SD increase (decrease) generates a decrease of 89 bubble days (increase of 97 days). Finally, consistent with the estimated coefficient and marginal effect reported in Table 4, the effect of exchange rate is very small in our simulation analysis. A SD increase in exchange rate generates a change of only 5 days in total bubble days.

Table 5 also reports interesting patterns on the effects of macroeconomic factors. For instance, Table 5 shows that a one SD increase in economic growth increases the bubble count by 314 days for "1", 97 days for "2", 14 days for "3". It also predicts 2 days for bubble count "4".[12] Compared to the base scenario, the percentage increase is higher for larger bubble counts. Similar results can be found for a one SD decrease in economic growth, which reduces bubble count by 164 days for "1", 16 days for "2" and 1 day for "3", for a total reduction of 181 bubble days. Other factors also show similar results.

Finally, Table 5 presents evidence of asymmetric effects of macroeconomic factors on the occurrence of commodity bubbles. The total number of bubble days tends to increase more than its corresponding reduction when comparing a one SD increase versus decrease in each independent variable. For instance, if the index for economic growth increases by one SD, the total number of bubble days would increase by 427 days, while the same magnitude decrease in economic growth would lead to a reduction of only 181 bubble days. Similar asymmetric effects on bubble occurrences can be found for other macroeconomic factors as well. These results suggest that the formation of commodity price bubbles are dynamic and complex.

In summary, our analysis finds different effects of macroeconomic factors on the nature and determinants of commodity bubbles. Economic growth and money supply are

[12] Bubble count "4" was not observed in our sample. Seeing this simulated high-magnitude bubble gives us a hint that bubbles could erupt in more extreme forms if macroeconomic policies changed dramatically.

shown to be the most important contributors to bubble formation in Chinese agricultural commodity markets. We also find that the increase in bubble counts are not proportional – larger bubble counts tend to increase (decrease) more compared to lower bubble counts. Further, results suggest that macroeconomic factors have an asymmetric effect on the occurrence of commodity bubbles. The increase in total number of bubble days is much higher compared to the reduction in bubble days when a same degree of change (but of opposite sign) occurs to each independent variable. To the extent that reducing price bubbles is seen as a desirable outcome of policy interventions, our analysis indicates that policy makers and market participants may wish to focus more on economic growth and money supply.

7. Conclusion

This study proposes an analytical framework to investigate the linkages between commodity bubbles and macroeconomic factors, with an application to Chinese agricultural commodity markets. We use a recently developed bubble-testing and date-stamping procedure to identify the specific bubbles in agricultural commodity markets. Based on the bubble detection results, we then investigate the relationships between "bubble count" and macroeconomic factors, and clarify the role of each factor on the occurrence of price bubbles. As far as we know, this is the first paper to directly connect macroeconomic variables with bubble behavior in commodity markets.

We apply this framework to Chinese key agricultural commodity markets from 2006 to 2014, including wheat, corn, soybean, cotton, sugar, and food oil. We find that with the exception of wheat, price bubbles occurred in all other five markets. However, bubbles only represent a small proportion of the price behavior during the sample period in the Chinese agricultural commodity markets. The soybean and cotton markets exhibited most bubble days, with about 10 percent of the sample period classified as explosive episodes based on the bubble detection procedure. Furthermore, an examination of "bubble count", as the number of markets simultaneously experiencing bubbles, suggests that strong bubbles occurred mainly in 2008 and 2010, and bubbles became much less likely after 2011.

In our investigation of the macroeconomic determinants of bubbles, we find that economic growth, money supply and inflation have positive effects on price bubbles, and interest rate negatively affects the likelihood of bubbles. By contrast, exchange rate is shown to have no significant impact on bubble occurrences. Through simulations, we show that economic growth and money supply are the strongest contributors to commodity bubbles. Fast economic growth and expansionary monetary policy can lead to large increases in the likelihood and severity of price bubbles in commodity markets. We also find that macroeconomic factors have asymmetric effect on bubbles, with quantitative effects that differ between increases and decreases in their values.

Our investigation provides useful information on the nature and formation of bubble behavior. It sheds new light on the impacts of macroeconomic policy on commodity markets in China. Our results suggest that, though less frequently discussed in literature, macroeconomic factors may be as important a source of commodity price bubbles as the traditional microeconomic factors. Extending the common finding of "overshooting" effects (e.g., Frankel, 1986; Akram, 2009), our findings show evidence that such "overshooting" response can lead to “overreaction” (occurrence of bubbles) triggered by macroeconomic policies. Commodity price bubbles tend to occur in booming economy with simulative policies (e.g. expansionary monetary policy). Among all macroeconomic factors considered, economic growth and money supply are found to have the strongest effect on bubble occurrence. To the extent that price bubbles are seen as an undesirable outcome of policy interventions, our analysis indicates that policy makers and market participants may wish to focus more on economic growth and money supply. Besides, if the government are concerned about bubbles in commodity markets, the asymmetric and complex market responses should also be taken into account when government chooses its macroeconomic policies.

References

Akerlof, G. and R. Shiller. 2009. *Animal Spirits*. Princeton University Press, Princeton, NJ.

Akram, Q. 2009. Commodity Prices, Interest Rates and the Dollar. *Energy Economics* 31: 838–851

Baffes, J. and X. L. Etienne. 2016. Analysing Food Price Trends in the Context of Engel's Law and the Prebisch-Singer Hypothesis. *Oxford Economic Papers*, forthcoming.

Caballero, R. J., E. Farhi and P. O. Gourinchas. 2008. Financial Crash, Commodity Prices and Global Imbalances. NBER Working Paper 14521, National Bureau of Economic Research, Cambridge, MA.

Carter, C.A. and J.P. Janzen. 2009. The 2008 Cotton Price Spike and Extraordinary Hedging Costs. *Agricultural and Resource Economics Update*, 13(2), 9-11.

Carter, C.A., G.C. Rausser and A. Smith. 2011. Commodity Booms and Busts. *Annual Review of Resource Economics* 3: 87-118.

Chambers, R.G., and R.E. Just. 1982. Effects of Exchange Rate Changes on U.S. Agriculture. *American Journal of Agricultural Economics* 9: 235-247.

Deaton, A. and G. Laroque. 1992. On the Behavior of Commodity Prices. *Review of Economic Studies* 59: 1-23.

Deaton, A. and G. Laroque. 1996. Competitive Storage and Commodity Price Dynamics. *Journal of Political Economy* 104: 896-923.

De Long, J., Shlefier A., Summers L. and Waldman J. 1990. Noise Trader Risk in Financial Market. *Journal of Political Economy* 98(4):703-738.

Esposti, R. and G. Listorti. 2013. Agricultural Price Transmission across Space and

Commodities during Price Bubbles. *Agricultural Economics* 44(1): 125-139.

Etienne, X.L., S.H. Irwin, and P. Garcia. 2014. Bubbles in Food Commodity Markets: Four Decade of Evidence. *Journal of International Money and Finance* 42: 129-155.

Etienne, X.L., S.H. Irwin, and P. Garcia. 2015. Price Explosiveness, Speculation, and Grain Futures Prices. *American Journal of Agricultural Economics* 97(1): 65-87.

Frankel, J. 1986. Expectations and Commodity Price Dynamics: The Overshooting Model. *American Journal of Agricultural Economics* 68(2): 344-348.

Frankel, J. 2006. The Effect of Monetary Policy on Real Commodity Prices. NBER Working Paper 12713, National Bureau of Economic Research, Cambridge, MA.

Garber, P.M. 1989. Tulipmania. *Journal of Political Economy* 97: 535-560.

Garber, P.M. 1990. Famous First Bubbles. *Journal of Economic Perspectives* 4: 35-54.

Gilbert, C. L. 2010. How to Understand High Food Prices? *Journal of Agricultural Economics* 61(2): 398-425.

Gürkaynak, R. S. 2008. Econometric Tests of Asset Price Bubbles: Taking Stock. *Journal of Economic Surveys* 22(1): 166-186.

Gutierrez, L. 2013. Speculative Bubbles in Agricultural Commodity Markets. *European Review of Agricultural Economics* 40(2): 217-238.

Jacks, D.S. 2013. From Boom to Bust: A Typology of Real Commodity Prices in the Long Run. NBER Working Paper 18874, National Bureau of Economic Research.

Kang, H., B.K. Yu, and J. Yu. 2016. Global liquidity and commodity prices. *Review of International Economics*, 24(1): 20-36.

Karali, B. and G.J. Power. 2013. Short- and Long-run Determinants of Commodity Price

Volatility. *American Journal of Agricultural Economics* 95(3): 724-738.

Kilian, L. 2009. Not All Oil Price Shocks Are Alike: Disentangling Demand and Supply Shocks in the Crude Oil Market. *American Economic Review* 99(3): 1053-1069.

Kindleberger, C.P. and R. Aliber. 2005. *Manias, Panics and Crashes: A History of Financial Crises.* John Wiley & Sons, New York.

Kyrtsoua, C. and W. Labysb. 2006. Evidence for Chaotic Dependence between US Inflation and Commodity Prices. *Journal of Macroeconomics* 28: 256-266.

Lambert, D. 1992. Zero-inflated Poisson Regression, with an Application to Defects in Manufacturing. *Technometrics* 34(1): 1-14.

Levine, S.S. and E.J. Zajac. 2007. The Institutional Nature of Price Bubbles. SSRN Working Paper 960178, Social Science Research Network.

Li, J., C. Li and J. P. Chavas. 2016. Food price bubbles and government intervention. *Canadian Journal of Agricultural Economics*. (forthcoming).

Magdalinos, T. and P. C. Phillips. 2009. Limit Theory for Cointegrated Systems with Moderately Integrated and Moderately Explosive Regressors. *Econometric Theory* 25(2): 482.

Masters M W. 2008. Testimony before the Committee on Homeland Security and Governmental Affairs.

Okina, K., Shirakawa M. and Shiratsuka S. 2001. The Asset Price Bubble and Monetary Policy: Japan's Experience in the Late 1980's and the Lessons. *Monetary and Economic Studies*. 19(2):395-450.

Phillips, P. C. and T. Magdalinos. 2007. Limit Theory for Moderate Deviations from A Unit

Root. *Journal of Econometrics* 136(1): 115-130.

Phillips, P. C. and T. Magdalinos. 2008. Limit Theory for Explosively Cointegrated Systems. *Econometric Theory* 24(4): 865-887.

Phillips, P.C., T. Magdalinos and L. Giraitis. 2010. Smoothing Local-to-moderate Unit Root Theory. *Journal of Econometrics* 158(2): 274-279.

Phillips, P.C., Y. Wu and J. Yu. 2011. Explosive Behavior in the 1990s Nasdaq: When Did Exuberance Escalate Asset Values. *International Economic Review* 52(1): 201–226.

Phillips, P.C., S.P. Shi and J. Yu. 2015. Testing for Multiple Bubbles: Historical Episodes of Exuberance and Collapse in the S&P 500. *International Economic Review* 56 (4): 1043-1078.

Pindyck, R. and J. Rotemberg. 1990. The Excess Co-movement of Commodity Prices. *The Economic Journal* 100: 1173-1189.

Shiller, R.J. 2014. Speculative Asset Prices. Nobel Lecture, *American Economic Review* 104: 1486-1517.

Shiller, R.J. 2015. *Irrational Exuberance*. Third Edition, Princeton University Press, Princeton, NJ.

Tang, K. and W. Xiong. 2012. Index Investment and the Financialization of Commodities. *Financial Analysts Journal*. 68(5):54-74.

Yang, J., H. Qiu, J. Huang and S. Rozelle. 2008. Fighting Global Food Price Rises in the Developing World: The Response of China and Its Effect on Domestic and World Markets. *Agricultural Economics* 39(s1): 453-464.