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# Price bubbles in agricultural commodity markets and contributing factors: evidence for corn and soybeans in China

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## Abstract

**Purpose** – The purpose of this paper is to detect the existence of price bubbles and examine the possible contributing factors that associate with price bubble occurrences in China agricultural commodity markets.

**Design/methodology/approach** – Using recently developed rolling window right-side augmented Dickey–Fuller test, we first detect the dates of price bubbles in China's two important agricultural commodity markets, namely corn and soybeans. Then, we use a penalized maximum likelihood estimation of a multinomial logistic model to estimate the contributing factors of price bubbles in both markets, respectively.

**Findings** – Results from the bubble detection indicate that price bubbles account for 5.48% (3.91%) of the studied periods for corn (soybeans). More importantly, we find that market liquidity and speculation have opposite effects on the occurrences of bubbles in the corn and soybeans market. World stocks-to-use and exchange rates affect the occurrences of bubbles in a different way for each commodity, as well. Price bubbles are more likely associated with strong economic activity, high interest rates and low inflation levels.

**Originality/value** – This is the first study considering commodity-specific features into the formation of price bubbles. Through accurately identifying the bubble dates and fixing the estimation bias of rare events models, this study enables us to obtain robust results for each commodity. The results imply that China's corn and soybeans market respond differently to the speculative activity and external shocks from international markets. Therefore, future policy regulations on commodity markets should focus on more commodity-specific factors when aiming at avoiding bubble occurrences.

**Keywords** Price bubbles, Agricultural commodities, Futures markets, China

**Paper type** Research paper

## 1. Introduction

The word "price bubble" creates a mental picture of an expanding soap bubble, which is destined to burst suddenly and irrevocably (Shiller, 2015). Among the substantive research on the global financial crisis in 2007/2008, the controversy on price bubbles in commodity futures markets is long lasting (Gutierrez, 2013). It has been widely recognized that price bubbles could distort market trades since prices are the most important signals for traders (Phillips *et al.*, 2012). Meanwhile, price explosiveness on agricultural commodity markets may reduce the welfare of the poor due to rising food expenditures (Carter *et al.*, 2011). Such crisis may even cause economic and political instabilities (Bellemare, 2015). World Bank (2008) reports that 130 million people in developing countries fell into extreme poverty and suffered from food shortages due to the sudden increasing prices in food and fuel markets around

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2007/2008. This has urged scholars and policymakers to further understand the explosive nature of commodity prices.

A price bubble is a situation in which an asset price is higher (lower) than its fundamental value derived from the discounted dividend stream (Brunnermeier, 2008; Gürkaynak, 2008; Gutierrez, 2013). A price spike is a comparatively large upward or downward movement of a price over a short period of time. Price bubbles are price spikes, but the reverse is not necessarily true. Price spikes can be caused by structural changes of fundamental values (Harvey *et al.*, 2016). Many studies show that some historical price spikes are not price bubbles. Those spikes are systematic and rational responses to underlying economic structural changes (Etienne *et al.*, 2015; Meltzer, 2002).

After the financial crisis, the two main strings of studies on the possible factors contributing to price bubbles result in mixed findings. One string of these studies attributes bubbles to massive speculation or growing inflow of institutional funds into the commodity markets, and particularly argues that the motivation of commodity index traders is to diversify their own portfolios, rather than based on the market fundamentals (Basak and Pavlova, 2016; Master, 2008, 2009). Speculators are commonly considered to be any trader who is not engaged in the physical trade of a commodity (Working, 1960), and speculation is regularly defined as a process of transferring price risks for market traders with different beliefs, prospects or risk aversions (Tirole, 1982). Nevertheless, speculation has long been suspected to distort the normal market trades in the extant literature (Boyd *et al.*, 2018). Master (2008, 2009) states that excessive speculation is the major reason for commodity price bubbles in futures markets during the global financial crisis, which is often cited as "Master hypothesis". He strongly urges restrictive rules on speculative positions in commodity futures markets. It is argued that futures markets with a relative inelastic supply of futures contracts experience dramatic price changes if new demand from excessive speculation is introduced or if speculative activities are not based on market fundamentals (Henderson *et al.*, 2015; Sockin and Xiong, 2015). Tang and Xiong (2012) find that financialization of commodities leads to a co-movement in returns between commodity futures and financial assets. Basak and Pavlova (2016) then construct a model of financialization of commodities which suggests that both (commodity) index trades and non-index trades could drive up commodity futures prices, volatilities and correlations under the financialization of commodities.

Another stream of studies sees fundamental supply and demand as well as macroeconomic factors as the main contributing factors for the significant price rise in 2007/2008 (Boyd *et al.*, 2018; Will *et al.*, 2013). One example in this area is the huge demand from bio-energy industries and the increasing demand from emerging economies (Carter *et al.*, 2012; Hamilton, 2009; Kilian and Murphy, 2014; Krugman, 2008). Rapid growth among the major emerging markets and developing economies over the past 20 years has boosted the global demand for commodities, especially given that 39% of the increase in global food consumption between 1996 and 2016 is from emerging economies (World Bank, 2018). Some studies even argue that the implementation of the limits on institutional positions may even take the liquidity out of the commodity futures markets and result in high price volatility (Brunetti and Buyuksahin, 2009; Sanders and Irwin, 2010, 2011). Using pooled data from different agricultural commodity markets in United States, Etienne *et al.* (2017, 2015) find no effects of increasing commodity index trades on bubbles; they conclude that positive price bubbles mostly occur in the presence of inventory shortages, strong exports, weak US$ exchange rates and booming economic growth. This is in line with the idea that price bubbles grow when insufficiently informed traders overreact to market news (Scheinkman and Xiong, 2003).

Likewise, macroeconomic factors have been shown to play significant roles in explaining the price movements in agricultural commodities (Bailey and Chan, 1993; Carter *et al.*, 2011;

Pindyck and Rotemberg, 1988), which might contribute to price bubbles. For instance, Pindyck and Rotemberg (1988) find that inflation, industrial production, interest rates and exchange rates can be used to explain the co-movements of different commodity prices. Phillips and Yu (2011) even point out that varying interest rates could induce temporary explosive behaviors in asset prices. Li *et al.* (2017a, b) find that price bubbles are more likely to happen under certain macroeconomic conditions. In addition, some other studies concerning commodity price volatility prove that macroeconomic factors significantly affect the low-frequency component of price volatility (Engle and Rangel, 2008; Karali and Power, 2013). Therefore, macroeconomic factors can capture the critical features of the economy and may further affect traders' expectations of commodity markets.

This paper concentrates on the price bubbles of corn and soybeans futures market in China and hopes to find the potential contributing factors behind these bubbles. China has a huge, rigid and everlasting demand for agricultural commodities from its home and global market. Its rising food consumption demand has profound effects on the world food balance and trade pattern (Coxhead and Jayasuriya, 2010) and is often taken as the main sources of global commodity price spikes. It is also a special case for China that it is the major player as an important agricultural producer and consumer in the global market, such as corn and soybeans. Hernandez *et al.* (2014) also find that China is a locally oriented and highly regulated market (2014). They verify the dynamic international interlink between China market and many other major international markets. Therefore, as the most populated country, it is extremely important for China to maintain food safety and keep a stable agricultural commodity market. An additional background is that retailing investors are the main force of China's commodity futures market. Since commodity index funds are beginning to enter into the futures market recently, it is necessary to study the latent impact of speculation and other factors through available data.

To the best of our knowledge, this study is the first one considering the commodity-specific factors into the formation of price bubbles for important Chinese agricultural markets. Using a newly developed rolling window right-side ADF test (GSADF) with the wild bootstrap procedure [1], we first accurately identify price bubble dates in China's corn and soybeans futures markets. Afterwards, we adopt a penalized maximum likelihood estimation of a multinomial logistic model to explore the potential factors contributing to price bubbles for each commodity, respectively.

Importantly, our study is different from the other studies in the way of estimating the contributing factors of price bubbles. Due to the rare occurrences of bubbles, the existing empirical studies would pool different commodities together, when estimating the common potential influencing factors of price bubbles (Etienne *et al.*, 2015; Li *et al.*, 2017a, b). This is no longer appropriate if considering the specific features of different commodity markets and may even result in misleading conclusions. Especially, the commodities we consider here are corn and soybeans. These two commodities have different restrictive rules regarding importing from the international market in China. One may expect some different effects of world stocks-to-use and exchange rates in the model of corn and soybeans. In this case, the penalized maximum likelihood estimation method of a multinomial logistic model enables us to avoid the bias caused by rare events.

In this paper, we try to fix the estimation bias of rare events models and obtain a robust result using data from individual commodity market. If the "Master hypothesis" is true that price bubbles are mainly driven by excessive speculation, we may expect price bubbles to be accompanied by high futures trade volumes or open interests, and do not reflect fundamentals of supply and demand in the market. If the "Master hypothesis" is rejected, price bubbles would be the outcome of extreme supply and demand conditions on the corresponding commodity, as well as an outcome of macroeconomic activities. These hypotheses will be investigated for each commodity market, respectively.

The outline of the rest of the paper is as following. Section 2 briefly introduces the methods to detecting price bubbles, including bubble testing and the penalized multinomial logistic model to determine the factors that contribute to price bubbles. Section 3 describes the data and provides some descriptive statistics. Section 4 discusses the main model estimation results. Section 5 summarizes the paper and presents conclusion.

## 2. Methodology

### *2.1 Testing for price bubbles*

A conventional definition of a price bubble is that it is a situation in which an asset price is higher (lower) than its fundamental value derived from the discounted dividend stream (Brunnermeier, 2008; Gürkaynak, 2008; Gutierrez, 2013). If investors already know that the present price of an asset is biased from its fundamental value and investors are still buying or holding the asset to acquire benefits from future sales, price bubbles are rational. The cross-period arbitrage-free condition always holds in the case of rational price bubbles, which means the bubble would grow in the risk-free rate. Following the study of Blanchard and Watson (1982), the price process of one asset should follow the form:

$$P_t = \frac{E_t[P_{t+1} + D_{t+1}]}{1 + r_f} \tag{1}$$

where $P_t$ represents the price at time $t$, $D_t$ represents the dividend or payoff for time $t$, $r_f$ represents the risk-free interest rate and $E_t[\cdot]$ represents the expectation based on the information at time $t$. Taking the convenience yields as the dividends for commodities, Pindyck (2001) then finds that Eqn (1) can be used to explain the formation of commodity futures price. Forward iterating Eqn (1) to infinite periods, we can get the fundamental price of the asset:

$$P_t^f = \sum_{i=1}^{\infty} \frac{1}{(1 + r_f)^i} E_t(D_{t+i}) \tag{2}$$

Eqn (2) is the unique solution of Eqn (1) only when the transversality condition is fulfilled, that is the price at the infinite future point is zero:

$$\lim_{k\to\infty} E_t\left[\frac{1}{(1 + r_f)^k} P_{t+k}\right] = 0 \tag{3}$$

However, when Eqn (3) does not hold, Eqn (2) will no longer be the unique solution of Eqn (1). This suggests that a deviation from the fundamental price could occur even under the constraint of non-arbitrage. Consider a bubble component $B_t$ with the property

$$E_t[B_{t+1}] = (1 + r_f)B_t \tag{4}$$

adding this $B_t$ into Eqn (2) will also satisfy Eqn (1). That is

$$P_t = P_t^f + B_t \tag{5}$$

In this case, the non-arbitrage condition still holds, because the bubble component grows at rate $r_f$, and the rational expectation of investors is not biased. Thus, this kind of price bubble is called as rational price bubbles.

Moreover, under the plausible assumption that the dividends would follow a random walk with a drift $\mu$.

$$D_{t+1} = \mu + D_t + \varepsilon_t \tag{6}$$

where $\varepsilon_t$ is a white noise process. Substituting Eqn (6) into Eqn (2), we can get

$$P_t^f = \frac{r_f}{1+r_f}\mu + \frac{1}{r_f} D_t \tag{7}$$

The first term of the right side of Eqn (7) is constant, while the second term is a random walk process based on Eqn (6). Thus, Eqn (7) shows that the fundamental price should be a random walk series and will become an explosive process when there is bubble component as in Eqn (4). For more details, please refer to the study of Blanchard and Watson (1982), Gürkaynak (2008), and Hamilton (1994).

Another important issue is about the existence of negative bubbles, or price bubbles during the price downward process. Similar with Etienne *et al.* (2015), we define the positive bubbles as phases in which the average price is higher than the fundamental value, while negative bubbles occur when the average price is below the fundamental value. Based on the deduction above, it seems that $B_t$ cannot be negative because it will result in a negative price which is not allowed in the markets (Diba and Grossman, 1988). However, it has been found that there are two situations in which bubbles can occur during the price downward process. Firstly, the existence of a bubble may lead to an increase in interest rates which so depresses the fundamental value that the sum of the bubble component and the fundamental falls short of the nonbubbly fundamental value. Hence, a rational bubble component may in fact decrease the overall price of an asset (Weil, 1990). Secondly, Payne and Waters (2005) find that negative bubbles are allowed in the case of periodically collapsing bubbles, which also satisfy the conditions of Eqn (1) to (5). Thus, bubbles could occur along both with the upward and downward price movements. This suggests that we should separate the negative bubbles from positive ones, because the potential contributing factors may have opposite effects for these two types of bubbles [2].

The definition of price bubbles above provides the basis for the right-tailed unit root test to testing bubbles (Diba and Grossman, 1988). When price bubbles occur, the rational bubble component of prices is an explosive process, while the remaining part is a stationary or integrated process of order one at the most. Phillips *et al.* (2011, Phillips and Yu, 2009) further develop the right-tailed unit root test into a new forward recursive right-tailed ADF test (SADF), which suggest implementing the right-tailed ADF test repeatedly on a forward expanding sample sequence and performing inference based on the supreme value of the corresponding ADF statistic sequence.

A great advantage of this SADF test is that it can identify the points of origination and termination of a bubble. Homm and Breitung (2012) use extensive simulations prove that the SADF test works satisfactorily for structural breaks, when comparing to other bubble testing approaches (such as sequential Chow-tests and CUSUM tests), especially it can detect market exuberance induced by a variety of sources, such as speculation or the time-varying discount factor. However, all of these methods suffer from reduced power when detecting the periodically collapsing bubbles. To solve this, Phillips *et al.* (2012, 2015) propose an alternative approach named the generalized supreme ADF test (GSADF). Currently, the GASDF test has been widely accepted and used to detect bubbles in many markets, such as stock markets (Caspi and Graham, 2018; Hu and Oxley, 2018), real estate markets(Anundsen *et al.*, 2016; Engsted *et al.*, 2016; Pavlidis *et al.*, 2016) and energy markets (Caspi *et al.*, 2018; Tsvetanov *et al.*, 2016). Recently, many studies also try to apply this method into the agricultural commodity markets (Etienne *et al.*, 2015; Gutierrez, 2013; Li *et al.*, 2017a, b). Detailed introduction of the GSADF test is described as following.

According to Phillips *et al.* (2015), a recommended empirical regression model of random walk process for bubble detection has the following weak (local to zero) intercept form:

$$P_t = dT^{-\eta} + \theta P_{t-1} + \varepsilon_t \text{ with } \varepsilon_t \sim iid\left(\sigma^2\right) \text{ and } \theta = 1 \tag{8}$$

where $P_t$ is the asset price, $d$ is a constant, $T$ is the sample size and $\eta$ is a localizing coefficient that controls the magnitude of the intercept and drift as $T \to \infty$.

The main idea of the GASDF method is to implement the ADF test on the sequential subsets (rolling window) of the whole sample. Suppose that the rolling window sample starts from the $r_1^{th}$ fraction of the total sample ($T$) and ends at the $r_2^{th}$ fraction of the sample, where $r_2 = r_1 + r_w$ and $r_w > 0$ is the fractional window size of the regression. The empirical regression model can then be written as

$$\Delta P_t = \widehat{\alpha}_{r_1,r_2} + \widehat{\beta}_{r_1,r_2} P_{t-1} + \sum_{i=1}^{k} \widehat{\varphi}^{i}_{r_1,r_2} \Delta P_{t-i} + \widehat{\varepsilon}_t \tag{9}$$

where $k$ is the lag order. The number of observations in the regression is $T_W = [Tr_w]$, where [.] is the floor function (given the integer part of the argument). The ADF statistic ($t$-ratio) based on this regression is denoted as $ADF_{r_1}^{r_2}$. Then, the rolling regression of the repeated ADF test is implemented for the bubble detection using the subsamples of the data. The GSADF relies on the repeated estimation of the ADF model. It varies the endpoint of the ADF regression $r_2$ from $r_0$ (the minimum window width) to 1, and it allows the starting point $r_1$ to change within a feasible range, that is, from 0 to $r_2 - r_0$. The GSADF test statistic of $r_2$ is then obtained as the sup value of the corresponding ADF statistic sequence:

$$\text{GSADF}(r_0) = \sup_{\substack{r_2 \in [r_0,1] \\ r_1 \in [0,r_0]}} \left\{ \text{ADF}_{r_1}^{r_2} \right\} \tag{10}$$

The origination date of a bubble $[T_{r_e}]$ is calculated as the first chronological observation whose GSADF statistic exceeds the critical value. The calculated origination date is denoted by $[T_{\widehat{r_e}}]$. The estimated termination date of a bubble $[T_{\widehat{r_f}}]$ is the first chronological observation after $[T_{\widehat{r_e}}] + L_T$ whose GSADF statistic is below the critical value. We set the minimum window size to 20 observations, which is amount to one month's trading days [3]. The bubble duration must exceed the length of $\log(T)$. Here, in our paper, it is around $\log(264) = 2.42$. The bubble duration should at least last 3 days.

For the calculation of critical values in the GSADF method, Phillips *et al.* (2012) firstly propose to use the Monte Carlo simulation. However, Harvey *et al.* (2016) find that the Monte Carlo method will mistake the potential structural breaks in the price series as price bubbles and the results of bubble detection will be quite severely over-sized. They propose to use the wild bootstrap method to calculate the critical values, which will consider the underlying structural break of the time series and thus find fewer but more accurate bubble days than the Monte Carlo method. In this paper, we adopt the wild bootstrap method. The number of iterations of wild bootstrapping is 2000.

*2.2 Estimation of possible contributing factors on price bubbles*

Employing the GSADF approach, we could identify the bubble dates and types in the sample period. Each observation has three possible states, namely no bubble, positive bubble and negative bubble. In the case of discrete response models with three outcomes, a multinomial logistic model is adequate to test for possible contributing factors on the different outcomes (Wooldrige, 2010). There are two commodities, namely corn and soybeans, indexed by $i = 1,\ 2$. The variables of the multinomial logistic model are as shown in the equation below:

$$\begin{aligned} \text{Bubbles}_{it} = {} & \text{Cons}_i + \beta_{i1}\text{MLF}_{it} + \beta_{i2}\text{Stocks}_{it} + \beta_{i3}\text{SOI}_t + \beta_{i4}\text{USBubbles}_t \\ & + \beta_{i5}\text{Exchange}_t + \beta_{i6}\text{ECI}_t + \beta_{i7}\text{Shibor}_t + \beta_{i8}\text{PPI}_t \quad + \beta_{i9}\text{Gasoline}_t + \varepsilon_{it} \end{aligned} \tag{11}$$

where $i = 1$ for corn and 2 for soybeans, the dependent variable "Bubbles" are dummy variables which include three categories: positive, negative and no bubbles (base category). As presented in the introduction, the current discussion on the origin of agricultural price bubbles mainly focuses on two directions: excessive speculative trade and fundamental economic factors. Speculation in futures market has long been considered as the source of market instability, because speculators are thought to be irrational traders who only want to make extra profits (Boyd *et al.*, 2018). However, speculation is also important for risk transferring and price discovery in futures markets, and speculators are important counterparties to commercial traders (Tirole, 1982). The trade volume and open interests are used to capture the effects of speculation (Castro Campos, 2019; Tadesse *et al.*, 2014; Hong and Yogo, 2012; Irwin *et al.*, 2009). Similarly, bubbles from international commodity markets, e.g. US markets, can affect markets in China. Market information from international exchanges is available in real time and processed by arbitrage brokers, which leads to tightly linked futures markets (Hernandez *et al.*, 2014). Price bubbles may thus transmit between different markets by these mechanisms.

The fundamental factors include the stock-to-use ratio, macroeconomic factors and weather shocks (Southern Oscillation Index, SOI). All factors have been found to influence the expectation of commodity price (Adämmer and Bohl, 2015; Castro Campos, 2019; Etienne *et al.*, 2015; Gilbert, 2010; Li *et al.*, 2017a, b; Pindyck and Rotemberg, 1988). Specifically, the factors of domestic and global stocks-to-use ratios mirror the degree of demand pressure for corn and soybeans, while the weather shocks (SOI) significantly affect the traders' expectations on future supplies. Thereby we cover the supply and demand effects. The macroeconomic factors, e.g. the exchange rate, the economic climate index (ECI), the interest rates, inflation, and gasoline prices, reflect the various economic activities and the impact of business cycles. There is plenty of evidence for the impact of macroeconomic factors on the movement of commodity prices (Li *et al.*, 2017a, b; Etienne *et al.*, 2015; Adämmer and Bohl, 2015; Frankel, 2014; Pindyck and Rotemberg, 1988).

Exchange rate changes the incentives to international trade of corn and soybeans. The economic climate index reflects the degree of economic activity, which affects the demand on various commodities. Interest rates affect investments and commodity storage costs. By considering the inflation rate, we control the general price level. Gasoline prices reflect energy price, which have direct and indirect effects on agricultural commodity markets. More details of the variables will be stated in Table 1.

One problem in existing studies is that they usually pool the data of different commodities together to estimate the effects of the possible contributing factors (Etienne *et al.*, 2015; Li *et al.*, 2017a, b). This pooling is due to the rare occurrences of bubbles, which may result in a biased estimation of the parameters using the conventional multinomial logistic model (King and Zeng, 2001). However, though some price co-movement caused by common macroeconomic factors can be seen in the commodity markets, Ghoshray (2018), Kellard and Wohar (2006) find that the price dynamics for related commodities, such as corn and soybeans, tend to be distinctly different from each other and warn against the aggregation of commodities. This is particularly true in the case of China. China is still a self-sustaining market and has high domestic inventory volumes for corn, while China imports more than half of its soybean consumption from global markets. According to the statistics from China's General Administration of Customs, the import volume of soybeans in 2017 is about 95.54 mt. This is a historic peak that increased by 13.9% compared with 2016. However, the import volume of corn is only 2.83 mt. Its import share decreases by 11% compared with 2016. As the largest soybean importer, it is important to consider international shocks for soybeans market. In order to avoid the biased estimation problem caused by rare events when estimating each market, we adopt the penalized maximum likelihood estimation for the multinomial logistic model, which can provide an unbiased estimation of the potential

| Variables | Description | Corn | Soybean |
|---|---|---|---|
| Price | Price for each commodity (¥/ton) | 1935.48 (345.24) | 3982.82 (575.46) |
| *Daily controls* | | | |
| Trade volume | Daily hands of futures contracts exchanged in the Dalian Commodity Exchange (thousand hands) | 128.13 (227.20) | 107.80 (201.2729) |
| Open interest | Daily number of futures contracts that are still open and held by traders (thousand contracts). These contracts have not been closed out, expired or exercised | 285.43 (403.42) | 131.14 (120.41) |
| Exchange rate | Daily RMB to Dollar exchange rate (¥/$) | 6.72 (0.53) | 6.72 (0.53) |
| Shibor | The "Shanghai Interbank Offered Rate", which is used to represent the interest rates. Shibor is regularly considered as the risk-free interest rate in China | 2.34 (0.94) | 2.34 (0.94) |
| USBubbles_positive | Dummy variable for positive bubbles in US corn and soybeans markets | 0.015 (0.125) | 0.028 (0.166) |
| USBubbles_Negative | Dummy variable for negative bubbles in US corn and soybeans markets | 0.015 (0.121) | 0.014 (0.118) |
| *Monthly controls* | | | |
| China Stocks-to-use | The ratio of changes in the inventory volume of each commodity over the beginning stocks of each period in China | 0.15 (1.13) | 0.20 (1.11) |
| World Stocks-to-use | The ratio of changes in the inventory volume of each commodity over the beginning stocks of each period at a global scale | 0.26 (1.26) | 0.26 (1.26) |
| SOI | Southern Oscillation Index: Predicting the El Niño (La Niña) episodes across the eastern tropical Pacific area | 0.31 (0.97) | 0.31 (0.97) |
| ECI | Index indicator of the economic activity in China (baseline = 100) | 91.79 (17.54) | 91.79 (17.54) |
| PPI | Producer Price Index, which is used to represent the inflation rate. It indicates the monthly average changes in the price levels received by producers for their output. (PPI = 100 in 2002) | 128.11 (6.17) | 128.11 (6.17) |
| Gasoline | Gasoline price (¥/100*ton) | 69.80 (12.77) | 69.80 (12.77) |

**Note(s)**: The last two columns report the mean value of corresponding variables and the standard deviations are in the parentheses. Monthly data will be converted into daily data by assuming constant values throughout the month and their mean value could be calculated on this basis

**Table 1.** Price and possible factors contributing to price bubbles (2006–2017)

contributing factors to price bubbles for corn and soybeans, respectively. The penalized maximum likelihood estimation (PLE) is developed by Firth (1993) and it penalizes the likelihood estimates of a logistic regression using the Jeffreys prior. Similar to the method proposed by King and Zeng (2001), the PLE method can reduce the bias of the maximum likelihood estimation in the case of rare events for discrete choice models (Paul, 2012). Fortunately, Colby *et al.* (2010) has further developed an R package "PMLR" to employ this method for the multinomial logistic model.

## 3. Data

Our study focuses on China, which is one of the most important emerging economies. China has a huge, rigid and lasting demand for agricultural commodities not only from its domestic market but also from global markets. Forecasts of the world economy to 2030 suggest China would continue to become more food import-dependent (Anderson, 2018). Its rising demand for food consumption has profound effects on the world food balance and trade patterns (Coxhead and Jayasuriya, 2010). Effective policies and regulations to keep commodity prices stable require better insights into the dates and formation of price bubbles.

China has established futures markets for many agricultural commodities in the last decades (Chang, 2020), and they serve important functions for price discovery during the process of marketization for most agricultural commodities (Ju and Yang, 2019). We collect the price data from the Dalian Commodity Exchange (DCE) in China. According to the Futures Industry Association (FIA), the DCE was the eighth largest exchange in the world in 2016. Our sample period runs from 2006 to 2017, including the periods of global price peaks in 2007/2008 and 2010/2011. Here, we use the sequences of individual futures contract prices and detect bubbles on each futures contract price series. The rolling nearby contract price behaving like cash prices is not used, because bubbles within it could be entirely driven by fundamental demand and supply factors rather than speculative trades in the futures market (Etienne *et al.*, 2015). Meanwhile, nearby futures prices may suffer the potential "splicing bias", because the price jumps generated from rolling one futures contract to the next nearby futures contract would result in "pseudo bubbles". Unlike nearby contract price, the individual contract price should behave as a random walk and reflect the complete evolvement of traders' continuous expectation on the market over the whole trading year (Fama and French, 2013).

We choose the futures contract with the highest trade volume per commodity each year. Taking the corn contract "c1701" as an instance, its time span is from 2016.01.18 to 2017.01.15. The price data in the delivery month (2017 January) is excluded and only the price data from 2016.01.18 to 2016.12.30 is kept. Due to the min-window size of the bubble testing method, we further use the price data from 2015.11.16 to 2016.01.17 of the nearest corn contract "c1611" as our initial window period. Thus, we can get a 13-month price series for each commodity in 2016. The same procedure goes for the other sample periods. Then, we will use the bubble detecting method (GSADF) to test each price series and date-stamp the bubbles.

Table 1 presents detailed information on the model variables in Eqn (11). Trade volume and open interest represent the market liquidity and speculation for different commodities. The domestic and world stocks-to-use data is from the U.S. Department of Agriculture (USDA). We take the initial (not corrected) data available at the respective period. The stocks-to-use ratio is the ratio of net consumption over initial stocks of each period. For weather shocks, the Southern Oscillation Index (SOI) is used to predict El Niño and La Niña episodes, which affects yields of grains in the western and eastern tropical Pacific area (Shuai *et al.*, 2016). The "USBubbles" is a dummy variable indicating price bubbles for US corn and soybeans markets. This information is taken from the study of Etienne *et al.* (2015) [4]. The exchange rate and Shibor are from China Central Bank. Gasoline is the refined oil price obtained from China Ministry of the Commerce. ECI is the economic climate index measuring the economic activity and PPI is the production price index (China National Statistical Bureau). Based on the literature, all these factors may have direct and indirect effects on traders' expectations (Gilbert, 2010; Hong and Yogo, 2012; Pindyck and Rotemberg, 1988).

Most of the independent variables have a daily frequency, except domestic and world stocks-to-use ratios, SOI, Gasoline, ECI and PPI. These variables indicate a monthly frequency. We convert monthly data to daily by simply filling up the days of the month with the respective monthly observation. As these monthly data do not show significant changes in the short-term, the changes in frequency may not affect the estimation results (Etienne *et al.*, 2015; Li *et al.*, 2017a, b).

## 4. Results

### 4.1 Bubble dates

Figures 1 and 2 illustrate the relationship between the price trends and bubble periods for corn and soybeans, respectively. Similar to global markets, the prices of corn and soybeans in China both experience dramatic fluctuations during 2007/08 and 2010/11. However, we can see that not all bubbles occur at times when prices of individual futures contract sharply increase or decrease [5]. This seemingly counterintuitive result is also found in other studies using the same methodology (Etienne *et al.*, 2015; Harvey *et al.*, 2016). Generally, this kind of results will be accepted in former studies. According to asset pricing theory, a normal price series should be a random walk process. Here, we should distinguish two types of price series. One is a process containing explosive root, and the other one is a process behaving as random walk with high price volatility. The price period between 01 Jan 2008 and 01 Jan 2009 has been proved to be a random walk without explosive roots, its dramatic fluctuations thus should be attributed to the high volatility. To verify this, we further implement the GASDF test on a simulated random walk process with high price volatility and still get no evidence of price bubbles [6], though the simulated random walk also seems to have explosive periods. Another explanation is that the wild bootstrap method considers the underlying structural breaks in the price process and improves the critical values in certain periods.

Generally, most bubble episodes last less than 10 days. The maximum single bubble duration of corn lasts 24 days from 2008.11.28 to 2008.12.31 and the maximum duration of a single soybean price bubble lasts 28 days from 2007.10.11 to 2007.11.19. For the bubble frequencies, there are 19 bubbles in the corn market and 16 bubbles in the soybean market during the whole sample period.

As mentioned earlier in the part of methodology, we classify the bubbles into two types: positive and negative bubbles. There are 158 days (5.48% of the sample period) of price bubbles for corn, 46 days of which are positive bubbles and 112 days of which are negative bubbles. In contrast, 113 days (3.91% of the sample period) are found to be price bubbles for soybeans, 91 days of which are positive bubbles and 22 days of which are negative bubbles. Negative bubbles are most frequently observed in the corn market, while positive bubbles are more prominent in the soybeans market. The different performances of bubbles may also reflect that the corn market is highly self-sustaining while the soybean market always experiences shortages. These facts suggest there may be different market conditions behind these two markets and we cannot simply pool them together as in other studies (Etienne *et al.*, 2015; Li *et al.*, 2017a, b). Moreover, the positive and negative bubbles are not tightly connected with each other and tend to be independent events. This supports our use of the multinomial logistic model to estimate the contributing factors of positive and negative bubbles, respectively.

More detailed information about the bubble dates is presented in Table A1 and Table A2 in the appendix. In line with former studies using the same bubble testing method, we could conclude that price bubbles are rare events and only comprise a limited proportion of the sample period. In the following part, we will further discuss the effects of possible contributing factors on price bubbles.

### 4.2 Multinomial logistic regression results

We first calculate the descriptive statistics for the independent variables in Table 2. Compared with periods without bubbles, the mean values of the trade volume and open interest are much lower during bubble periods. It may imply that price bubbles are more likely to occur under low market liquidity. For the domestic and world stocks-to-use ratios, we could see different trends of mean values during positive bubbles and negative bubble episodes. The SOI tends to be negative during negative bubble periods. The rest macroeconomic factors do not show significant trends.

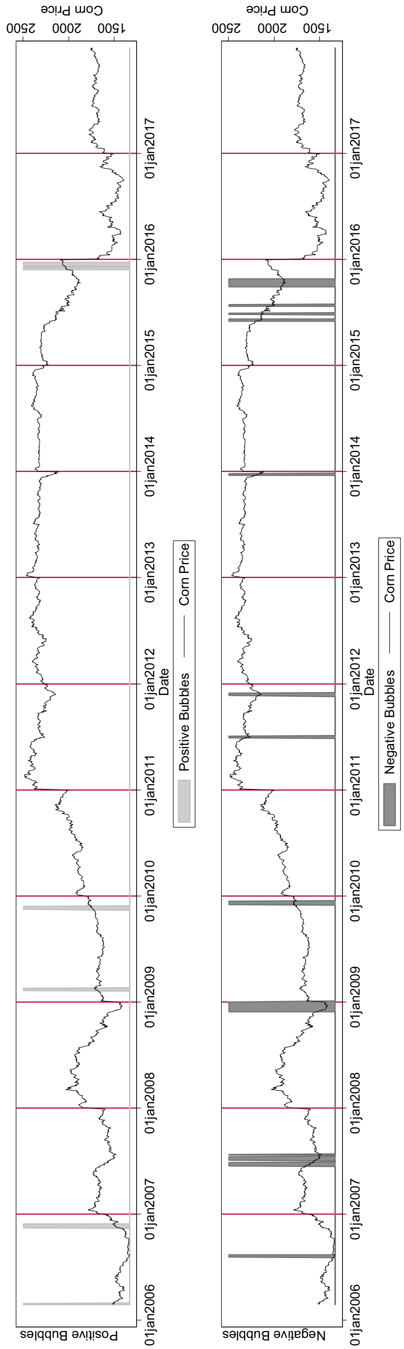


**Figure 1.**
Price bubbles for corn

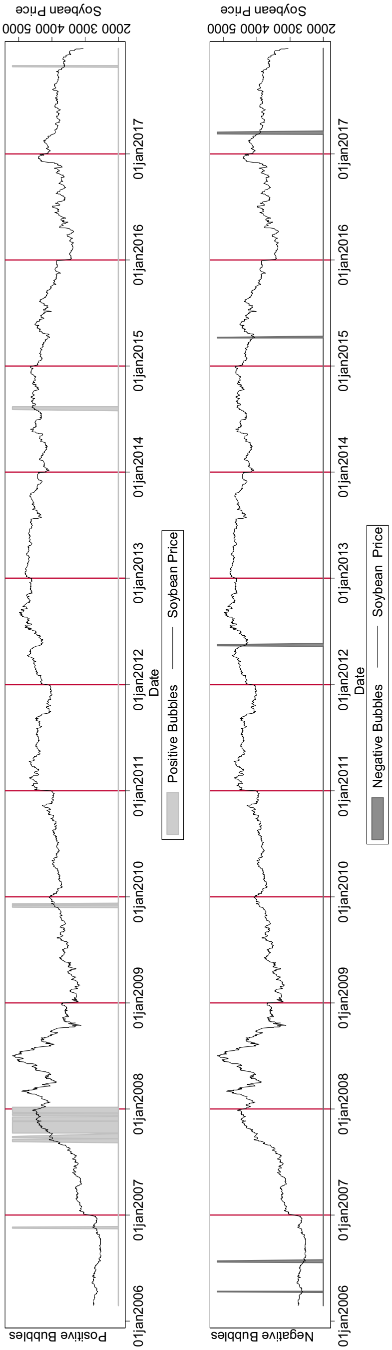


**Figure 2.**
Price bubbles for
soybeans

**Table 2.** Summary statistics of the contributing variables

| | Corn | | | Soybean | | |
|---|---|---|---|---|---|---|
| | No bubbles | Positive | Negative | No bubbles | Positive | Negative |
| Trade volume | 131.74 (233.39) | 19.98 (44.12) | 125.56 (144.76) | 111.11 (207.99) | 39.38 (91.61) | 48.85 (87.42) |
| Open interest | 290.10 (408.54) | 41.25 (51.67) | 259.30 (261.23) | 132.77 (120.94) | 92.98 (95.28) | 78.74 (98.26) |
| China stocks-to-use | 0.02 (0.11) | −0.03 (0.12) | 0.01 (0.11) | 0.02 (0.11) | 0.06 (0.04) | 0.09 (0.06) |
| World stocks-to-use | 0.03 (0.13) | 0.07 (0.13) | 0.04 (0.09) | 0.03 (0.13) | −0.02 (0.08) | 0.02 (0.18) |
| SOI | 0.33 (0.96) | 0.02 (0.88) | −0.05 (1.05) | 0.30 (0.97) | 0.02 (0.88) | −0.05 (1.05) |
| US bubbles positive | 0.02 (0.13) | 0.00 (0.00) | 0.01 (0.10) | 0.02 (0.15) | 0.16 (0.37) | 0.00 (0.00) |
| US bubbles negative | 0.02 (0.13) | 0.00 (0.00) | 0.00 (0.00) | 0.01 (0.12) | 0.04 (0.20) | 0.00 (0.00) |
| Exchange Rate | 6.74 (0.54) | 7.05 (0.62) | 6.82 (0.60) | 6.73 (0.54) | 7.24 (0.45) | 7.17 (0.80) |
| ECI | 92.06 (17.31) | 90.28 (20.14) | 91.57 (20.39) | 91.33 (17.16) | 112.66 (15.13) | 91.52 (15.25) |
| Shibor | 2.36 (0.96) | 1.89 (0.88) | 2.08 (1.15) | 2.34 (0.97) | 2.45 (1.06) | 2.18 (0.26) |
| PPI | 128.21 (6.25) | 120.94 (2.86) | 125.32 (5.68) | 128.10 (6.31) | 124.83 (2.86) | 125.36 (7.97) |
| Gasoline | 7023.51 (1271.36) | 5889.1 (773.39) | 6388.93 (1232.85) | 7018.72 (1264.21) | 5919.73 (1101.97) | 6552.22 (1576.23) |
| *Observations* | 2194 | 38 | 91 | 2231 | 74 | 18 |

**Note(s)**: The cells report the mean value of corresponding variables and the standard deviations are in the parentheses. The number of bubble days here is different from that in the previous part because there are some missing values in the independent variables, such as Shibor

We will use a multinomial logistic model to estimate the effects of the potential contributing factors. A penalized maximum likelihood estimation method is applied to avoid biases, which occur with conventional multinomial logistic regression. Tables 3 and 4 present the main results. Tables A3 and A4 in the appendix show the marginal effects of the independent variables. Signs of the marginal effects are consistent with the signs of the corresponding coefficients in Tables 3 and 4.

*4.2.1 Contributing factors of price bubbles for the corn market.* We use two variables to measure the futures market liquidity and speculation, namely the trading volume and open

| | Model 1 | | Model 2 | |
|---|---|---|---|---|
| | Positive | Negative | Positive | Negative |
| Cons | 202.84*** (32.13) | 10.01 (1.03) | 220.12*** (3.39) | 11.46 (10.41) |
| Trade volume/100 | −3.32*** (0.88) | −0.05 (0.06) | | |
| Open interest/100 | | | −1.88*** (0.47) | −0.05 (0.04) |
| China stocks-to-use | −0.58 (4.45) | −1.64 (1.52) | −3.96 (3.94) | −1.31 (1.56) |
| World stocks-to-use | 1.77 (3.23) | −0.15 (1.35) | 5.07 (3.31) | −0.10 (1.35) |
| SOI | 2.00*** (3.23) | −0.34** (0.17) | 1.96*** (0.46) | −0.34** (0.17) |
| USBubbles positive | −0.93 (1.53) | −0.93 (0.88) | −0.70 (1.54) | −0.92 (0.88) |
| USBubbles negative | 3.17 (2.05) | −0.44 (1.50) | 3.95 (2.18) | −0.48 (1.50) |
| Exchange rate | −4.99*** (1.51) | −1.75** (0.72) | −7.49*** (1.71) | −1.84*** (0.72) |
| ECI | 0.11*** (0.04) | 0.01 (0.01) | 0.14*** (0.04) | 0.02 (0.01) |
| Shibor | 0.29 (0.26) | 0.01 (0.17) | 0.57** (0.25) | 0.02 (0.17) |
| PPI | −1.66*** (0.25) | 0.01 (0.06) | −1.64*** (0.24) | 0.01 (0.06) |
| Gasoline | 0.34*** (0.00) | −0.12*** (0.00) | 0.25*** (0.00) | −0.12*** (0.02) |
| Quarter 2 | −2.40** (1.37) | 3.90*** (1.40) | −1.81 (1.35) | 3.94*** (1.40) |
| Quarter 3 | −1.88 (1.49) | 4.17*** (1.40) | −0.55 (1.51) | 4.26*** (1.40) |
| Quarter 4 | 1.98*** (0.59) | 5.11*** (1.39) | 2.53*** (0.61) | 5.12*** (1.39) |
| *Observations* | 2321 | 2321 | 2321 | 2321 |

**Note(s)**: Standard errors are in parentheses. ****p < 0.01, **p < 0.05, *p < 0.1*

**Table 3.** Penalized maximum likelihood estimation for the multinomial logistic regression: Corn

| | Model 1 | | Model 2 | |
|---|---|---|---|---|
| | Positive | Negative | Positive | Negative |
| Cons | 38.60** (1.78) | −66.44*** (17.76) | 47.54** (19.38) | −57.55*** (17.01) |
| Trade volume/100 | 0.27** (0.10) | 0.07 (0.17) | | |
| Open Interest/100 | | | 0.70*** (0.23) | −0.63 (0.34) |
| China stocks-to-use | 6.76** (2.77) | 4.21 (2.86) | 6.02** (2.83) | 6.80* (3.41) |
| World stocks-to-use | −6.19*** (1.87) | −7.83*** (2.42) | −4.87*** (1.90) | −9.88*** (2.84) |
| SOI | 0.35 (0.28) | 0.12 (0.36) | 0.48 (0.29) | −0.06 (0.35) |
| USBubbles positive | 1.37** (0.73) | 1.53 (1.37) | 1.42** (0.73) | 1.54 (1.43) |
| USBubbles negative | 2.84 (0.78) | 1.65 (1.64) | 2.14 (0.85) | 1.83 (1.56) |
| Exchange rate | −1.59 (1.22) | 6.34*** (1.44) | −2.10 (1.30) | 5.19*** (1.35) |
| ECI | 0.14*** (0.02) | −0.08*** (0.03) | 0.16*** (0.02) | −0.05** (0.03) |
| Shibor | 0.94*** (0.20) | −0.78 (0.50) | 0.97*** (0.20) | −0.74 (0.49) |
| PPI | −0.43*** (0.12) | 0.15 (0.12) | −0.51*** (0.14) | 0.13 (0.13) |
| Gasoline | 0.04 (0.06) | 0.11 (0.07) | 0.06 (0.06) | 0.11 (0.08) |
| Quarter 2 | −1.61 (1.82) | 1.23* (0.67) | −1.68 (1.90) | 1.56** (0.68) |
| Quarter 3 | 3.18*** (0.99) | 1.26 (0.78) | 3.52 (1.06) | 1.65* (0.81) |
| Quarter 4 | 4.83*** (0.93) | −1.72 (1.38) | 5.47 (1.05) | −1.49 (1.35) |
| *Observations* | 2321 | 2321 | 2321 | 2321 |

**Note(s)**: Standard errors are in parentheses. ****p < 0.01, **p < 0.05, *p < 0.1*

**Table 4.** Penalized maximum likelihood estimation for the multinomial logistic regression: Soybeans

interest of the futures contracts under study. Because of the highly co-linearity, we introduce each of these two factors separately into the model. Table 3 shows that all coefficients remain robust in the two models. Trade volume and open interest both have significant negative effects on positive bubbles, while their coefficients for negative bubbles are insignificant. Higher liquidity and more speculation seem not to increase the likelihood of price bubbles for corn. If future markets with higher liquidity attract more speculators or if more liquid markets imply more speculation, we may conclude that price bubbles of corn are more likely to occur during the illiquidity periods with less speculation activities. The futures market of corn with higher liquidity is more likely to be invulnerable to external shocks.

The fundamental stocks-to-use factors measure the net consumption of each period relative to its beginning stocks and are expected to explain the differences in price dynamics of commodities (Wright, 2009). However, we find no significant effects of China and World stocks-to-use on the occurrences of bubbles. This may be due to that China has a relatively self-sustaining market for corn. Meanwhile, there are various policies that prevent excessive price changes of corn. All of these may result in the insensitivity of corn price to the changes of domestic and world stocks-to-use. In addition, we introduce the (positive/negative) bubble dummy variable in the US futures market of corn into the model and find no significant effects. This further proves that China's corn market is more invulnerable to international shocks. Instead, the SOI is a significant predictor for both positive and negative bubbles of corn. Prolonged positive (negative) SOI index coincides with abnormally cold (warm) weather and thus lower (increase) the yield of grains. Therefore, low (high) yield of corn suggested by higher (lower) SOI index predicts more positive (negative) bubbles in its futures market. Traders in China's futures market are more sensitive to the temperature changes or future yields in the main production area of corn.

Moreover, considering the significant negative effects of the exchange rate on both kinds of bubbles, a weak RMB (higher exchange rate) may suspend imports from international markets and thus reduce external shocks on domestic corn markets. Lin and Xu (2019) also find that exchange rate has an inverse "U-shaped" nonlinear effect on commodity price in China. Therefore, higher exchange rate may even inhibit positive price bubbles. In addition, based on the cost information regularly published by Dalian Commodity Exchange (DCE), the price of domestic corn is always higher than that of the imported corn. When positive bubbles occur in domestic market and exchange rate is relatively high, the imported corn is still cheaper than the domestic corn and may even help stabilize the domestic corn price. For the other macroeconomic factors, higher economic activity could increase the demand for raw materials, our results also show that ECI has a significant positive effect on positive price bubbles in both models. A higher Shibor (Shanghai Interbank Offered Rate) significantly increases the probability of positive price bubbles. We may imply that less money would flow into the futures market during periods with high interest rates. Another possible explanation is that higher interest rates may reduce capital investments by suppliers of various commodities, thereby reducing the future supply and raising current prices (Pindyck and Rotemberg, 1988). With respect to the negative effect of inflation, it has been found that there is a chaotic and nonlinear interdependence between inflation and commodity price movement (Kyrtsou and Labys, 2006). A perturbation on inflation level will not necessarily have the expected impact on commodity price and can even lead to wide distortions. Zhang *et al.* (2019) further show that PPI has a negative effect on commodity prices in China. As we have seen in Figure 1, most price bubbles do not occur during the historical high price periods. Thus, the negative effect of PPI on positive price bubbles is counterintuitive at first glance, but it does reflect the complex and chaotic relationship between inflation and commodity prices [7]. Finally, for the gasoline price, it is often used to predict the fundamental prices of commodities and many studies have shown the connectedness between energy prices (ethanol) and agricultural prices (Adämmer and Bohl, 2015; Tyner, 2010; Wu *et al.*, 2011). We use this variable to estimate the influence of energy prices and find that a higher gasoline price will lead to more positive bubbles and fewer negative bubbles in our models. Thus, it may increase the costs of agricultural production and even increase the demand for ethanol producing from corn.

*4.2.2 Contributing factors of price bubbles for the soybean market.* As we can see in Table 4, the results of the two models for soybeans are also robust. However, compared with the case of corn, the trade volume and open interest of soybeans both have positive and significant effects on positive price bubbles. This again indicates that the soybeans market has different characteristics or structure with the corn market in China. Compared with corn, China always suffers a tight demand/supply balance for soybeans. In this case, traders may be more easily to be misled by speculative trades. Higher speculation in the soybean futures market could thus induce more price bubbles.

Regarding China’s stocks-to-use for soybeans, positive effects on positive bubbles are significant across both model specifications. Price bubbles tend to occur more easily during periods of high domestic consumption. We already discussed that China has lost control over its soybeans market and faces a shortage problem since joining the WTO in 2001. Chinese soybeans market is more open to global markets and thus more easily affected by international price shocks. In our model, it is easy to understand that the world stocks-to-use ratio has a significant negative effect on negative bubbles, which means high demand pressure refrains the soybeans price from collapsing. Nevertheless, we find no reasonable explanations for the negative effect of world stocks-to-use on positive bubbles, except that many positive bubbles may be caused by speculation. Furthermore, though SOI could affect the yield of soybeans, it does not change the likelihood of soybeans price bubbles. These results may suggest that positive bubbles in soybeans market could be partly caused by speculation. More importantly, we find that the positive bubbles in US soybeans futures market have significant positive effects on those in China, which proves that soybeans markets in China and United States are highly connected with each other. All of these mixed effects make soybeans price bubbles in China more complicated to predict.

When further considering the effects of the exchange rate, negative price bubbles occur more frequently in the presence of a weak RMB (higher exchange rate), though the costs of importing soybeans increase. As expected for the rest macroeconomic factors, a higher ECI increases the likelihood of positive bubbles and reduces negative bubbles. Shibor has a positive effect on the positive bubbles, similar to the case of corn. PPI has a negative effect on the positive bubbles. The gasoline price has no direct effects on the bubbles in the soybeans market.

So far, higher market liquidity and speculation have opposite effects on the bubble occurrences in Chinese corn and soybeans markets. Thus, the “Master hypothesis” cannot fully explain the origin of bubbles for Chinese agricultural commodities. Meanwhile, the fundamental demand/supply factors contribute to price bubble occurrences for soybeans, but not for corn. The macroeconomic factors are also found to significantly affect the probability of price bubbles, and their effects are not completely the same for the two commodity species. These results cannot be obtained if we only use pooled data of these two commodity markets.

Finally, in order to estimate the Independence of Irrelevant Alternatives (IIA) assumption on the categories of price bubbles, we use two individual penalized maximum likelihood estimations and only consider the positive or negative bubbles in the model each time. If the IIA is accurate, the individual model that removes one category of dependent variables will get a consistent estimation just as with the multinomial logistic model but in a less efficient way. Tables A5 and A6 in the appendix show the results of the individual models. Compared with results in Tables 3 and 4, we can see that almost every sign and magnitude of the coefficients remain robust. The same holds for the significance levels. We may thus conclude that the IIA condition is satisfied in our study.

## 5. Discussion and conclusions

Agricultural commodity price bubbles often read as signals for food crises or disruptions of normal market operations. After the financial crisis in 2007/2008, researchers start to find evidence of commodity price bubbles and explore the possible contributing factors. Based on daily data from China's main futures market, this study aims to detect the exact dates of bubble occurrences using a recently developed rolling window right-sided ADF-test. After determining price bubbles' dates in the corn and soybeans futures market, we examine potential factors contributing to price bubbles in each market separately. In the presence of rare events, the penalized maximum likelihood method avoids the estimation bias of the regular multinomial logistic model.

Our results show that bubbles only occur in a very low proportion of days in our sample period (2006–2017), namely, 5.48% for corn and 3.91% for soybean. The magnitudes of the price changes during these bubble periods are generally small and price bubbles usually do not coincide with price peaks or troughs. Bubbles often show up when prices suddenly increase or crash.

The different dates and types of bubbles in the corn and soybean markets imply a separate investigation of the potential factors contributing to price bubbles for the two markets. Unlike those studies that pool the price bubbles of different commodities together, we try to introduce more commodity-specific factors and estimate their effects on bubbles. Specifically, considering the different openness to international markets and different self-sufficiency rate of domestic consumption, we use the trade volume, open interest, domestic stocks-to-use and world stocks-to-use for corn and soybeans, respectively.

The results show that higher market liquidity and speculation have no significant positive effects on bubbles and even reduces the likelihood of positive bubbles for corn, while they increase the likelihood of positive bubbles for soybeans. The difference becomes more significant, considering that the daily average trade volume and open interest of corn are relatively higher than those of soybeans (see Table 1). This supports the idea that these two markets have different characteristics and may thus react differently to speculative attacks. The main difference between Chinese corn and soybean markets is the self-sufficiency rate of domestic production/consumption. Chinese corn has a high self-sufficiency rate of over 95%, while soybean is the largest imported agricultural commodity with the self-sufficiency rate less than 25% (Li, *et al.*, 2017a, b). The commodities with higher self-sufficiency rate have shown less volatile price movements in China, such as corn, rice and wheat (Li, *et al.*, 2017a, b; Yang *et al.*, 2008). In the contrary, Chinese soybean market is often confronted with a tight balance of supply/demand and may thus become more sensitive to price fluctuations. This is consistent with our findings that Chinese soybean market is more vulnerable to speculative attacks, while corn market is more stable under higher market liquidity and speculation.

For the rest of fundamental economic factors, domestic and world stocks-to-use and external bubble shocks (from corresponding USA futures market) exhibit different effects across these two commodity markets. Again, we find that Chinese corn market is relatively stable, while the soybean price bubbles are more easily to be affected by its domestic and world stocks-to-use, and external bubble shocks. This may reflect the different market openness for corn and soybeans, since China is highly connected with international markets and imports more than half of its soybeans for domestic consumption. Moreover, higher exchange rate tends to reduce both types of bubbles for corn, while it increases the negative bubbles for soybeans. The weather shocks (SOI) and gasoline price are found to only affect the bubble occurrences in the corn market. The probability of positive (negative) bubbles increases when the weather condition is bad (good) for the growth of corn. Higher gasoline prices are associated with more (less) positive (negative) bubbles. This is consistent with previous studies that find increasing demand of corn for producing biofuels leads to a higher corn price (Adämmer and Bohl, 2015; Wu *et al.*, 2011). Finally, positive bubbles for both corn and soybeans are more likely to occur in the presence of strong economic activity, high interest rates and low inflation level.

Furthermore, it should be clarified that relating bubbles to fundamental economic factors may be viewed as identifying market conditions when investors are more likely to generate different views to the same information (Scheinkman and Xiong, 2003; Singleton, 2013). Taking positive bubbles as an instance, when exposed to the same public information, optimistic traders would be likely to pay more if they believe they can get an even higher payoff in the future. China's futures market participants (mainly consisting of retailing investors [8]) could be sensitive to the fundamental economic factors and have more divergent beliefs about futures price. In this case, due to the herding behaviors of retailing investors, divergent beliefs toward the changes in the fundamental economic factors may thus result in massive herding trades, which may further contribute to bubbles.

We also consider the effects of market intervention policies by Chinese government, which may have significantly affected China's grain futures prices (Xiao *et al.*, 2019). China has implemented many national policies to stabilize its agricultural markets during the sample period, such as the Minimum Procurement Price Program (MPP), National Provisional Reserve Program (NPR) and Target Price Policy (TPP). Some studies show mixed results about the effects of the intervention policies in Chinese food market. For instance, through a qualitative analysis, Li *et al.* (2017a, b) find that domestic policy instruments have different effects on the bubbles for corn and soybeans in China. Yang *et al.* (2008) find that around 2008 global food crisis, Chinese officials responded to higher world prices by drawing down domestic stocks and limiting exports of major grains. Meanwhile, Tan and Zeng (2019) find that the reserve policy induces hypercorrection and impels greater price volatility in the pork market, and Sun *et al.* (2018) conclude that China's temporary soybean trade policies do not improve market integration and stability.

In order to ensure the robustness of our estimation results, we further use dummy variables to indicate the implementing period of two important policies (NPR and TPP) for corn and soybeans, respectively. The estimation results (see Table A9 and Table A10 in the appendix) remain with consideration of the dummy variables for NPR and TPP. The policy dummy variables for NPR and TPP seem not to affect the bubble occurrences.

Through comparing futures market for corn and soybean in China, we could conclude that these two commodity markets have different frequencies and types of bubbles and exhibit different responses to the same contributing factors. This is different from the underlying assumption in previous studies that these contributing factors have same effects on bubble occurrences, regardless of commodity species (Etienne *et al.*, 2015; Li, *et al.*, 2017a, b). More importantly, our estimation results indicate that higher market liquidity and speculation only increase the probability of bubble occurrences for soybean market. Thus, the "Master hypothesis" cannot fully explain the origin of bubbles for Chinese agricultural commodities. Our results are more likely to support the idea that price bubbles are associated with commodity-specific supply/demand pressure and other macroeconomic factors [9].

In conclusion, compared with previous studies that pool different commodities together, our result suggests that regulators of commodity markets aiming to avoid price bubbles should pay more attention to the specific conditions of each commodity market. More information and data on production, consumption and stocks of agricultural commodities should be regularly collected and published. This could reduce the traders' wrong expectations and enhance the efficiency of price discovery in futures market. Meanwhile, the regulators should be more cautious with the measure of restricting speculative positions and focus on the extreme cases of economic fundamentals, because speculation activity may have different effects on different commodity markets.

## Notes

1. The newly developed rolling window right-side ADF test combined with the bootstrap procedure has been proved to be an adequate procedure to detecting the location of bubbles, because it could avoid "pseudo bubbles" caused by underlying economic structural changes (Harvey *et al.*, 2016). Specifically, this method outperforms the other bubble testing procedures, such as sequential Chow-test and CUSUM tests, in the case of multiple periodically collapsing bubbles (Homm and Breitung, 2012; Phillips *et al.*, 2012, 2015).
2. It should be noted that both types of bubbles may distort normal market trades and affect farmers' decisions on future consumption and agricultural investments. Positive bubbles occur during the price upward movement, while negative bubbles occur during the price downward movement. The main reason to distinguish between these two types of bubbles is that they may be derived from different mechanisms or contributing factors. The deviating effects of the two types of bubbles depend on the income and consumption structures of poorer farm households. Poorer farm households mostly engage in agricultural production for their own consumption (Gouel, 2014). For net food buyer households, positive bubbles increase their food budget. For net food seller households, negative bubbles lower their revenues, which may hinder their agricultural investments and production. Therefore, both positive and negative bubbles affect the wellbeing of the poor.
3. We adjust the minimum window size and find that the result of bubble dates is rather robust.
4. The bubble dates from 2016 to 2017 are calculated by us using the same bubble testing procedure as theirs.
5. There are some steep changes in the pricing process at the end or beginning of each year because we use individual futures contract price for each year.
6. The simulated random walk is defined as $y_t = 0.1 + y_{t-1} + \varepsilon_t,\ \ \varepsilon_t \sim N(0, 5)$. The length of the random walk is 264, that is amount to the length of an individual contract price series. The results remain constant when the drift term or the random error term varies.
7. We further conduct a robustness check of the lagged effects for PPI and find that the estimation results remain unchanged (see Table-A7 and Table A8 in the appendix).
8. According to the China Securities Regulatory Commission and China Futures Association (2016), the proportion of investors whose equity is lower than 100 000 *Yuan* is 87.58%, while the proportion of investors whose equity higher than 1 million *Yuan* is merely 0.61%.
9. Please notice that the results from the multinomial logistic model does not necessarily imply a causality relationship between the dependent variable and independent variables, and it mainly helps us to identify which factors will affect the bubble occurrences significantly. Thus, the endogeneity problem is not our major concern in this analysis. The endogeneity problem may be solved if a more specific dataset is available in the future.

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## Appendix

| Bubble periods | Length (days) | Positive bubbles | | | | | Negative bubbles | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Start | Peak | End | % Price Change (Start to peak) | % Price Change (peak to end) | Start | Trough | End | %Price change (start to trough) | %Price change (trough to end) |
| 2006/02/24–2006/02/28 | 3 | 1504 | 1514 | 1501 | 0.66 | −0.86 | | | | | |
| 2006/08/07–2006/08/14 | 6 | | | | | | 1342 | 1342 | 1326 | 0.00 | −1.19 |
| 2006/11/14–2006/11/28 | 11 | 1436 | 1513 | 1513 | 5.36 | 0.00 | | | | | |
| 2007/06/15–2007/06/28 | 10 | | | | | | 1653 | 1561 | 1561 | −5.57 | 0.00 |
| 2007/07/05–2007/07/18 | 10 | | | | | | 1539 | 1496 | 1505 | −2.79 | 0.60 |
| 2007/07/24–2007/07/26 | 3 | | | | | | 1496 | 1481 | 1484 | −1.00 | 0.20 |
| 2008/11/28–2008/12/31 | 24 | | | | | | 1517 | 1411 | 1438 | −6.99 | 1.91 |
| 2009/02/09–2009/02/17 | 7 | 1681 | 1720 | 1716 | 2.32 | −0.23 | | | | | |
| 2009/11/16–2009/11/26 | 9 | 1734 | 1762 | 1762 | 1.61 | 0.00 | | | | | |
| 2009/12/01–2009/12/14 | 10 | | | | | | 1786 | 1778 | 1783 | −0.45 | 0.28 |
| 2011/06/28–2011/07/05 | 6 | | | | | | 2310 | 2265 | 2275 | −1.95 | 0.44 |
| 2011/11/21–2011/11/30 | 8 | | | | | | 2179 | 2143 | 2156 | −1.65 | 0.61 |
| 2013/12/19–2013/12/25 | 5 | | | | | | 2203 | 2131 | 2131 | −3.27 | 0.00 |
| 2015/06/03–2015/06/10 | 6 | | | | | | 2209 | 2128 | 2128 | −3.67 | 0.00 |

*(continued)*

**Table A1.** Summary of price bubbles for corn

Table A1.

| Bubble periods | Length (days) | Positive bubbles Start | Peak | End | % Price Change (Start to peak) | % Price Change (peak to end) | Negative bubbles Start | Trough | End | %Price change (start to trough) | %Price change (trough to end) |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 2015/06/25–2015/06/30 | 4 | | | | | | 2137 | 2111 | 2111 | −1.22 | 0.00 |
| 2015/07/24–2015/07/30 | 5 | | | | | | 2052 | 1994 | 2005 | −2.83 | 0.55 |
| 2015/09/29–2015/10/26 | 15 | | | | | | 1922 | 1873 | 1899 | −2.55 | 1.39 |
| 2015/11/27–2015/12/04 | 6 | 2022 | 2033 | 2033 | 0.54 | 0.00 | | | | | |
| 2015/12/09–2015/12/22 | 10 | 2046 | 2069 | 2063 | 1.12 | −0.29 | | | | | |
| Sum | 158 days (5.48%) | | | | Positive: 46 days (29.11%) | | | | | Negative: 112 days (70.89%) | |
| Maximum Single Bubble Duration | 24 days | | | | | | | | | | |

**Table A2.** Summary of price bubbles for soybeans

| Bubble periods | Length (days) | Positive bubbles Start | Peak | End | %Price change (start to peak) | %Price change (peak to end) | Negative bubbles Start | Trough | End | %Price change (start to trough) | %Price change (trough to end) |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 2006/04/11–2006/04/13 | 3 | | | | | | 2635 | 2632 | 2632 | −0.11 | 0.00 |
| 2006/07/24–2006/07/28 | 5 | | | | | | 2595 | 2541 | 2541 | −2.08 | 0.00 |
| 2006/11/16–2006/11/21 | 4 | 2707 | 2773 | 2756 | 2.44 | −0.61 | | | | | |
| 2007/09/10–2007/09/19 | 8 | 3833 | 4092 | 4032 | 6.76 | −1.47 | | | | | |
| 2007/09/24–2007/09/28 | 5 | 3990 | 4081 | 4081 | 2.28 | 0.00 | | | | | |
| 2007/10/11–2007/11/19 | 28 | 4083 | 4449 | 4431 | 8.96 | −0.40 | | | | | |
| 2007/11/21–2007/12/05 | 11 | 4385 | 4486 | 4387 | 2.30 | −2.21 | | | | | |
| 2007/12/11–2007/12/17 | 5 | 4421 | 4488 | 4488 | 1.52 | 0.00 | | | | | |
| 2007/12/20–2008/01/07 | 9 | 4464 | 4590 | 4300 | 2.82 | −6.32 | | | | | |
| 2009/11/25–2009/12/02 | 6 | 3860 | 3944 | 3944 | 2.18 | 0.00 | | | | | |
| 2009/12/04–2009/12/08 | 3 | 3943 | 4022 | 4022 | 2.00 | 0.00 | | | | | |
| 2012/05/14–2012/05/18 | 5 | | | | | | 4397 | 4310 | 4310 | −1.98 | 0.00 |
| 2014/08/04–2014/08/14 | 9 | 4497 | 4610 | 4610 | 2.51 | 0.00 | | | | | |
| 2015/04/08–2015/04/10 | 3 | | | | | | 4101 | 4075 | 4075 | −0.63 | 0.00 |

(*continued*)

Table A2.

| Bubble periods | Length (days) | Positive bubbles Start | Peak | End | %Price change (start to peak) | %Price change (peak to end) | Negative bubbles Start | Trough | End | %Price change (start to trough) | %Price change (trough to end) |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 2017/03/10–2017/03/17 | 6 | | | | | | 3943 | 3897 | 3897 | −1.17 | 0.00 |
| 2017/10/27–2017/10/31 | 3 | 3627 | 3630 | 3627 | 0.08 | −0.08 | | | | | |
| Sum | 113 days (3.91%) | | | | Positive: 91 days (80.53%) | | | | | Negative: 22 days (19.47%) | |
| Maximum Single Bubble Duration | 28 days | | | | | | | | | | |

| | (1) Positive | (2) Negative | (3) Positive | (4) Negative |
|---|---|---|---|---|
| Cons | 2.69 (8.59) | 0.06 (1.59) | 2.71 (8.77) | 0.13 (1.53) |
| Trade volume/100 | −0.04 (0.14) | 0.01 (0.03) | | |
| Open interest/100 | | | −0.02 (0.07) | 0.00 (0.01) |
| China stocks-to-use | −0.01 (0.02) | −0.06 (0.07) | −0.05 (0.15) | −0.04 (0.05) |
| World stocks-to-use | 0.02 (0.08) | −0.01 (0.02) | 0.06 (0.20) | −0.01 (0.04) |
| SOI | 0.03 (0.09) | −0.02 (0.03) | 0.02 (0.08) | −0.02 (0.02) |
| USBubbles positive | −0.01 (0.03) | −0.03 (0.04) | −0.01 (0.02) | −0.0 3 (0.04) |
| USBubbles negative | 0.04 (0.14) | −0.02 (0.04) | 0.05 (0.16) | −0.02 (0.04) |
| Exchange rate | −0.06 (0.20) | −0.06 (0.07) | −0.09 (0.29) | −0.06 (0.08) |
| ECI | 0.01 (0.01) | 0.00 (0.00) | 0.01 (0.01) | 0.00 (0.00) |
| Shibor | 0.01 (0.01) | −0.00 (0.00) | 0.01 (0.02) | 0.00 (0.00) |
| PPI | −0.02 (0.07) | 0.01 (0.01) | −0.02 (0.07) | 0.01 (0.01) |
| Gasoline | 0.01 (0.15) | −0.01 (0.01) | 0.01 (0.01) | −0.01 (0.01) |
| Q2 | −0.04 (0.13) | 0.15 (0.17) | −0.03 (0.10) | 0.15 (0.17) |
| Q3 | −0.03 (0.11) | 0.16 (0.18) | −0.01 (0.05) | 0.16 (0.18) |
| Q4 | 0.02 (0.06) | 0.19 (0.21) | 0.02 (0.08) | 0.19 (0.21) |
| *Observations* | 2321 | 2321 | 2321 | 2321 |

**Note(s)**: The standard deviations are in parentheses

**Table A3.**
Marginal Effects for PMLR model of Corn

| | (1) Positive | (2) Negative | (3) Positive | (4) Negative |
|---|---|---|---|---|
| Cons | 0.86 (2.01) | −1.14 (2.66) | 1.02 (2.52) | −1.06 (2.62) |
| Trade volume/100 | 0.01 (0.01) | 0.00 (0.00) | | |
| Open Interest/100 | | | 0.02 (0.04) | −0.01 (0.02) |
| China Stocks-to-use | 0.02 (0.04) | 0.00 (0.00) | 0.01 (0.04) | 0.01(0.01) |
| World Stocks-to-use | −0.01 (0.01) | −0.01 (0.01) | −0.01 (0.01) | −0.01 (0.01) |
| SOI | 0.01 (0.02) | 0.00 (0.00) | 0.01 (0.03) | −0.00 (0.01) |
| USBubbles Positive | 0.03 (0.08) | 0.03 (0.06) | 0.03 (0.08) | 0.03 (0.07) |
| USBubbles Negative | 0.06 (0.15) | 0.02 (0.04) | 0.04 (0.10) | 0.02 (0.06) |
| Exchange Rate | −0.03 (0.07) | 0.11 (0.24) | −0.04 (0.10) | 0.09 (0.23) |
| ECI | 0.01 (0.01) | −0.01 (0.01) | 0.00 (0.01) | −0.00 (0.00) |
| Shibor | 0.02(0.05) | −0.01(0.03) | 0.02(0.05) | −0.01(0.03) |
| PPI | −0.01 (0.02) | 0.00 (0.01) | −0.01 (0.03) | 0.00 (0.01) |
| Gasoline | 0.00(0.00) | 0.00(0.00) | 0.00(0.00) | 0.00(0.00) |
| Q2 | −0.04 (0.08) | 0.02 (0.05) | −0.04 (0.09) | 0.02 (0.06) |
| Q3 | 0.07 (0.17) | 0.02 (0.05) | 0.07 (0.18) | 0.03 (0.06) |
| Q4 | 0.11 (0.26) | −0.03 (0.07) | 0.11 (0.28) | −0.03 (0.06) |
| *Observations* | 2321 | 2321 | 2321 | 2321 |

**Note(s)**: The standard deviations are in parentheses

**Table A4.**
Marginal Effects for PMLR model of Soybeans

| | (1) Positive | (2) Negative | (3) Positive | (4) Negative |
|---|---|---|---|---|
| Cons | 199.52*** (31.56) | 5.94 (10.50) | 216.11*** (25.60) | 7.23 (10.38) |
| Trade volume/100 | −3.33*** (0.01) | −0.00 (0.00) | | |
| Open interest/100 | | | −0.02*** (0.00) | −0.00 (0.00) |
| China stocks-to-use | −1.06 (5.66) | −1.35 (1.56) | −4.24 (4.77) | −1.06 (1.59) |
| World stocks-to-use | 1.82 (3.72) | −0.56 (1.39) | 5.03 (3.55) | −0.51 (1.38) |
| SOI | 2.02*** (0.50) | −0.38** (0.18) | 1.97*** (0.45) | −0.37** (0.18) |
| USBubbles positive | −0.85 (1.51) | | −0.63 (1.51) | |
| USBubbles negative | | −0.47 (1.46) | | −0.51 (1.46) |
| Exchange rate | −4.83*** (1.48) | −1.58** (0.73) | −7.30*** (1.54) | −1.65** (0.72) |
| ECI | 0.12*** (0.04) | 0.02 (0.01) | 0.14*** (0.04) | 0.01 (0.01) |
| Shibor | 0.29 (0.26) | −0.04 (0.19) | 0.57** (0.23) | −0.03 (0.19) |
| PPI | −1.64*** (0.26) | 0.03 (0.06) | −1.62*** (0.17) | 0.03 (0.06) |
| Gasoline | 0.35*** (0.09) | −0.12*** (0.03) | 0.25*** (0.08) | −0.12*** (0.02) |
| Q2 | −2.40 (1.54) | 3.86*** (1.44) | −1.85 (1.50) | 3.89*** (1.44) |
| Q3 | −1.87 (1.51) | 4.14*** (1.44) | −0.63 (1.54) | 4.21*** (1.44) |
| Q4 | 1.83*** (0.70) | 4.92*** (1.43) | 2.35*** (0.68) | 4.92*** (1.43) |
| *Observations* | 2321 | 2321 | 2321 | 2321 |

**Note(s)**: Standard errors are in parenthesis. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

**Table A5.**
Individual model for penalized maximum likelihood estimation: Corn

| | (1) Positive | (2) Negative | (3) Positive | (4) Negative |
|---|---|---|---|---|
| Cons | 41.49** (19.46) | −67.10*** (21.88) | 58.09*** (18.04) | −57.38** (23.18) |
| Trade volume/100 | 0.29*** (0.09) | 0.09 (0.25) | | |
| Open interest/100 | | | 0.87*** (0.23) | −0.66 (0.44) |
| China stocks-to-use | 8.12*** (2.82) | 4.36 (3.68) | 7.22** (2.90) | 7.16 (4.66) |
| World stocks-to-use | −6.70*** (1.93) | −7.70***(2.79) | −5.22*** (1.93) | −9.87*** (3.48) |
| SOI | 0.42 (0.30) | 0.16(0.44) | 0.66** (0.29) | −0.02 (0.43) |
| USBubbles positive | 1.56* (0.80) | | 1.62** (0.82) | |
| USBubbles negative | | 1.61 (1.85) | | 1.76 (1.82) |
| Exchange rate | −1.36 (1.23) | 6.48*** (1.79) | −2.03 (1.26) | 5.26*** (1.77) |
| ECI | 0.14*** (0.02) | −0.08*** (0.03) | 0.17*** (0.02) | −0.06 (0.04) |
| Shibor | 0.96*** (0.23) | −0.80 (0.66) | 1.03*** (0.23) | −0.76 (0.66) |
| PPI | −0.49*** (0.15) | 0.14 (0.15) | −0.64*** (0.13) | 0.12 (0.18) |
| Gasoline | 0.09 (0.06) | 0.12 (0.09) | 0.13** (0.06) | 0.11 (0.10) |
| Q2 | −1.92 (2.37) | 1.29* (0.77) | −2.09 (2.66) | 1.66** (0.80) |
| Q3 | 3.41*** (1.03) | 1.28 (0.92) | 3.87*** (1.11) | 1.70* (1.00) |
| Q4 | 4.75*** (0.97) | −1.77 (1.5270) | 5.65*** (1.1162) | −1.57 (1.52) |
| *Observations* | 2321 | 2321 | 2321 | 2321 |

**Note(s)**: Standard errors are in parenthesis. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

**Table A6.**
Individual model for penalized maximum likelihood estimation: Soybeans

|  | Model 1 |  | Model 2 |  |
|---|---|---|---|---|
|  | Positive | Negative | Positive | Negative |
| Cons | 216.27*** (10.08) | −18.88** (9.44) | 225.28*** (27.00) | −18.08* (9.73) |
| Trade volume/100 | −3.79*** (0.67) | −0.03 (0.06) |  |  |
| Open interest/100 |  |  | −2.11*** (0.49) | −0.02 (0.04) |
| China stocks-to-use | −0.02 (4.75) | −2.36 (1.60) | −1.13 (4.82) | −2.26 (1.63) |
| World stocks-to-use | 5.14* (2.92) | −2.35* (1.32) | 7.83** (3.25) | −2.31* (1.33) |
| SOI | 2.56*** (0.37) | −0.73*** (0.18) | 2.32*** (0.42) | −0.72*** (0.18) |
| USBubbles positive | −1.13 (1.49) |  | −1.00 (1.51) |  |
| USBubbles negative |  | −0.22 (1.46) |  | −0.24 (1.46) |
| Exchange rate | −4.90*** (0.97) | −0.35 (0.67) | −7.32*** (1.40) | −0.38 (0.68) |
| ECI | 0.05* (0.03) | 0.00 (0.01) | 0.07* (0.04) | 0.00 (0.01) |
| Shibor | 0.31 (0.23) | −0.28 (0.21) | 0.52** (0.24) | −0.28 (0.21) |
| *Lagged PPI* | *−1.75*** (0.08)* | *0.19*** (0.05)* | *−1.63*** (0.20)* | *0.19*** (0.05)* |
| Gasoline | 0.38*** (0.06) | −0.15*** (0.02) | 0.25*** (0.08) | −0.15*** (0.02) |
| Q2 | −3.57** (1.53) | 3.85*** (1.44) | −2.76* (1.51) | 3.86*** (1.44) |
| Q3 | −3.38** (1.51) | 4.10*** (1.43) | −1.43 (1.54) | 4.12*** (1.44) |
| Q4 | 1.81*** (0.64) | 4.98*** (1.43) | 2.27*** (0.65) | 4.98*** (1.43) |
| *Observations* | 2321 | 2321 | 2321 | 2321 |

**Note(s)**: Standard errors are in parenthesis ****p < 0.01, **p < 0.05, *p < 0.1*

**Table A7.** Individual model for penalized maximum likelihood estimation: Corn (lagged PPI)

|  | Model 1 |  | Model 2 |  |
|---|---|---|---|---|
|  | Positive | Negative | Positive | Negative |
| Cons | 43.89** (21.86) | −70.56*** (21.44) | 63.77*** (22.15) | −61.75*** (18.83) |
| Trade volume/100 | 0.29*** (0.11) | 0.06 (0.25) |  |  |
| Open interest/100 |  |  | 0.86*** (0.23) | −0.68 (0.43) |
| China stocks-to-use | 8.13*** (2.78) | 4.72 (3.76) | 7.63*** (2.80) | 7.29 (4.48) |
| World stocks-to-use | −6.12*** (1.94) | −7.33*** (2.81) | −4.83*** (1.87) | −9.56*** (3.39) |
| SOI | 0.36 (0.27) | 0.21 (0.44) | 0.58** (0.27) | 0.00 (0.42) |
| USBubbles positive | 1.45* (0.79) |  | 1.50*(0.81) |  |
| USBubbles negative |  | 1.89 (1.93) |  | 2.05 (1.83) |
| Exchange rate | −1.64 (1.40) | 6.50*** (1.71) | −2.33 (1.46) | 5.30*** (1.54) |
| ECI | 0.13*** (0.02) | −0.08*** (0.03) | 0.16***(0.02) | −0.06*(0.03) |
| Shibor | 1.13*** (0.33) | −0.87 (0.67) | 1.27*** (0.31) | −0.87 (0.67) |
| *Lagged PPI* | *−0.48*** (0.15)* | *0.18 (0.15)* | *−0.66*** (0.15)* | *0.16 (0.15)* |
| Gasoline | 0.08 (0.06) | 0.10 (0.09) | 0.13** (0.06) | 0.09 (0.09) |
| Q2 | −3.08 (3.75) | 1.27* (0.75) | −4.02 (3.54) | 1.61** (0.77) |
| Q3 | 3.47*** (1.03) | 1.24 (0.88) | 3.95*** (1.09) | 1.65* (0.95) |
| Q4 | 4.74*** (0.98) | −1.5 7(1.53) | 5.68*** (1.1165) | −1.38 (1.52) |
| *Observations* | 2321 | 2321 | 2321 | 2321 |

**Note(s)**: Standard errors are in parenthesis. ****p < 0.01, **p < 0.05, *p < 0.1*

**Table A8.** Individual model for penalized maximum likelihood estimation: Soybean (lagged PPI)

|  | Model 1 |  | Model 2 |  |
|---|---|---|---|---|
|  | Positive | Negative | Positive | Negative |
| Cons | 268.25*** (59.97) | 1.17 (12.11) | 255.84*** (32.11) | 3.13 (12.17) |
| Trade volume/100 | −3.81*** (1.07) | −0.02 (0.06) |  |  |
| Open interest/100 |  |  | −2.08*** (0.52) | −0.03 (0.04) |
| China stocks-to-use | 4.87 (6.25) | −0.72 (1.75) | −1.04 (5.79) | −0.63 (1.74) |
| World stocks-to-use | 1.02 (3.47) | −0.75 (1.42) | 5.34 (4.85) | −0.67 (1.41) |
| SOI | 1.89*** (0.53) | −0.33* (0.18) | 2.18*** (0.72) | −0.33* (0.18) |
| USBubbles positive | −0.93 (1.53) | – | −0.77 (1.52) | – |
| USBubbles negative | – | −0.38 (1.46) | – | −0.43 (1.46) |
| Exchange rate | −7.36*** (2.36) | −1.21 (0.85) | −9.27*** (2.05) | −1.35 (0.85) |
| ECI | 0.13*** (0.05) | 0.01 (0.02) | 0.16*** (0.04) | 0.01 (0.02) |
| Shibor | 0.24 (0.25) | −0.06 (0.19) | 0.59** (0.25) | −0.05 (0.19) |
| PPI | −2.14*** (0.45) | 0.07 (0.08) | −1.86*** (0.17) | 0.06 (0.07) |
| Gasoline | 0.52*** (0.14) | −0.14*** (0.03) | 0.28*** (0.08) | −0.14*** (0.03) |
| *NPR* | *−3.12* (1.74)* | *0.544 (0.64)* | *−1.15 (1.51)* | *0.43 (0.64)* |
| Quarter 2 | −3.58* (1.92) | 3.89*** (1.44) | −1.81 (1.35) | 3.92*** (1.44) |
| Quarter 3 | −1.25 (1.63) | 4.06*** (1.44) | 0.38 (1.69) | 4.14*** (1.44) |
| Quarter 4 | 1.82*** (0.71) | 4.87*** (1.42) | 2.95*** (0.67) | 4.87*** (1.42) |
| *Observations* | 2321 | 2321 | 2321 | 2321 |

**Note(s)**: Standard errors are in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. The variable of "NPR" takes value 1 when it belongs to the duration of National Provisional Reserve Program (2008.06–2016.03) and 0 otherwise

**Table A9.**
Individual model for penalized maximum likelihood estimation: Corn (NPR)

|  | Model 1 |  | Model 2 |  |
|---|---|---|---|---|
|  | Positive | Negative | Positive | Negative |
| Cons | 34.33 (22.42) | −65.18*** (25.45) | 48.64** (20.32) | −58.06*** (21.44) |
| Trade volume/100 | 0.29*** (0.09) | 0.13 (0.23) |  |  |
| Open interest/100 |  |  | 0.93*** (0.24) | −0.66 (0.49) |
| China stocks-to-use | 7.46** (3.02) | 3.75 (3.82) | 6.10** (3.08) | 6.51 (4.41) |
| World stocks-to-use | −6.92*** (1.95) | −8.04*** (3.02) | −5.67*** (1.95) | −9.39*** (3.35) |
| SOI | 0.41 (0.29) | 0.09 (0.46) | 0.65** (0.29) | −0.03 (0.43) |
| USBubbles positive | 1.59** (0.81) | – | 1.67** (0.81) | – |
| USBubbles negative | – | 1.58 (1.89) | – | 1.86 (1.80) |
| Exchange rate | −0.83 (1.54) | 6.47*** (2.02) | −1.19 (1.49) | 5.11*** (1.62) |
| ECI | 0.15*** (0.03) | −0.06 (0.07) | 0.18*** (0.03) | −0.07 (0.03) |
| Shibor | 0.96*** (0.23) | −0.87 (0.68) | 1.02*** (0.23) | −0.80 (0.64) |
| PPI | −0.48*** (0.14) | 0.09 (0.21) | −0.64*** (0.14) | 0.15 (0.20) |
| Gasoline | 0.11 (0.07) | 0.15 (0.12) | 0.17** (0.07) | 0.08 (0.12) |
| *TPP* | *0.88 (1.52)* | *0.73 (1.66)* | *1.36 (1.34)* | *−0.29 (1.71)* |
| Quarter 2 | −1.90 (2.36) | 1.27 (0.80) | −2.08 (2.56) | 1.59** (0.78) |
| Quarter 3 | 3.39*** (1.03) | 1.29 (1.00) | 3.79*** (1.10) | 1.57* (0.96) |
| Quarter 4 | 4.67*** (0.97) | −1.77 (1.52) | 5.56*** (1.12) | −1.58 (1.51) |
| *Observations* | 2321 | 2321 | 2321 | 2321 |

**Note(s)**: Standard errors are in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. The variable of "TPP" takes value 1 when it belongs to the duration of Target Price Policy (2014.11-) and 0 otherwise

**Table A10.**
Individual model for penalized maximum likelihood estimation: Soybeans (TPP)

| | Model 1 | | Model 2 | |
|---|---|---|---|---|
| | Positive | Negative | Positive | Negative |
| Cons | 176.52*** (17.20) | 8.61 (9.62) | 232.22*** (13.40) | 9.46 (9.83) |
| Trade volume/100 | −1.83*** (0.63) | 0.01 (0.05) | | |
| Open interests/100 | | | −1.85*** (0.45) | −0.01 (0.03) |
| China stocks-to-use | −5.03 (5.10) | −2.26 (1.48) | −4.65 (5.28) | −1.95 (1.54) |
| World stocks-to-use | 3.37 (2.79) | −1.02 (1.31) | 3.74 (3.14) | −1.04 (1.31) |
| SOI | 1.29*** (0.35) | −0.25 (0.17) | 1.50*** (0.37) | −0.23 (0.17) |
| USBubbles positive | −1.70 (1.48) | −0.71 (0.87) | −1.48 (1.49) | −0.71 (0.87) |
| USBubbles negative | 3.13 (2.19) | −1.21 (1.45) | 4.38 (2.22) | −1.25 (1.45) |
| Exchange rate | −7.02*** (0.96) | −0.44 (0.64) | −9.69*** (0.94) | −0.47 (0.65) |
| ECI | 0.16*** (0.03) | 0.02 (0.01) | 0.19*** (0.03) | 0.02 (0.01) |
| Shibor | 0.25 (0.24) | −0.04 (0.18) | 0.44* (0.23) | −0.05 (0.18) |
| PPI | −1.20*** (0.12) | −0.12 (0.05) | −1.53*** (0.09) | −0.12 (0.05) |
| Q2 | −1.84 (1.50) | 3.71*** (1.44) | −1.54 (1.56) | 3.74*** (1.44) |
| Q3 | −0.91 (1.57) | 4.00*** (1.43) | 0.28 (1.51) | 4.04*** (1.43) |
| Q4 | 2.48*** (0.61) | 4.82*** (1.43) | 2.91*** (0.63) | 4.82*** (1.43) |
| Obs | 2321 | 2321 | 2321 | 2321 |

**Note(s)**: Standard errors are in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

**Table A11.**
Penalized Maximum Likelihood Estimation for the Multinomial Logistic Regression: Corn (without gasoline price)

| | Model 1 | | Model 2 | |
|---|---|---|---|---|
| | Positive | Negative | Positive | Negative |
| Cons | 38.81** (18.32) | −73.82*** (22.26) | 46.56** (20.84) | −65.55*** (21.53) |
| Trade volume/100 | 0.25*** (0.09) | −0.09 (0.31) | | |
| Open interests/100 | | | 0.60*** (0.22) | −0.70* (0.41) |
| China stocks-to-use | 6.06** (2.85) | 4.73 (3.45) | 5.23* (2.89) | 6.93* (4.12) |
| World stocks-to-use | −5.59*** (1.79) | −7.07*** (2.57) | −4.15** (1.90) | −9.09*** (3.04) |
| SOI | 0.27 (0.27) | 0.12 (0.42) | 0.35 (0.29) | −0.06 (0.42) |
| USBubbles positive | 1.34* (0.77) | 1.39 (1.60) | 1.36* (0.77) | 1.39 (1.63) |
| USBubbles negative | 3.07 (0.75) | 2.52 (1.78) | 2.63 (0.74) | 2.29 (1.84) |
| Exchange Rate | −2.09* (1.10) | 5.61*** (1.61) | −2.77*(1.28) | 4.62*** (1.55) |
| ECI | 0.14*** (0.02) | −0.09*** (0.03) | 0.15*** (0.03) | −0.07** (0.03) |
| Shibor | 0.95*** (0.22) | −0.85 (0.67) | 0.99*** (0.23) | −0.85 (0.66) |
| PPI | −0.38*** (0.11) | 0.31* (0.11) | −0.42*** (0.12) | 0.29 (0.11) |
| Q2 | −1.65 (2.10) | 1.38* (0.76) | −1.70 (2.24) | 1.68** (0.78) |
| Q3 | 3.17*** (1.06) | 1.18 (0.87) | 3.52*** (1.15) | 1.56* (0.94) |
| Q4 | 4.88*** (0.99) | −1.83 (1.51) | 5.53*** (1.15) | −1.66 (1.51) |
| Obs | 2321 | 2321 | 2321 | 2321 |

**Note(s)**: Standard errors are in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

Through uncentered VIF test, we find that there may be highly collinearity among exchange rate, PPI and gasoline price (their VIF values are above 10). However, both economic theory and extant studies show that we cannot simply remove these three variables from the estimated equation (Castro Campos, 2019; Li, *et al.*, 2017a, b; Etienne *et al.*, 2015; Adämmer; Bohl, 2015; Pindyck; Rotemberg, 1988), otherwise, it may lead to omitted variables in the error term. Meanwhile, the influence of multicollinearity would become very weak under relatively large sample observations (Goldberger, 1991). In our study, the number of sample observations is relatively large *(2321)*, which could reduce the potential bias caused by multicollinearity.

To examine whether multicollinearity affects our results, we also remove the variable of gasoline price from the estimated equation. As presented in Tables A11 and A12, the coefficients and significant levels for the variables remain, suggesting the robustness of our estimation with regard to multicollinearity

**Table A12.**
Penalized Maximum Likelihood Estimation for the Multinomial Logistic Regression: Soybeans (without gasoline price)