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List of Abbreviations

CBOT	Chicago Board of Trade
DCE	Dalian Commodity Exchange
ZCE	Zhengzhou Commodity Exchange
PDV	Present Discounted Value
OLG	Overlapping Generations
LOP	Law of One Price
VECM	Vector Error Correction Model
GSADF	Generalized Supreme Augmented Dickey Fuller Test
SADF	Supreme Augmented Dickey Fuller Test
MSECM	Markov Switching Error Correction Model
DCC MGARCH	Dynamic Conditional Correlation Multivariate Generalized Autoregressive Conditional Heteroskadasticity Model
BEKK MGARCH	Baba, Engle, Kraft and Kroner Multivariate Generalized Autoregressive Conditional Heteroskadasticity Model
SOI	Southern Oscillation Index
ECI	Economic Climate Index
PLE	Penalized Maximum Likelihood Estimation
FIA	Futures Industry Association
PPI	Producer Price Index
SHIBOR	Shanghai Interbank Offered Rate
WTO	World Trade Organization
IIA	Independence of Irrelevant Alternatives
MPP	Minimum Procurement Price Program
TPP	Target Price Policy
NPR	National Provisional Reserve Program

Abstract in English

This cumulative dissertation presents four contributions that attempt to shed light on the issues regarding price bubbles in Chinese agricultural commodity market.

Given that the public and policymakers show their concern on the price bubbles in Chinese agricultural commodity market, chapter 2 and 3 investigate the origin of price bubbles in futures and spot markets, respectively. In particular, after accurately identifying the bubble dates in agricultural futures market and fixing the estimation bias of rare events models, our empirical results in chapter 2 indicate that bubble episodes only account for a very limited proportion of the sample period, meanwhile, China's corn and soybeans markets respond differently to the speculative activity and external shocks from international markets. Price bubbles are more likely to be associated with strong economic activity, high interest rates and low inflation levels. Furthermore, by gauging the synchronization level of bubble occurrences between futures and spot markets in chapter 3, we find that even cointegrated futures and spot prices for agricultural commodities seldom bubble together. Further analysis through a regime-switching approach of price transmission reveals that the adjustment effect of futures prices on spot prices is the lowest during the regime where bubbles occur the most frequently for spot prices, while the spot price returns are more likely to be affected by its own lagged terms. All these results challenge the idea that bubbles are originated from over-financialization in futures markets and are then transmitted to spot markets. Therefore, we conclude that futures price bubbles are more sensitive to fundamental factors, while spot price bubbles are more likely to be affected by their own market features. Apart from empirical analyses on the origin of price bubbles, it is widely believed that bubbles could distort resource allocation and a recession usually follows the collapse of bubbles. Inspired by the findings from chapter 2 and 3, chapter 4 attempts to build a systematic theoretical framework that explains the observed economic process with bubbles. From a new perspective of firm growth, we construct a theoretical model to describe the evolvement of bubbles, including their origin, development, collapse, and their effect on the output of economy. Following our research topic, chapter 5 tends to investigate the effects of the newly established futures contract for apples in China. The results of various tests suggest that the apple futures market does not serve well for the price discovery and may reduce the spot price volatility to some extent. In order to improve the efficiency of the apple futures market, the regulators should consider effective measures to attract more commercial traders from different regions in China into the futures market.

Abstract in German

Diese kumulative Dissertation besteht aus vier Beiträgen; dabei gilt es, die Probleme bezüglich Preisblasen auf dem chinesischen Agrarrohstoffmarkt zu beleuchten.

Angesichts der Aufmerksamkeit der Öffentlichkeit und der politischen Entscheidungsträger bezüglich der Preisblasen auf dem chinesischen Agrarrohstoffmarkt wird jeweils in Kapitel 2 und 3 die Entstehung von Preisblasen auf den Termin- und Kassamärkten untersucht. Insbesondere nach genauer Identifizierung des Blasendatums auf dem Agrar-Terminmarkt und Korrektur der geschätzten Abweichung von Modellen für seltene Ereignisse zeigen unsere empirischen Ergebnisse in Kapitel 2, dass die Blasenepisoden nur einen sehr begrenzten Anteil der Abtastperiode ausmachen, und dass die Märkte für Mais und Sojabohnen in China unterschiedlich auf spekulative Aktivitäten und externe Schocks auf den internationalen Märkten reagieren. Die Preisblasen hängen eher mit der starken Wirtschaftstätigkeit, den hohen Zinssätzen und der niedrigen Inflation zusammen. Darüber hinaus wird in Kapitel 3 durch die Messung des Synchronisationsgrades der Blasen zwischen dem Termin- und Kassamarkt festgestellt, dass selbst die kointegrierten Termin- und Kassapreise der Agrarrohstoffe selten gleichzeitig Blasen bilden. Eine weitere Analyse durch den Regime-Switching Ansatz der Preisübertragung zeigt, dass der Anpassungseffekt des Terminpreises an den Kassapreis am geringsten ist während des Zeitraumes, in dem die Kassapreisblasen am häufigsten auftreten. Zudem werden die Kassapreisrenditen eher von ihren eigenen verzögerten Konditionen beeinflusst. Alle diese Ergebnisse stellen die Idee in Frage, dass Blasen durch Überfinanzialisierung auf den Terminmärkten entstehen und dann auf die Kassamärkte übertragen werden. Daraus schließen wir, dass die Termin-Preisblasen empfindlicher auf fundamentale Faktoren reagieren, während die Kassa-Preisblasen eher von ihren eigenen Merkmalen des Marktes beeinflusst werden. Abgesehen von empirischen Analysen zur Entstehung von Preisblasen wird allgemein angenommen, dass Blasen die Ressourcenallokation verzerren könnten und die Rezession der Wirtschaft normalerweise auf den Zusammenbruch der Blase folgt. Inspiriert von den Ergebnissen aus Kapitel 2 und 3 wird in Kapitel 4 versucht, einen systematischen theoretischen Rahmen aufzubauen, um den beobachteten wirtschaftlichen Prozess mit Blasen zu erklären. Aus einer neuen Perspektive konstruieren wir ein theoretisches Modell, um die Entwicklungsübersicht der Blasen zu beschreiben, das ihre Entstehung, ihre Entwicklung, ihren Zusammenbruch und ihre Auswirkung auf die Wirtschaftsleistung einschließt. Im Rahmen des Forschungsthemas

werden in Kapitel 5 die Auswirkungen des neueingerichteten Apfel-Terminkontrakts in China erforscht. Die Ergebnisse verschiedener Tests zeigen an, dass der Apfel-Terminmarkt die Preisfindung nicht gut fördern, aber die Volatilität der Kassapreise in gewissem Maße verringern kann. Um die Effizienz des Apfel-Terminmarktes zu erhöhen, sollten die Regulierungsbehörden wirksame Maßnahmen in Betracht ziehen, mehr gewerbliche Händler aus verschiedenen Regionen Chinas für die Teilnahme an Termingeschäften zu gewinnen.

Chapter 1 Introduction and Summary

The global agricultural commodity markets have witnessed price booms and busts during the last decades. Around the financial crisis of 2007/08, agricultural commodity prices, such as corn and soybeans, reached their historical high levels. Fig. 1.1 and 1.2 below show the (log) corn and soybeans futures prices in Chicago Board of Trade (CBOT) from 2006 to 2017. It indicates that both corn and soybeans have experienced significant price booms and busts around 2007-2008 and 2010-2012. This has triggered a lasting public and academic concern on the existence, causes, and effects of agricultural commodity price bubbles.

Due to that food expenditure takes a large proportion of the poor's income, the welfare of people in developing countries could be strongly affected by a large increase in grain prices (Tadesse et al. 2014, Bellemare 2015). In addition, the livelihood of farmers mainly depends on agricultural production. The drastic fluctuations of agricultural commodity prices may further affect farmers' production decisions (Gouel 2014). Therefore, the agricultural price anomalies are supposed to have profound and complicated effects on the welfare of the poor in developing countries.

As pointed out by the World Bank (2018), the rapid growth among the major emerging markets and developing economies over the past 20 years has boosted the global demand for various commodities, especially given that 39 percent of the increase in global food consumption between 1996 and 2016 is from emerging economies. Being the most populous emerging economy, China plays an important role in global markets and suffers welfare losses from volatile agricultural commodity prices. Especially after becoming a member of the World Trade Organization (WTO) at 2001, China's agricultural market has become more and more integrated into the international market (Hernandez et al. 2014). Figure 1.1 and 1.2

show that both Chinese corn and soybeans prices (from Dalian Commodity Exchange, DCE) have experienced similar booms and busts as the US market. Meanwhile, as an important producer and consumer of many agricultural commodities, China significantly impacts the global supply/demand balance (Coxhead and Jayasuriya 2010). One extremely case is that China imported more than half of its consumption volume for soybeans in 2017.

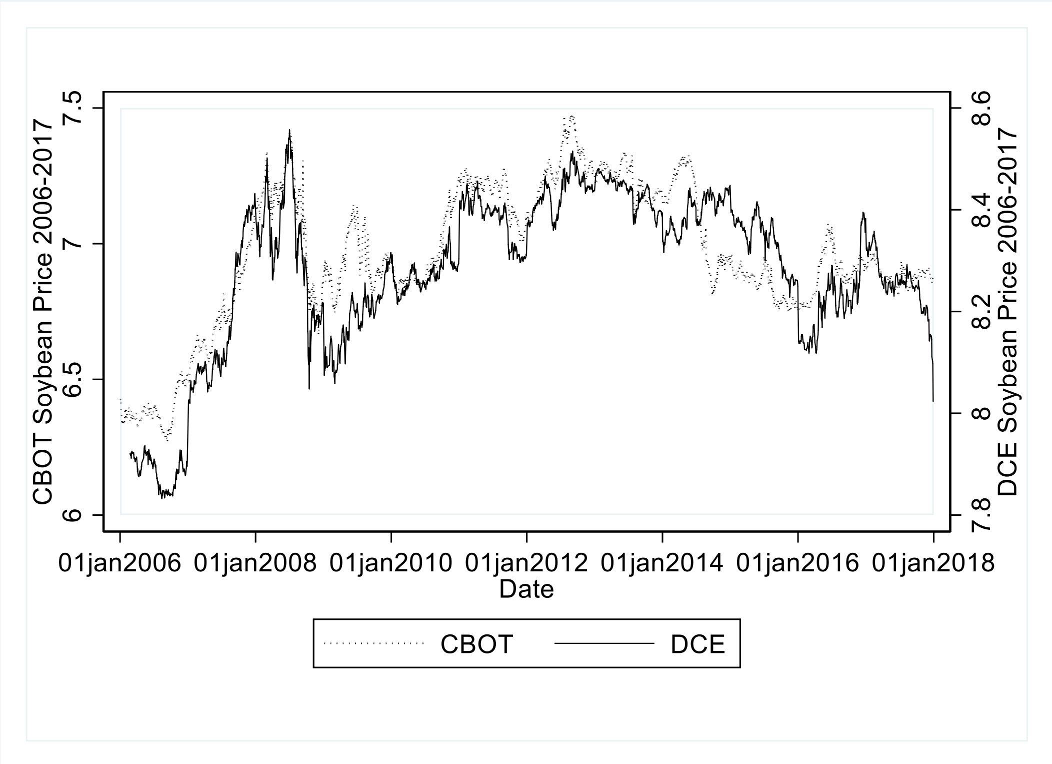

Figure 1.1 CBOT and DCE Soybean Prices 2006-2017

Source: Own calculations based on data from CBOT and DCE using Stata 15.

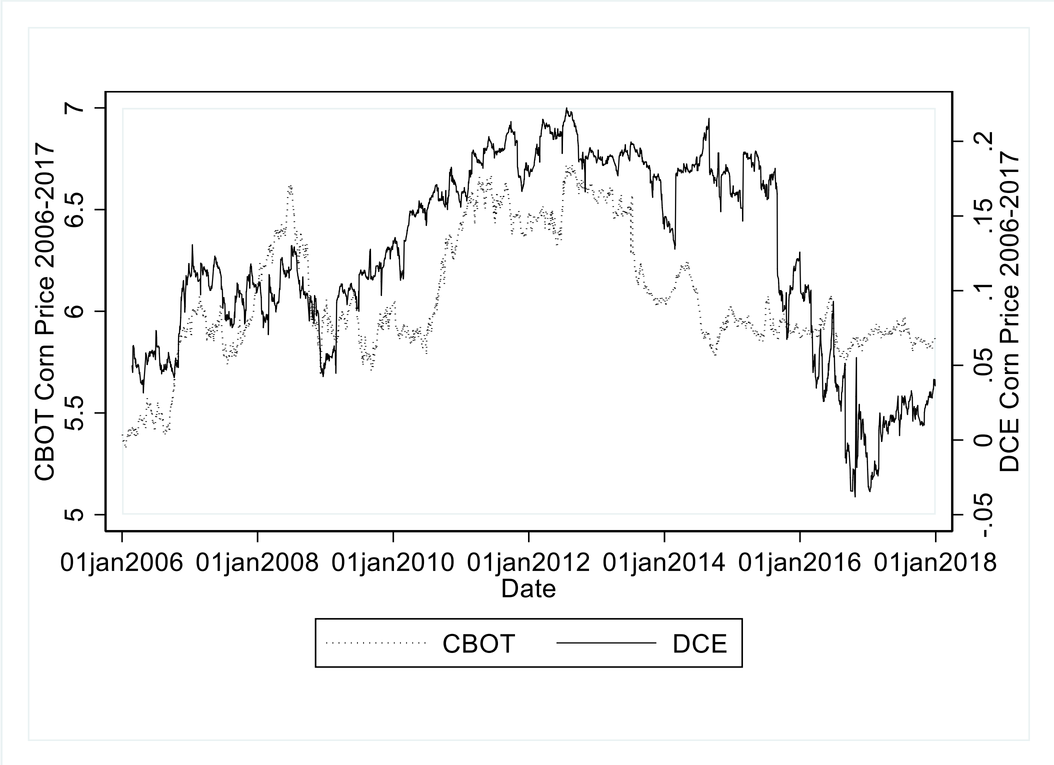

Figure 1.2 CBOT and DCE Corn Prices 2006-2017

Source: Own calculations based on data from CBOT and DCE using Stata 15.

Another important feature about the agricultural commodity markets is the increasing financialization over the last decades. As stated by Master (2008), ‘assets allocated to commodity index replication trading strategies have grown from $13 billion in 2003 to $317 billion in July 2008. At the same time, the prices for the 25 commodities that make up these indices have risen by an average of over 200%’. The unprecedented inflow of institutional funds into commodity futures market has been considered as the primary reason for agricultural price bubbles (Master 2008, 2009, Basak and Pavlova 2016). Irwin and Sanders (2012) refer to this argument as Masters Hypothesis, which is often cited by sequent studies in this field.

Although many people describe commodity price booms coupled with massive speculation as price bubbles, the basic definition of asset price bubbles is straightforward: if the reason that the price is high today is only because investors believe that the resale price will be higher tomorrow and the fundamental factors do not seem to justify such a price (Stiglitz 1990, Scheinkman and Xiong 2003, Gürkaynak 2008). The fundamental value of an asset is determined by the standard present discounted value (PDV) of its future dividends. Pindyck

(1992) further develops the present discounted value model of rational commodity pricing, which uses convenience yields as future payoffs for storable commodities. Thereby, the standard theoretical framework of asset price bubbles could be applied to commodity prices. More importantly, it is noticeable that rational expectations cannot prevent the occurrence of price bubbles defined above. The intertemporal no-arbitrage condition holds in the case of rational price bubbles, namely the bubble would grow in the risk-free interest rate. The standard PDV model would have multiple equilibria under the hypothesis of rational expectations, which suggests the indeterminacy of bubble solutions (Blanchard and Watson 1982). Price series containing with various bubble paths could evolve without violating rational expectations. A detailed mathematical deduction of this process will be presented in the methodology part of Chapter 2. Evans (1991) further generalizes the model of rational price bubbles into a periodically collapsing form. The type of bubbles in this dissertation is constrained to rational price bubbles. For irrational bubbles, please refer to the research work of Shiller (2015).

So far, no consensus has been reached about the underlying factors driving the price bubbles in agricultural commodity futures markets. There are two main strings of studies on the possible factors. The first one is consistent with the 'Master hypothesis', arguing that agricultural commodity price bubbles are caused by over-financialization. Related studies empirically investigate the effect of over-financialization on agricultural price bubbles and find mixed evidences (Headey and Fan 2008, Sanders and Irwin 2011, 2017, Will et al. 2013, Etienne et al. 2015, Etienne 2017). Nevertheless, the regulators have taken measures to curb speculative positions in agricultural futures markets. Scholars show their worries that these anti-speculation measures may lower the efficiency of agricultural futures markets, due to that speculators play an important role in price discovery and are important counterparties to commercial traders (Tirole 1982, Sanders and Irwin 2010). Another string of studies focuses on fundamental economic factors, such as supply/demand pressure, economic climate index, exchange rate and so on (Krugman 2008, Frankel 2014, Etienne et al. 2017, Li, Chavas, et al. 2017). They argue that price bubbles are more likely to occur under certain conditions of fundamental economic factors. Increasing empirical evidences tend to support this point (Boyd et al. 2018).

Meanwhile, it is noticeable that few studies have investigated price bubbles in agricultural spot markets. The co-integration relationship between agricultural futures and spot prices guarantees a long run equilibrium across markets (Pindyck 2001). The return on purchasing a commodity and selling it for deliver using futures contracts equals the interest forgone less the convenience yield net of storage costs (Kaldor 1939, Working 1948, Telser 1958, Casassus et al. 2013). This link is supposed to guarantee the Law of One Price (LOP) (Listorti and Esposti 2012). Hence, one underlying point of the 'Master hypothesis' is that agricultural price bubbles caused by over-speculation in futures market would simultaneously transmit to agricultural spot markets. As a result, commodity prices in spot market would also exceed their fundamental values.

However, the deduction from the cointegrated relationship to the bubbles' synchronisation between futures and spot prices lacks solid support from theories and empirical studies. Futures contracts are generally supposed to speed up the homogenizing process of traders' common expectations concerning a future event. Evidences from experimental economics show that futures markets dampen, though do not eliminate, bubbles (Porter and Smith 2003). Moreover, nonlinear price transmission or sluggish response to market information could result in temporary disjunction between cointegrated prices (Listorti and Esposti 2012, Loy et al. 2016, Alexakis et al. 2017). This raises our suspect about the bubble synchronisation between the agricultural futures and spot markets. If bubbles in agricultural futures market truly reflect the changes of fundamental economic factors, bubbles in spot market should not be caused by speculation in futures market. The true origin of commodity price bubbles may be attributable to certain features of the spot market.

Apart from the empirical studies on agricultural commodity price bubbles, there is still an urgent issue regarding the theoretical modelling of bubbles. Many insightful theoretical models for price bubbles have been constructed on the basis of the Overlapping Generations (OLG) framework proposed by Samuelson (1958). The advantage for this kind of models is that they do not impose any terminal conditions on price series and explain the economic process with bubbles (Samuelson 1958, Tirole 1985, Olivier 2000, Martin and Ventura 2012). Nevertheless, the finite lived agents of OLG framework cannot be used for empirical analyses on the price data, which is based on calendar time (Miao 2014). Kocherlakota (1992, 2008) made important contributions to the infinite-horizon models. The bubble is considered as a windfall to the firms and relax their borrow constraints. In the presence of financial frictions, bubble trades could enhance financial market efficiency and economic growth.

The moment we notice the bubbles in the market, their potential precipitating factors has long been existed in the economy (Shiller 2015). Thus, it needs a more comprehensive explanation on the formation of price bubbles in agricultural markets, especially considering that most previous studies only focus on the effect of over-financialization and seldom refer to other bubble theories. Although the model of rational bubbles is useful to explain the existence of bubbles, it doesn't explain the underlying market process: neither the timing of a bubble, nor the reasons for its onset, nor the type of transactions that occur during the bubble episodes are explained by this model (Lux and Sornette 2002). Meanwhile, the shortage of the theoretical models based on the OLG framework is the assumption of finite lived agents, who could only live for two or three periods, otherwise the model would be extremely complicated. Therefore, we still need new efforts to explain the economic process with bubbles. Inspired by the studies by Kocherlakota (1992, 2008) and Martin and Ventura (2012), we try to construct a new model that embodies the rational bubbles into economic process.

Given that there are only a few empirical researches into the agricultural commodity price bubbles in China, this cumulative dissertation consists of four independent studies that contribute to the research on the origin of agricultural price bubbles, price transmission during bubble episodes, as well as a new theoretical model that explains the effects of bubbles on economic growth. The first study (Chapter 2) is devoted to identifying the exact bubble dates in Chinese agricultural corn and soybeans futures markets and to investigating the possible contributing factors to the formation of bubbles. The second study (Chapter 3) measures the degree of bubble synchronisation between agricultural futures and spot markets and attempts to analyse the price transmission processes during bubble episodes. The third study (Chapter 4) provides a new theoretical framework of asset price bubbles and sheds light on the economic effects of bubbles by assuming infinite lived agents. The last study (Chapter 5) evaluates the performance of the global first fresh fruit futures contract for apples (red Fuji) in China.

Each study is summarized below. The summary includes the aim of the study, the data, the methods applied, and the main results. The main conclusions, policy implications, and limitations of each contribution are presented in Chapter 7.

Price Bubbles in Agricultural Commodity Markets and Contributing Factors: Evidence for Corn and Soybeans in China

Given the fact that Chinese agricultural commodity futures markets have experienced similar fluctuations as the international market (see Figure 1.1 and 1.2), the objectives of this study are to detect the bubble dates for corn and soybeans futures prices, and to investigate the possible contributing factors to agricultural price bubbles in China.

We concentrate on the two highly traded agricultural commodities in Chinese futures market, namely corn and soybeans. Using individual futures contract prices drawn from the Dalian Commodity Exchange (DCE) during the period 2006-2017, we apply a recently developed rolling window right-side augmented Dickey-Fuller test to identify the bubble dates. After detecting the bubble dates for each commodity species, we examine the contributing factors to agricultural price bubbles in China using a multinomial logistic model.

The results indicate that price bubbles account for 5.48 % (3.91 %) of the sample period for corn (soybeans). For the contributing factors, we find that market liquidity and speculation have opposite effects on the occurrences of bubbles in the corn and soybeans futures markets. 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 to be associated with strong economic activity, high interest rates and low inflation levels.

Agricultural Price Transmission between Futures and Spot Markets during Price Bubbles

Using the weekly price data from Dalian Commodity Exchange (DCE) and China Grain Reserves Group Company over the period 2009-2017, this article measures the degree of bubble synchronisation between futures and spot markets for corn and soybeans in China. A new approach comparing the standard deviation of bubble shares with that of perfect bubble synchronisation/staggering is applied to gauge the degree of bubble synchronisation between markets. To further investigate the interdependence between agricultural futures and spot prices during their bubble episodes, we use the Markov Switching Error Correction Model (MSECM) and the Dynamic Conditional Correlation Multivariate GARCH Model (DCC-MGARCH).

Our results provide little evidence for bubble synchronisation between the agricultural futures and spot prices. This does not support the prediction from the conventional co-integration and Granger-causality relationships. Bubbles are more frequent and durable for agricultural spot prices, even though futures prices dominate the price discovery. Specifically, the results from the MSECM model suggest a nonlinear transmission across the futures and spot prices. The co-integration relationship becomes weak and the adjustment effect of the spot price toward the long-run equilibrium is the lowest during the regime with the most frequent spot price bubbles. The agricultural spot price returns are more likely to be affected by its own lagged terms. Through the DCC-MGARCH model, we further find a very loose dynamic volatility interdependence between these two prices. These features of agricultural spot markets could have resulted in more frequent bubbles.

Economic Growth, Bubbles, and Firm Size Distribution

The relationship between bubbles and economic growth has received increasing attention by scholars, particularly in a production economy with financial frictions. The existing literature generally investigates the effect of bubbles on economic growth by embedding the bubbles into the framework of Overlapping Generations (OLG); however, the interpretation of these models for economic data are limited. A new theoretical model is constructed in this chapter to combine the model of rational bubbles and the stochastic model of firm growth proposed by Ijiri and Simon (1967). Under the assumption of infinite lived agents, we relax the propositions that allow the occurrences of bubbles and investigate the effects of bubbles on the dynamic economic process. A simulation is then conducted to show that our model is useful to demonstrate the bubble's process and economic development.

Price discovery and volatility spillovers in Chinese apple futures market

The Red Fuji apple futures contracts introduced in China at the end of 2017 marked the first fresh fruit trade at a futures exchange. This paper investigates the performance of the newly established apple futures market, using the data from the Zhengzhou Commodity Exchange (ZCE) in China. After identifying a weak correlation between apple futures and spot prices, we gauge the synchronisation degree of price changes across major apple spot markets nationwide and investigate the volatility spillovers between the apple futures and spot markets.

We find that the apple futures market has a limited function of price discovery, which undermines its hedging effectiveness for commercial traders. The establishment of apple futures market doesn't improve the synchronisation level of price changes among the major apple markets in China. Moreover, the volatility analyses through GARCH and BEKK-MGARCH models indicate that the apple spot price volatility has increased significantly during the last two years, but we find that futures price tends to reduce the spot price volatility in the short term. Our study reveals that apple futures market does not serve well for the price discovery and may reduce the spot price volatility. This raises a doubt about whether fresh fruit is suitable for futures trading.

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Chapter 2 Price Bubbles in Agricultural Commodity Markets and Contributing Factors: Evidence for Corn and Soybeans in China

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Abstract

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. 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. 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. 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

2.1 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 2007/08, 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 2007/08. 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 (Meltzer 2002, Etienne et al. 2015).

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 (Master 2008, 2009, Basak and Pavlova 2016). 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 2015a). 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 2007/08 (Will et al. 2013, Boyd et al. 2018). One example in this area is the huge demand from bio-energy industries and the increasing demand from emerging economies (Krugman 2008, Hamilton 2009, Carter et al. 2012, Kilian and Murphy 2014). 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 percent 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 USA, 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 (Pindyck and Rotemberg 1988, Bailey and Chan 1993, Carter et al. 2011), 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 behaviours in asset prices. Li et al. (2017) 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., 2017). 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

[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).

macroeconomic activities. These hypotheses will be investigated for each commodity market, respectively.

The outline of the rest of the paper is as following. Section 2.2 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 2.3 describes the data and provides some descriptive statistics. Section 2.4 discusses the main model estimation results. Section 2.5 summarizes the paper and presents conclusion.

2.2 Methodology

2.2.1 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 equation (1) can be used to explain the formation of commodity futures price. Forward iterating equation (1) to infinite periods, we can get the fundamental price of the asset:

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

equation (2) is the unique solution of equation (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 equation (3) does not hold, the equation (2) will no longer be the unique solution of equation (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

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

adding this B_t into equation (2) will also satisfy equation (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 μ

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

where ε_t is a white noise process. Substituting equation (6) into equation (2), we can get

$$P_t^f = \frac{r_f}{1+r_f}\mu + \frac{1}{r_f}D_t \qquad (7).$$

The first term of the right side of Equation (7) is constant, while the second term is a random walk process based on equation (6). Thus, equation (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 equation (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 equation (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, 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.

[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.

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 (Tsvetanov et al. 2016, Caspi et al. 2018). Recently, many studies also try to apply this method into the agricultural commodity markets (Etienne et al., 2015; Gutierrez, 2013; Li, et al., 2017). 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:

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

where P_t is the asset price, d is a constant, T is the sample size and η 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

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

where k is the lag order. The number of observations in the regression is $T_W = \lfloor Tr_w \rfloor$, where$\lfloor . \rfloor$ 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:

$$GSADF(r_0) = sup_{r_1 \in [0, r_0]}^{r_2 \in [r_0, 1]} \{ ADF_{r_1}^{r_2} \} \tag{10}$$

The origination date of a bubble $\lfloor T_{r_e} \rfloor$ is calculated as the first chronological observation whose GSADF statistic exceeds the critical value. The calculated origination date is denoted by $\lfloor T_{\widehat{r_e}} \rfloor$. The estimated termination date of a bubble $\lfloor T_{\widehat{r_f}} \rfloor$ is the first chronological observation after $\lfloor T_{\widehat{r_e}} \rfloor + L_T$ 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 $\log(\mathrm{T})$. 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.

[3] We adjust the minimum window size and find that the result of bubble dates is rather robust.

2.2.2 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:

$$Bubbles_{it} = Cons_i + \beta_{i1}MLF_{it} + \beta_{i2}Stocks_{it} + \beta_{i3}SOI_t + \beta_{i4}USBubbles_t + \beta_{i5}Exchange_t + \beta_{i6}ECI_t + \beta_{i7}Shibor_t + \beta_{i8}PPI_t + \beta_{i9}Gasoline_t + \varepsilon_{it} \quad (11)$$

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 (Pindyck and Rotemberg 1988, Gilbert 2010, Adämmer and Bohl 2015, Etienne et al. 2015, Li, Chavas, et al. 2017, Castro Campos 2019). 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., 2017; 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 2.1.

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, Chavas, et al. 2017). 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 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.

2.3 Data

Our study focusses 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 8th largest exchange in the world in 2016. Our sample period runs from 2006 to 2017, including the periods of global price peaks in 2007/08 and 2010/11. 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 thirteen-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 2.1 presents detailed information on the model variables in equation (11). Trade volume and open interest represent the market liquidity and speculation for different commodities. Data comes from the Dalian Commodity Exchange (2019). 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

[4] The bubble dates from 2016 to 2017 are calculated by us using the same bubble testing procedure as theirs.

literature, all these factors may have direct and indirect effects on traders' expectations (Pindyck and Rotemberg 1988, Gilbert 2010, Hong and Yogo 2012).

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., 2017).

Table 2.1 Price and Possible Factors Contributing to Price Bubbles (2006-2017)

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)

Notes: 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.
Source: Own calculations with Stata 15.

2.4 Results

2.4.1 Bubble Dates

Figures 2.1 and 2.2 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 01jan2008 and 01 jan2009 has been proved to be a random walk without explosive roots, its dramatic fluctuations thus should be attributed to the high volatility. To

[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.

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., 2017). 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.

[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.

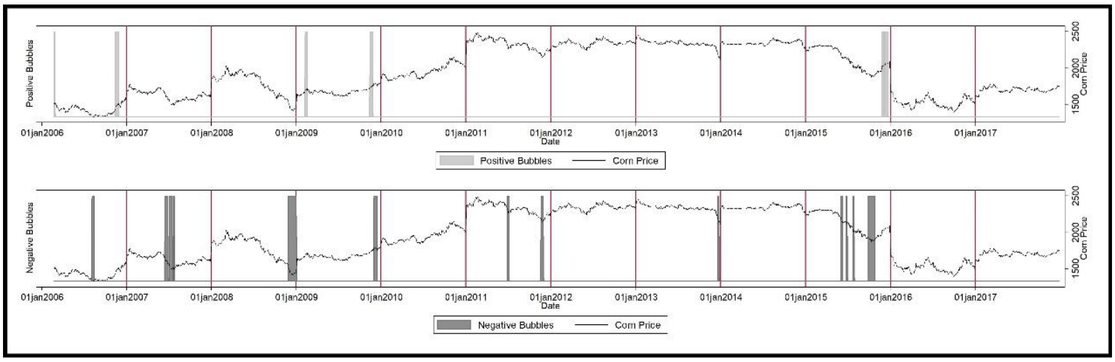

Figure 2.1 Price Bubbles for Corn

Source: Own calculations based on data from DCE using Stata 15.

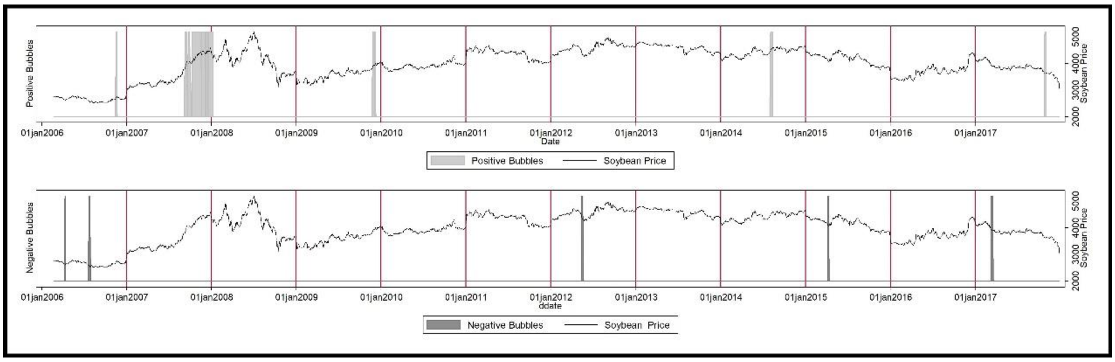

Figure 2.2 Price Bubbles for Soybeans

Source: Own calculations based on data from DCE using Stata 15.

More detailed information about the bubble dates is presented in Table 2.5A-1 and Table 2.6A-2 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.

2.4.2 Multinomial Logistic Regression Results

We first calculate the descriptive statistics for the independent variables in Table 2.2. 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.

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 2.3 and 2.4 present the main results. Tables 2.7A-3 and 2.8A-4 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 2.3 and 2.4.

Table 2.2 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)
USBubbles 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)
USBubbles 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)	5889.13 (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

Notes: 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.

Source: Own calculations with Stata 15.

2.4.2.1 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 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 2.3 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 2.1, 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 (Tyner 2010, Wu et al. 2011, Adämmer and Bohl 2015). We use this variable to estimate the

[7] We further conduct a robustness check of the lagged effects for PPI and find that the estimation results remain unchanged (see Table 2.11A-7 and Table 2.12A-8 in the appendix).

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.

2.4.2.2 Contributing Factors of Price Bubbles for the Soybean Market

As we can see in Table 2.4, 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 doesn't 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 USA are highly connected with each other. All 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.

Table 2.3 Penalized Maximum Likelihood Estimation for the Multinomial Logistic Regression: Corn

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

Notes: Standard errors are in parentheses. *** *p<0.01*, ** *p<0.05*, * *p<0.1*

Source: Own calculations with R software.

Table 2.4 Penalized Maximum Likelihood Estimation for the Multinomial Logistic Regression: Soybeans

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

Notes: Standard errors are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Source: Own calculations with R software.

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 2.9A-5 and 2.10A-6 in the appendix show the results of the individual models. Compared with results in Tables 2.3 and 2.4, 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.

2.5 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 2007/08, 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 2.1). 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., 2017). The commodities with higher self-sufficiency rate have shown less volatile price movements in China, such as corn, rice and wheat (Li, et al., 2017; 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 (Wu et al. 2011, Adämmer and Bohl 2015). 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 behaviours of retailing investors, divergent beliefs towards 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 (2017) 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,

[8] According to the China Futures Market Yearbook (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%.

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 2.13A-9 and Table 2.14A-10 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., 2017). 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

[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.

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.

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Appendix

Table 2.5 A-1: Summary of Price Bubbles for Corn

		Positive Bubbles					Negative Bubbles				
Bubble Periods	Length (days)	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%
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	158days (5.48%)				Positive: 46 days (29.11%)					Negative:112 days (70.89%)	
Maximum Single Bubble Duration	24 days										

Table 2.6 A-2: Summary of Price Bubbles for Soybeans

	Positive Bubbles						Negative Bubbles				
Bubble Periods	Length (days)	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)
2006/04/11-2006/04/13	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%
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	113days (3.91%)				Positive: 91 days (80.53%)				Negative: 22days (19.47%)		
Maximum Single Bubble Duration:	28 days										

Table 2.7 A-3: Marginal Effects for PMLR model of Corn

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

Notes: The standard deviations are in parentheses.

Source: Own calculations with R software.

Table 2.8 A-4：Marginal Effects for PMLR model of Soybeans

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

Notes: The standard deviations are in parentheses.

Source: Own calculations with R software.

Table 2.9 A-5: Individual Model for Penalized Maximum Likelihood Estimation: Corn

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

Notes: Standard errors are in parenthesis. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Source: Own calculations with Stata 15.

Table 2.10 A-6: Individual Model for Penalized Maximum Likelihood Estimation: Soybeans

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

Notes: Standard errors are in parenthesis. *** *p<0.01*, ** *p<0.05*, * *p<0.1*

Source: Own calculations with Stata 15.

Table 2.11 A-7: Individual Model for Penalized Maximum Likelihood Estimation: Corn (Lagged PPI)

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

Notes: Standard errors are in parenthesis **** p<0.01, ** p<0.05, * p<0.1*

Source: Own calculations with Stata 15.

Table 2.12 A-8: Individual Model for Penalized Maximum Likelihood Estimation: Soybean (Lagged PPI)

	Model 1		Model 2	
	Positive	Negative	Positive	Negative
Cons	43.89**	-70.56***	63.77***	-61.75***
	(21.86)	(21.44)	(22.15)	(18.83)
Trade volume/100	0.29***	0.06		
	(0.11)	(0.25)		
Open Interest/100			0.86***	-0.68
			(0.23)	(0.43)
China Stocks-to-use	8.13***	4.72	7.63***	7.29
	(2.78)	(3.76)	(2.80)	(4.48)
World Stocks-to-use	-6.12***	-7.33***	-4.83***	-9.56***
	(1.94)	(2.81)	(1.87)	(3.39)
SOI	0.36	0.21	0.58**	0.00
	(0.27)	(0.44)	(0.27)	(0.42)
USBubbles Positive	1.45*		1.50*	
	(0.79)		(0.81)	
USBubbles Negative		1.89		2.05
		(1.93)		(1.83)
Exchange Rate	-1.64	6.50***	-2.33	5.30***
	(1.40)	(1.71)	(1.46)	(1.54)
ECI	0.13***	-0.08***	0.16***	-0.06*
	(0.02)	(0.03)	(0.02)	(0.03)
Shibor	1.13***	-0.87	1.27***	-0.87
	(0.33)	(0.67)	(0.31)	(0.67)
Lagged PPI	**-0.48*** **	**0.18**	**-0.66*** **	**0.16**
	(0.15)	**(0.15)**	**(0.15)**	**(0.15)**
Gasoline	0.08	0.10	0.13**	0.09
	(0.06)	(0.09)	(0.06)	(0.09)
Q2	-3.08	1.27*	-4.02	1.61**
	(3.75)	(0.75)	(3.54)	(0.77)
Q3	3.47***	1.24	3.95***	1.65*
	(1.03)	(0.88)	(1.09)	(0.95)
Q4	4.74***	-1.57	5.68***	-1.38
	(0.98)	(1.53)	(1.1165)	(1.52)
Observations	2321	2321	2321	2321

Standard errors are in parenthesis. **** p<0.01, ** p<0.05, * p<0.1*

Source: Own calculations with Stata 15.

Table 2.13 A-9: Individual Model for Penalized Maximum Likelihood Estimation: Corn (NPR)

	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

Notes: 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.
Source: Own calculations with Stata 15.

Table 2.14 A-10: Individual Model for Penalized Maximum Likelihood Estimation: Soybeans (TPP)

	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

Notes: 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.

Source: Own calculations with Stata 15.

Table 2.15 A-11: Penalized Maximum Likelihood Estimation for the Multinomial Logistic Regression: Corn (without gasoline price)

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

Notes: Standard errors are in parentheses. *** *p<0.01*, ** *p<0.05*, * *p<0.1*

Source: Own calculations with Stata 15.

Table 2.16 A-12: Penalized Maximum Likelihood Estimation for the Multinomial Logistic Regression: Soybeans (without gasoline price)

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

Notes: Standard errors are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Source: Own calculations with Stata 15.

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., 2017; Etienne et al., 2015; Adämmer and Bohl, 2015; Wooldridge, 2005; Pindyck and 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, Wooldridge 2005). 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 A-11 and A-12, the coefficients and significant levels for the variables remain, suggesting the robustness of our estimation with regard to multicollinearity.

Chapter 3 Agricultural Price Transmission between Futures and Spot Markets during Price Bubbles

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Abstract

Many studies have identified significant long-run and short-run relationships between commodity futures and spot prices; this article extends the analysis by investigating the price transmission across markets during bubble episodes. We find that bubbles seldom synchronise across futures and spot prices, even though the co-integration and Granger-causality relationships remain. Bubbles are more frequent in spot prices, while futures prices dominate the price discovery. Moreover, a non-linear transmission between futures and spot markets in the first and second moments of price returns is found through the Markov-switching error-correction model and the dynamic conditional correlation multivariate GARCH model. The lack of immediate and linear transmission between co-integrated prices inhibits the synchronisation of bubbles. During the regimes with most bubbles, spot prices adjust slowly toward the long-run equilibrium. Own lagged terms of spot price returns more likely drive the spot prices, which may lead to more frequent bubbles in spot markets. Policy makers should pay more attention on the structure of spot markets, rather than merely restricting the positions of speculation in commodity futures markets.

JEL codes: D84, G12, G13, G14, Q13, Q41.

Keywords: Price Bubbles; Agricultural Commodities; Futures Market; Spot Market

3.1 Introduction

Agricultural commodity prices have experienced rapid increases in the last decade. This has raised global concerns about bubbles of food price. Many people attribute the bubble phenomenon to aggressive financialization of agricultural futures markets (Master 2008, 2009, Basak and Pavlova 2016), arguing that too many institutional funds enter into futures contracts with long positions and drive the agricultural commodity prices up in the short run. This results in a wrong price expectation by commercial traders in futures markets, who aim to hedge against risk. Then, the mispricing effect in the futures market impacts spot markets and distorts physical trades and inventories. Although this argument is seemingly quite convincing, recent empirical studies find little evidence to support it (Sanders and Irwin 2017, Boyd et al. 2018). Instead, increasing studies repeatedly find that the fundamental economic factors associated with price bubbles in various commodity (futures) markets are responsible (Gutierrez 2013, Etienne et al. 2014, 2015, Li et al. 2017). Despite the heated discussion on the role of the over-financialization of the commodity markets, the studies focusing on this only detect and analyse price bubbles for commodity futures price series. A particularly ignored issue is whether the spot market of a commodity shows similar and synchronous bubbles. If not, there may be different reasons or mechanisms behind the price bubbles in the futures and spot markets. This study seeks to close the research gap by identifying how futures prices affect spot prices during bubble periods.

Futures markets serve important functions in price discovery and for hedging. Trading futures is supposed to speed up the homogenising process of traders' common expectations of a future event. Evidence from experimental economics even shows that futures markets dampen, though do not eliminate, price bubbles (Porter and Smith 2003). As for the relationship between futures and spot prices, the theory of storage by Kaldor (1939), Working (1948) and Telser (1958) predicts that the returns on purchasing a commodity and selling it for delivery using futures contracts equals the interest forgone less the convenience yield net of the storage costs (Casassus et al. 2013). Based on this theoretical framework and the present discounted value model (Campbell and Shiller 1987), Pindyck (1992) deduces a co-integration relationship between the futures and spot prices of a commodity. Using data from various commodity markets, numerous empirical studies have verified the long-run co-integration relationship (Garbade and Silber 1983, Crain and Lee 1996, Mattos and Garcia 2004, Hernandez and Torero 2010). To date, this has become the common ground for studies on commodity markets; nearby futures prices are often used as a proxy for spot prices. Thus, in terms of the argument on commodity price bubbles, a seemingly plausible deduction is that bubbles would synchronise between the futures and spot markets. If bubbles are mainly caused by over-financialization in the futures market, these bubbles would be transmitted to the spot market almost simultaneously.

However, there are two other points that call into question the direct transmission of bubbles across futures and spot markets. The first is the non-linearity of price transmission process across markets. Theoretically, the co-integration relationship indicates the underlying common stochastic trend between correlated price series (Engle and Granger 1987). If the commodity spot prices are regarded as lower (higher) than their expected future equilibrium, the futures prices are expected to increase (decrease) (Frankel 2014). This relationship is based on the hypothesis of linear transmission between futures and spot prices, but the immediate and linear transmission between co-integrated prices has long been challenged in real markets (Listorti and Esposti 2012; Loy et al. 2015, 2016).

Moreover, some studies have theoretically proven that the co-integration relationship between prices remains even for bubbles that occur within one of the co-integrated price series (Engsted 2006, Magdalinos and Phillips 2009, Nielsen 2010). Alexakis et al. (2017) are one of the first to doubt the direct transmission of price bubbles within the context of the hog supply chain (hog, corn and soybeans). Based on the co-integration residuals among these three commodity prices, they find that the bubbles in feed prices and lack of associated bubbles in hog prices do not affect the long-run co-integration relationship and that the hog prices will even drag the other explosive price episodes back to normal. Esposti and Listorti (2013) consider price bubbles as exogeneous structural breaks, finding that price bubbles only have very limited effects on the co-integrated international and Italy domestic grain prices. Therefore, the non-linear transmission effect may imply that the co-integrated price series would deviate from each other in a short period, allowing bubbles to take place. This raises our suspicion about the synchronisation of bubbles across the futures and spot prices, which to our knowledge has not been tested in previous empirical analysis.

Another point is that price bubbles do not necessarily imply price spikes or drastic price changes (Stiglitz 1990, Meltzer 2002). There is more to a bubble than a drastic price change. Some other characteristics are relevant such as the volatility of prices (Greenwood et al. 2019). Phillips et al. (2012; 2015) develop a new technique to date-stamp price bubbles, which has been widely accepted to detect price bubbles in various markets (Gutierrez 2013, Etienne et al. 2015, Engsted et al. 2016, Tsvetanov et al. 2016, Caspi and Graham 2018). Based on this new bubble testing method, a bubble period marks a temporary episode in which prices demonstrates an explosive root. Most studies using this method find that price bubbles do not always coincide with price spikes and do not even translate into drastic price changes. In the contrary, a price series with a relatively low volatility tends to have a narrow confidence interval for testing explosive roots and is more likely to have bubbles (Etienne et al. 2017).

The two points described above increase our doubts regarding the synchronisation of price bubbles across futures and spot markets. Any price changes within a limited extent will not directly affect the other price series in the case of non-linear transmission, especially when some of these price changes could be identified as bubbles.

Our paper is the first study to empirically analyse agricultural price transmission between futures and spot markets during bubble episodes. It aims to provide new insights into the formation of bubbles. We first detect the bubble dates and measure the degree of the bubbles' synchronisation across the futures and spot markets of corn and soybeans in China. We also use the *Markov-switching error-correction model* (MSECM) to estimate the non-linear transmission effect and identify the characteristics of the regime with the most bubbles. Finally, we use the *dynamic conditional correlation–multivariate GARCH* (DCC-MGARCH) model to measure the dynamic volatility interdependence between the futures and spot prices by analysing market interactions in terms of the conditional second moments during bubble periods.

Our estimation results indicate a very limited synchronisation of bubbles, and most bubbles occur only within the spot price series. Further analysis suggests a significant non-linear transmission across futures and spot prices. The leading role of futures prices becomes weak during frequent spot price bubbles. We find a strong persistence of spot price returns and a loose dynamic volatility interdependence across the futures and spot markets. The lack of immediate, linear transmission of first and second moments of co-integrated prices supports the idea of non-linear transmission, which inhibits the synchronisation of bubbles across futures and spot prices. As opposed to spot prices, futures prices have fewer bubbles and function better than spot prices in aggregating market information. This has also been shown by Yang et al. (2001), Will et al. (2013), Etienne et al. (2015), Li, Chavas, et al. (2017) and Boyd et al. (2018). Bubbles are more likely to occur in spot markets caused by their own persistence of price returns and their irresponsiveness to new information from futures markets.

The structure of the paper is as follows: Section 3.2 briefly introduces the bubble testing method. We use the MSECM model and the DCC-MGARCH model. Section 3.3 describes the price data. Section 3.4 presents the main estimation results and section 3.5 summarises the paper and gives our conclusion.

3.2 Methodology

3.2.1 Bubble Testing Method

A price bubble conventionally defines a situation in which an asset price cannot be justified by its fundamental value derived from the discounted expected payoff stream. The price is in excess of its fundamentals because investors believe the selling price to be higher tomorrow (Stiglitz 1990). This notion is widely accepted in the literature and applies to the case where asset prices and commodity prices might deviate from their intrinsic values based on market fundamentals (Tirole 1982, 1985, De Long et al. 1990, Gutierrez 2013). The present fundamental value of an asset equals the discounted expected future payoffs (Blanchard and Watson 1982, Campbell and Shiller 1987, Brunnermeier 2008, Gürkaynak 2008). Pindyck (1992) further develops the present value model of rational commodity pricing, which uses convenience yields as future payoffs for storable commodities. Specifically, the current and future changes of commodity supply and demand cause changes in current and expected convenience yields. Hence, the present value model of commodity pricing presents a highly reduced form of a dynamic supply and demand model. If investors already know that the present price of an asset or commodity deviates from its fundamental value and investors are still buying or holding commodities to acquire the benefits from future sales, price bubbles are rational. The intertemporal no arbitrage condition always holds in the case of rational price bubbles, which implies a bubble to grow at a risk-free rate and to result an explosive root in the price series.

This definition of price bubbles provides the basis for the right-tailed unit root test to detect bubbles (Diba and Grossman 1988). Price bubbles induce a temporary explosive root in price series. 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, 2009) develop the right-tailed unit root test into a new forward recursive right-tailed Augmented Dickey-

Fuller test (SADF), which suggests implementing the right-tailed Augmented Dickey-Fuller (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 the SADF test is that it can identify the beginning and end of a bubble. Homm and Breitung (2012) use extensive simulations to prove that the SADF test works satisfactorily for structural breaks by comparing with 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. All of methods suffer from reduced power when detecting the periodically collapsing bubbles. To solve this problem, 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, e.g. in 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 (Tsvetanov et al. 2016, Caspi et al. 2018). Recently, many studies also try to apply this method to agricultural commodity markets (Gutierrez 2013, Etienne et al. 2015, Li, Li, et al. 2017). In the following, we give an introduction to the GSADF test.

According to Phillips et al. (2015), the main idea of the GASDF method is to apply the ADF-test to sequential subsets (rolling window) of the whole sample. Suppose that the rolling window run from the r_1^{th} fraction of the total sample (T) to the r_2^{th} fractione, where $r_2 = r_1 + r_w$ and $r_w > 0$ is the fractional window size of the regression. Equation (1) shows the empirical model:

$$\Delta P_t = \hat{\alpha}_{r_1,r_2} + \hat{\beta}_{r_1,r_2} P_{t-1} + \sum_{i=1}^{k} \hat{\varphi}^i{}_{r_1,r_2} \Delta P_{t-i} + \hat{\varepsilon}_t \qquad (1)$$

k is the lag order. The number of observations in the model is $T_W = \lfloor T r_w \rfloor$, where$\lfloor . \rfloor$ is the floor function (given the integer part of the argument). The ADF-statistic (t-ratio) based on this regression is denoted as $ADF_{r_1}^{r_2}$. The rolling regression of the repeated ADF-test is used for 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 supreme value of the corresponding ADF-statistic sequence (see Equation (2)).

$$GSADF(r_0) = sup_{r_1 \in [0,r_0]}^{r_2 \in [r_0,1]} \{ ADF_{r_1}^{r_2} \} \tag{2}$$

The origination date of a bubble $\lfloor T_{r_e} \rfloor$ is calculated as the first chronological observation with a GSADF-statistic above the critical value. The calculated origination date is denoted by $\lfloor T_{\widehat{r_e}} \rfloor$. The estimated termination date of a bubble $\lfloor T_{\widehat{r_f}} \rfloor$ is the first chronological observation after $\lfloor T_{\widehat{r_e}} \rfloor + L_T$ with a GSADF-statistic below the critical value. The bubble duration must exceed the length of $\log(\mathrm{T})$. For the sample under study, we calculate $\log(460) = 2.66$. Thus, the bubble duration should at least last 3 weeks.

For the calculation of critical values for the GSADF method, Phillips et al. (2012) firstly propose to use the Monte Carlo simulations. However, Gutierrez (2013) and Harvey et al. (2016) find that the Monte Carlo method may incorrectly he 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 (Etienne et al. 2014, 2015, Phillips et al. 2015).

3.2.2 Vector Error Correction Models

We proceed to test the co-integration relationship between the futures and spot price series for each commodity. When a co-integration relationship exists, the *vector error-correction model* (VECM) representation will be used to distinguish the long-run and short-run interactions between the co-integrated price series. The VECM representation is listed as follows:

$$\triangle \boldsymbol{p_t} = \boldsymbol{\alpha\beta}'\boldsymbol{p_{t-1}} + \sum_{i=1}^{m-1} \boldsymbol{\Gamma_i} \triangle \boldsymbol{p_{t-i}} + \boldsymbol{\varepsilon_t} \qquad (3),$$

where $\boldsymbol{p_t} = [\boldsymbol{p_t^s} \quad \boldsymbol{p_t^f}]'$ is the (2×1) vector containing the spot and futures prices at time *t*. $\boldsymbol{\beta}$ is the co-integration vector containing the long-run coefficients, and $\boldsymbol{\beta}'\boldsymbol{p_{t-1}}$ represents the error-correction term (ECT). $\boldsymbol{\alpha}$ is the loading matrix containing the long-run adjustment coefficients of the error-correction term. $\boldsymbol{\Gamma_i}$ is the matrix containing the coefficients that account for the short-run adjustment coefficients, and m is the lag length of the underlying vector autoregressive (VAR) model. $\boldsymbol{\varepsilon_t}$ is the matrix of white noise errors. As long as the co-integration relationship is maintained, the VECM representation would allow for temporary explosive roots in one price series (Engsted 2006, Magdalinos and Phillips 2009, Nielsen 2010). Therefore, we can still use equation (3) to model the relationship between the futures and spot prices, even when bubbles occur.

Markov-Switching Error-Correction Model (MSECM)

Already knowing the applicability of the VECM representation, we can use the MSECM to analyse the non-linearity of price transmission across the futures and spot prices. The MSECM assumes that the data-generating process underlying the state variable follows a Markov chain:

$$\Delta p_t^s = \upsilon_{s_t} + \alpha_{s_t}(\boldsymbol{\beta}'\boldsymbol{p_{t-1}}) + \sum_{i=1}^{m-1} \boldsymbol{\Gamma}_{i,s_t} \Delta \boldsymbol{p_{t-i}} + \varepsilon_t \qquad (4),$$

where Δp_t^s is the spot price returns and the state variable s_t represents the underlying state of the observation at time *t*. For the MSECM, the intercept term υ_{s_t}, the loading parameter α_{s_t}, and the short-run adjustment parameter Γ_{i,s_t} are all state dependent. The probability of switching to a new state depends only on the state of the one-step proceeding period, and a switching matrix will control the whole evolving process. Through the MSECM, we can identify the characteristics of the state where bubbles occur the most frequently. Further details about the Markov-switching model can be found in Hamilton (1994).

3.2.3 Dynamic Conditional Correlation Multivariate GARCH Model (DCC-MGARCH)

The dynamic conditional correlation multivariate GARCH model (DCC-MGARCH) measures the degree of volatility interdependence between futures and spot markets (Engle 2002). Through a dynamic conditional correlation matrix, it allows us to identify a time-varying volatility interdependence between the markets. Suppose that $\boldsymbol{H_t}$ is the conditional covariance matrix of $\boldsymbol{\varepsilon_t}$ in equation (3):

$$\boldsymbol{H_t} = \mathrm{Var}\begin{pmatrix}\varepsilon_{1t}\\ \varepsilon_{2t}\end{pmatrix} = \begin{pmatrix}\sigma_{11,t}^2 & \sigma_{12,t}^2\\ \sigma_{21,t}^2 & \sigma_{22,t}^2\end{pmatrix} \quad (5),$$

and $\boldsymbol{H_t}$ could be decomposed into the following form:

$$\boldsymbol{H_t} = \boldsymbol{D_t^{\frac{1}{2}} R_t D_t^{\frac{1}{2}}} \quad (6),$$

where $\boldsymbol{D_t} = \begin{pmatrix}\sigma_{11,t} & 0\\ 0 & \sigma_{22,t}\end{pmatrix}$, and $\boldsymbol{R_t} = \begin{pmatrix}1 & \rho_{12,t}\\ \rho_{12,t} & 1\end{pmatrix}$. For *i = 1 and 2,*

$$\sigma_{ii,t}^2 = \gamma_i + a_i\varepsilon_{i,t-1}^2 + b_i\sigma_{ii.t-1}^2 \quad (7),$$

$\rho_{12,t}$ is determined by the geometrically weighted average of standardised residuals:

$$\rho_{12,t} = \frac{\sum_{s=1}^{t-1}\lambda^s\tilde{\varepsilon}_{1,t-s}\tilde{\varepsilon}_{2,t-s}}{\sqrt{\left(\sum_{s=1}^{t-1}\lambda^s\tilde{\varepsilon}_{1,t-s}\right)\left(\sum_{s=1}^{t-1}\lambda^s\tilde{\varepsilon}_{2,t-s}\right)}} \quad (8),$$

where $\tilde{\varepsilon}_{i,t-s}$ is the standardised error term, and λ^s is the geometrical weight decreasing geometrically with time *t*. The dynamic process of $\boldsymbol{R_t}$ is determined by the following two equations.

$$\boldsymbol{R_t} = diag(\boldsymbol{Q_t})^{-\frac{1}{2}}\boldsymbol{Q_t}diag(\boldsymbol{Q_t})^{-\frac{1}{2}} \tag{9}$$

$$\boldsymbol{Q_t} = (1 - \lambda_1 - \lambda_2)\boldsymbol{R} + \lambda_1\tilde{\varepsilon}_{t-1}\tilde{\varepsilon}'_{t-1} + \lambda_2\boldsymbol{Q_{t-1}} \tag{10}$$

$\boldsymbol{R}$ is the mean of $\boldsymbol{R_t}$**.** Thus, the entire dynamic process is determined by the parameters λ_1 and λ_2. If $\lambda_1 = \lambda_2 = 0$, the DCC model becomes the constant conditional correlation model (CCC-MGARCH), and we can use a joint test for model selection.

3.3 Data

The present paper concentrates on the price bubbles on corn and soybeans commodity markets in China. China has a large, rigid and lasting demand for agricultural commodities, which affects domestic and international markets. The rising food consumption has profound effects on the world food balance and trade patterns and is often taken as the main source of global commodity price spikes (Coxhead and Jayasuriya 2010). China is also a major producer of corn and soybeans. Hernandez et al. (2014) verified the dynamic international interlinkage between China and many international markets. It is important for China to maintain its food safety and stable agricultural commodity markets.

Corn and soybeans show high trade volumes on international markets. We collect weekly price data (Monday) from two datasets. The sample period is from January 4th 2009 to December 31st 2017, including 460 observations. We first obtain the National Wholesale Price Index of each commodity as the spot price. This index is compiled by the China Grain Reserves Group, Ltd., which collects the price data of agricultural commodities from major markets nationwide. The wholesale price mainly reflects large wholesalers' trades. Large wholesalers may have strong market power that affects the supply chain and its price structures and relationships (Nakamura and

Zerom 2010). Futures prices come from the Dalian Commodity Exchange (DCE), which is the most important futures exchange for agricultural commodities in China. We use nearby futures contract prices. Specifically, each commodity has six futures contracts every year, namely the contracts starting in January, March, May, July, September and November. All futures contracts last for 12 months, not including the delivery month. The price series of the last two months for each contract build the nearby futures price. We use the logarithmic transformation of prices.

3.4 Results

3.4.1 Bubble Testing Results

Table 3.1 presents the descriptive statistics of price returns ($\log(P_t/P_{t-1})$). The futures price returns exhibit a higher absolute mean value for both commodities. The comparison of the maximum (minimum) values and standard deviations suggest that the futures price returns have a larger amplitude and volatility than spot prices. The kurtosis for all markets exceeds three, indicating a leptokurtic distribution. The results of the Jarque-Bera test further show that price returns do not follow a normal distribution. Given these results, a t-student distribution is considered for the estimation of the DCC-MGARCH model to solve the non-normality problem.

Table 3.1 Summary statistics for daily price returns

	Corn		Soybeans	
	Futures	Spot	Futures	Spot
Statistics				
Mean*100[a]	0.0153	0.0148	-0.0156	0.0048
Median*100[a]	0.0000	0.0550	0.0196	0.0139
Maximum	0.0940	0.0091	0.0474	0.0405
Minimum	-0.0667	-0.0322	-0.0465	-0.0465
Std. Dev.	0.0112	0.0040	0.0091	0.0062
Skewness	0.2549	-2.4111	-0.1729	-0.3622
Kurtosis	21.2756	15.7235	6.9729	22.0747
Jarque-Bera	6392.6870	3540.8044	304.1487	6968.5786
q-value	0.0000	0.0000	0.0000	0.0000
Number of obs	460	460	460	460

[a] Mean and median values are multiplied by 100.

Source: own calculations based on data from DCE and the China Grain Reserves Group, Ltd. using Stata 15.

We proceed to use the GSADF method to detect bubbles in each price series. The futures and spot prices indicate different bubble episodes shown in Figures 3.1 and 3.2, even though they are co-integrated with each other. Regardless of the commodity species, the spot price has more frequent and longer bubble episodes than the corresponding futures price. In the case of corn, 73 of 460 weeks (15.87 %) indicate bubbles for the spot price, while only 7 of 460 weeks (1.52 %) show bubbles for the futures price. Importantly, the corn futures price shows two short bubble episodes and only one of them coincides with a bubble episode of the spot price. In the case of soybeans, 54 of 460 weeks (11.73 %) show bubbles for the spot price, while only 10 of 460 weeks (2.17 %) for the futures price. Again, we only find one overlapping bubble episode. Table A-1 and A-2 in the Appendix present more details.

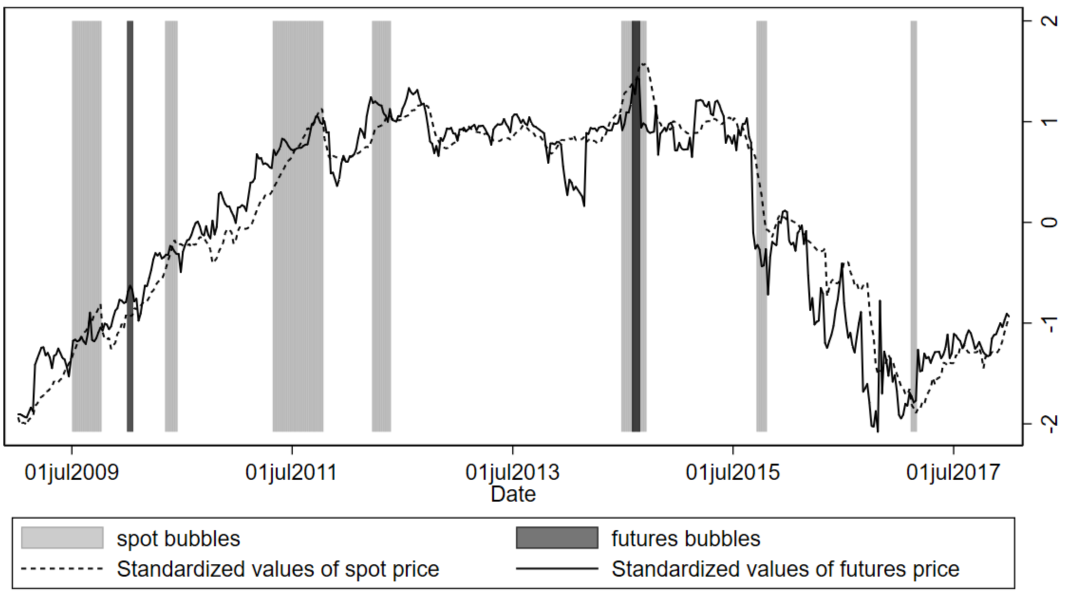

Figure 3.1 Corn: Price Bubble Periods for the Futures and Spot Prices

Source: own calculations based on data from DCE and the China Grain Reserves Group, Ltd. using Stata 15.

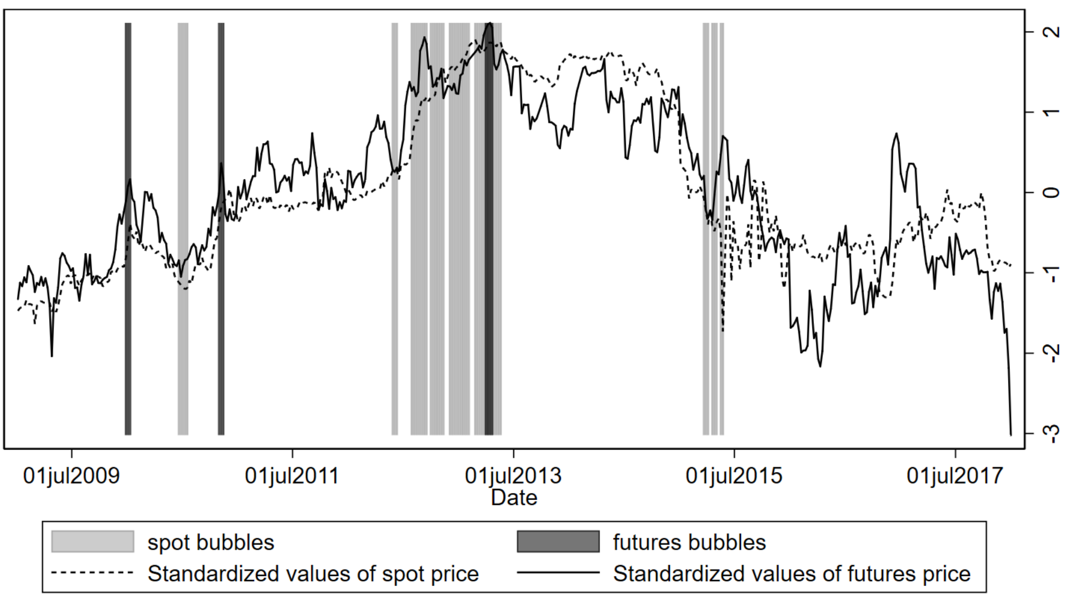

Figure 3.2 Soybeans: Price Bubble Periods for the Futures and Spot Prices

Source: own calculations based on data from DCE and the China Grain Reserves Group, Ltd. using Stata 15.

We apply another measure to quantify the degree of bubble synchronisation across two price series. When estimating the degree of price synchronisation and staggering among different prices, prior studies compare the standard deviations of the actual proportion of price changes in each period with the standard deviations of perfect price synchronisation or staggering (Fisher and Konieczny 2000, Loy and Weiss 2002). We use this method to measure the degree of bubble synchronisation and staggering across different price series. If the bubbles for futures and spot prices were perfectly staggered, we would expect the proportion of bubble occurrences in any period would be equal to the average proportion of bubbles over time. However, if the bubbles are perfectly synchronised, the proportion of bubbles in any period would be either 0 or 1. For instance, the number of corn (futures and spot) price bubbles is 76 out of 460 observations. In this case, assuming perfect synchronisation, the standard deviation is computed from a series of 76 ones and 384 zeros. Table 3.2 shows the main result of the standard deviations for these three cases. The final row of 'differences from perfect staggering' indicates the extent of deviation from perfect staggering. When this term is below 50 %, the actual data are closer to the perfect staggering situation.[1] As will be seen in Table 3.2, even though there are no bubbles within most observations (384 weeks, 83.5 % of the sample observations) for both the corn futures and spot prices, we find that the deviation from perfect staggering is still below 50 %. The same applies to the case of soybeans. This further proves that the bubbles for futures and spot prices hardly synchronise with each other.

[1] When more individual price series are available, a formal χ^2 test could be used to judge the significance level of the deviation from perfect staggering formally.

Table 3.2 Comparing standard deviations of different cases

Standard Deviation	Corn	Soybeans
In actual data	0.2009	0.1852
Assuming perfect staggering [a]	0.1859	0.1686
Assuming perfect synchronisation [a]	0.3718	0.3371
Difference from perfect staggering [b]	8.0689%	9.8516%

[a] The standard deviations are calculated from the actual number of bubbles for each commodity.

[b] Calculated as $(\sigma_{st} - \sigma_d)/(\sigma_{st} - \sigma_{sy}) * 100\%$, where σ_d, σ_{st} and σ_{sy} are the standard deviations in the data, the standard deviation under the assumption of perfect staggering, and the standard deviation under the assumption of perfect synchronisation, respectively.

Source: own calculations based on data from DCE and the China Grain Reserves Group, Ltd. using Stata 15.

Spot prices have more frequent and persistent bubbles than the futures prices. The comparison between the bubble episodes of different prices indicates that the bubbles rarely synchronise across futures and spot prices. This is inconsistent with the intuition that co-integrated futures and spot prices should show similar bubble periods. We further explore the relationship between the futures and spot prices for agricultural commodities during the bubble periods.

3.4.2 Price Transmission and Bubble Occurrences under Different Regimes

We start with basic tests of time series properties for all price series. The results of the ADF-test and KPSS-test in Table 3.3 indicate that the price series are integrated of order one (I(1)) and become stationary after first differencing. Table 3.4 presents the estimation results of the co-integration and Granger-causality tests. Futures and spot prices are co-integrated for both commodities, indicating a long-run equilibrium relationship. Based on the results of the Granger-causality tests, the null hypothesis that futures price returns do not Granger-cause spot price returns is rejected for corn and soybeans. The lagged values of futures price returns predict spot price returns. Thus, information and shocks move from the futures to the spot markets. These results are consistent with previous studies (Garbade and Silber 1983, Crain and Lee 1996, Mattos and Garcia 2004, Hernandez and Torero 2010). The futures market discovers prices and transmits to the sport markets. These results, however, contradict the finding that spot markets indicate a much higher rate of bubbles compared to the futures markets.

Table 3.3 Unit Root Tests

	Corn:		Soybeans:	
	Futures Price:	Spot Price:	Futures Price:	Spot Price:
ADF Test	-2.0840	-1.7720	-1.5140	-1.9610
P-value	0.2510	0.3945	0.5263	0.3037
KPSS Test [a]	1..94	2.0000	1.7	1.78
P-value	0.0100	0.0100	0.0100	0.0100
	Futures Price Returns:	Spot Price Returns:	Futures Price Returns:	Spot Price Returns:
ADF Test	-26.8850	-15.8580	-20.9910	-24.1340
P-value	0.0000	0.0000	0.0000	0.0000
KPSS Test	0.0543	0.0953	0.0335	0.0806
P-value	0.1000	0.1000	0.1000	0.1000

[a] The autocovariance function is to be weighted by the quadratic spectral kernel. Automatic bandwidth selection procedure proposed by Newey and West (Newey and West 1994) is applied here.

Source: Own calculations based on data from DCE and the China Grain Reserves Group, Ltd. using Stata 15.

Table 3.4 Co-integration Test and Granger Causality Test

	Trace Test	
Johansen Co-integration Test: (5% critical values in the parentheses)	r0	r1
Corn: Futures and Spot Prices	83.2115 (15.4100)	**3.4488**[a] **(3.7600)**
Soybeans: Futures and Spot Prices	25.1818 (15.4100)	**1.2377**[a] **(3.7600)**

Granger-causality tests: H_0 is the null hypothesis. (P-value in the parentheses)	F-statistics
H_0: Corn Spot Price Returns do not Granger-cause Futures Price Returns	0.8302 (0.5496)
H_0: Corn Futures Price Returns do not Granger-cause Spot Price Returns	9.9131*** (0.0000)
H_0: Soybean Spot Price Returns do not Granger-cause Futures Price Returns	0.0972 (0.9926)
H_0: Soybean Futures Price Returns do not Granger-cause Spot Price Returns	2.5440** (0.0276)

[a] indicates the accepted rank by Johansen Test.

*** statistically significant at 1% confidence level; **statistically significant at 5% confidence level; * statistically significant at 10% confidence level.

Source: own calculations based on data from DCE and the China Grain Reserves Group, Ltd. using Stata 15.

We adopt the MSECM to estimate the state where bubbles are most likely to occur. If bubbles are mainly attributed to the futures market, more bubbles would occur during the state where the futures price has strong and significant adjustment effects on the spot price. We document the estimated results of the model in Table 3.5.

In the case of corn, three regimes are identified based on Akaike's information criteria (AIC) and could be named as the 'normal', 'adjustment' and 'no adjustment' states, contingent on the degree of adjustment effect of the error-correction term in each regime. Moreover, concerning the distribution of bubbles among these three states, 71 of 73 spot price bubble days (97.2603%) are within the 'normal' (45, 61.6438%) and 'no adjustment' (26, 35.6164%) states. In other words, the 'normal' state and 'no adjustment' state could also be named as the 'bubble' state.

Specifically, the 'normal' state is characterised by a relatively small though significant coefficient value (-0.0462) of the error-correction term. This suggests that the spot price adjusts slowly to the long-term equilibrium in this state. Meanwhile, the average value of the error-correction term during this state is -0.0004, and its absolute value is the lowest when compared with the other two states, indicating a small deviation (on average) from the equilibrium. More importantly, the sum of the coefficients on the lagged spot price returns is 0.4695, implying a strong persistence of the spot price returns during the 'normal' state.

Compared with the 'normal' state, the 'adjustment' state is characterised by almost a three-fold increase in the coefficient value (-0.1655) of the error-correction term. It also corresponds to the largest average error-correction value (0.0088), indicating that the adjustment effect of the corn spot price toward the long-run equilibrium is the strongest in this regime. Meanwhile, both the coefficients of the lagged futures price returns and lagged spot price returns are significant, suggesting strong short-run effects of futures price returns on spot price returns.

Finally, the 'no adjustment' state is characterised by the insignificant coefficient value (-0.0277) of the error-correction term. The effects of lagged futures price returns on spot price returns are also insignificant. Thus, the futures price has lost the leadership in this regime, and the spot price returns are mainly affected by their own lagged terms.

As for the estimated results for soybeans, we find almost the same long-run and short-run effects as corn. Fifty-one of 54 (94.4444%) spot price bubble days are within the 'normal' (50, 92.5926%) and 'no adjustment' (1, 0.0002%) states. These results indicate that the adjustment effect of spot prices toward the long-run equilibrium becomes weak when spot price bubbles occur the most frequently. The bubbles in the spot price are not mainly caused by shocks from the futures market. Instead, the spot price returns have shown significant persistence in their own lagged terms. This implies that the spot price can hardly adjust to a new market clear price level when responding to changes in the futures price. Once a trend is established, it is more likely to continue in that direction than to move against or opposite the trend. This is consistent with previous studies that find a difference between the commodity spot and futures markets in the ability to incorporate relevant price information (Crain and Lee 1996, Yang and Leatham 1999, Yang et al. 2001). The stronger self-persistence of price returns may have resulted in more bubbles for the spot price series.

Another possible explanation for the autocorrelated price returns in spot markets is the theory of informational cascades by Bikhchandani et al. (1992) and Welch (1992). The core idea of the informational cascades is similar to price bubbles. Specifically, the current traders in a market obtain information by observing their previous traders' decisions to the point where they optimally and rationally ignore their own private information (Devenow and Welch 1996). In this case, current traders rationally herd after observing previous traders' actions. The self-persistence observed in the spot price returns could be partly explained by this herding behaviour. Traders in the spot market rationally herd to expect a future sale to their ensuing traders. In this case, spot markets are less efficient compared with futures markets.

Table 3.5 Results of Markov-switching Error Correction Model (3 states)

	Corn			Soybeans		
	Δp^s Regime:			Δp^s Regime:		
	Normal	Adjustment	No adjustment	Normal	Adjustment	No adjustment
N [a]	330(45)	16(2)	111(26)	400(50)	25(3)	31(1)
Average ECT [b]	-0.0004 (0.0172)	0.0088 (0.0319)	-0.0017 (0.0229)	-0.0004 (0.0201)	-0.0168 (0.0239)	-0.0117 (0.0490)
Constant	0.0002 (0.0002)	-0.0100*** (0.0008)	0.0022*** (0.0004)	0.0002* (0.0002)	-0.0014*** (0.0001)	-0.0069** (0.0032)
ECT_{t-1}	-0.0462*** (0.0155)	-0.1655*** (0.0238)	-0.0277 (0.0228)	-0.0215*** (0.0084)	-0.1009*** (0.0045)	-0.1950 (0.1255)
Δp^s_{t-1}	0.2092*** (0.0604)	-0.3821*** (0.0964)	-0.1356** (0.0642)	-0.0522 (0.0389)	0.5613*** (0.0122)	-0.5682*** (0.2102)
Δp^s_{t-2}	0.2603*** (0.0687)	-1.4504*** (0.2068)	-0.0060 (0.0500)	-0.0118 (0.0347)	0.0186** (0.0089)	-0.2205 (0.1821)
Δp^s_{t-3}	--	--	--	0.1019*** (0.0363)	-0.7734*** (0.0072)	-0.3287** (0.1820)
Δp^f_{t-1}	0.0025 (0.0204)	0.1549** (0.0658)	-0.0144 (0.0229)	-0.0003 (0.0175)	0.1299*** (0.0068)	-0.8036** (0.3767)
Δp^f_{t-2}	0.0502*** (0.0186)	1.0489*** (0.1727)	-0.0039 (0.0198)	-0.0128 (0.0177)	-0.1032*** (0.0081)	-0.1361 (0.2587)
Δp^f_{t-3}	--	--	--	-0.0073 (0.0172)	0.2713*** (0.0102)	-0.5331** (0.2659)

[a] the number of bubbles are included in the parentheses.

[b] the standard deviations are included in the parentheses.

*** statistically significant at 1% confidence level; **statistically significant at 5% confidence level; * statistically significant at 10% confidence level. The number of states and lags of price returns are determined by information criteria (AIC).

Source: own calculations based on data from DCE and the China Grain Reserves Group, Ltd. using Stata 15.

3.4.3 DCC-MGARCH

As Table 3.1 presents, the futures price is more volatile than the corresponding spot price. If the two price series are co-integrated, this difference in volatility may account for some differences in the frequencies of bubbles. Price volatility is also important for the GSADF method of bubble detection, and different volatilities could result in different bubble episodes, even for price series with similar movement. We then use the *dynamic conditional correlation multivariate GARCH model* (DCC-MGARCH) to investigate the dynamic volatility interdependence between futures and spot prices.

In Table 3.6, for both corn and soybeans, the spot price shows a significant volatility clustering effect (significant ARCH a_i and GARCH b_i parameters), while the volatility of futures prices tends to be constant over the sample period. Regarding the dynamic volatility correlation, λ_1 and λ_2 can be interpreted as the 'news' and 'decay' parameters, which represent the effect of innovations on the conditional correlations over time and their persistence. For corn, λ_1 is small and not significant, while λ_2 is close to 1 and highly significant, suggesting a slow decaying rate. For soybeans, the Wald joint test shows that λ_1 and λ_2 jointly insignificantly differ from zero, suggesting a constant conditional correlation between soybeans futures and spot price volatilities. We then estimate a *constant conditional correlation multivariate GARCH model* (CCC-MGARCH), and the value of the constant conditional correlation is 0.1304.

We further measure the extent to which the conditional volatilities correlate in time, especially during bubble episodes. From Figures 3.3 and 3.4, we can see that the predicted conditional variance of the corn spot price is always lower than the variance of futures prices. The time-variant volatility correlation is between -0.02 and 0.02. The spot price has shown to be relatively independent and with a lower volatility. The degree of volatility interdependence across the markets does not increase during bubble episodes. Particularly, there is a negative conditional correlation during the overlapped bubble episode. Similar results apply to the case of soybeans, as shown in Figure 3.5 and 3.6, except that the soybeans spot price volatility becomes higher around July 2015.[2] However, this does not result in a tighter correlation between volatilities during that period.

Therefore, the volatility interdependency between futures and spot markets is very limited. Combined with the results of the MSECM, bubbles occur more easily within the price series with a higher self-persistence of returns and lower volatility. This may imply that spot prices have a lower capacity to aggregate and respond to new information. Nonetheless, this does not mean that a higher volatility is desirable for commodity markets. Instead, our estimation results, which are based on weekly data, show that when information is efficiently incorporated into the price, a certain degree of volatility should reflect market efficiency to some extent, and much lower volatility may reflect the market inability to respond to new information quickly. In our case, this means an incomplete response of the spot market to changes in futures prices.

[2] To keep consistency and comparability, we continue to use the estimation results from the DCC-MAGRCH model for soybeans for Figures 3.5 and 3.6.

Table 3.6 Results of DCC-MGARCH

	Corn (DCC)		Soybeans (DCC)		Soybeans (CCC)	
	Futures(i=*1*)	Spot(i=*2*)	Futures(i=*1*)	Spot(i=*2*)	Futures(i=*1*)	Spot(i=*2*)
$cons * 100$	0.0170 (0.0116)	0.0014** (0.0000)	0.0000 (0.0007)	0.0013** (0.0000)	0.0000 (0.0007)	-0.0013** (0.0006)
a_i	0.5791* (0.3020)	0.25778* (0.1400)	0.0268* (0.0161)	0.3921*** (0.1520)	0.0266* (0.0162)	0.3928** (0.1537)
$b_i(1)$	0.3504 (0.2842)	0.6241*** (0.1431)	0.0163 (0.0415)	0.2674 (0.1837)	0.0163 (0.0418)	0.2700 (0.1839)
$b_i(2)$	--	--	0.9638*** (0.0484)	0.3018* (0.1816)	0.09638*** (0.0488)	0.2969* (0.1824)
λ_1	0.0017 (0.0081)		0.0221 (0.0570)			
λ_2	0.9888*** (0.0139)		0.1876 (0.9956)			
df	3.0377*** (0.37617)		3.8692*** (0.5752)		3.8689*** (0.5749)	
Wald joint test for adjustment coefficients ($H_0: \lambda_1 = \lambda_2 = 0$)						
Chi-squared	5577.5500		0.2100		--	
p-value	0.0000		0.9002		--	

a_i stands for the arch term and b_i stands for the garch term. Lagged terms are selected based on AIC.

*** statistically significant at 1% confidence level; **statistically significant at 5% confidence level; * statistically significant at 10% confidence level.

Source: own calculations based on data from DCE and the China Grain Reserves Group, Ltd. using Stata 15.

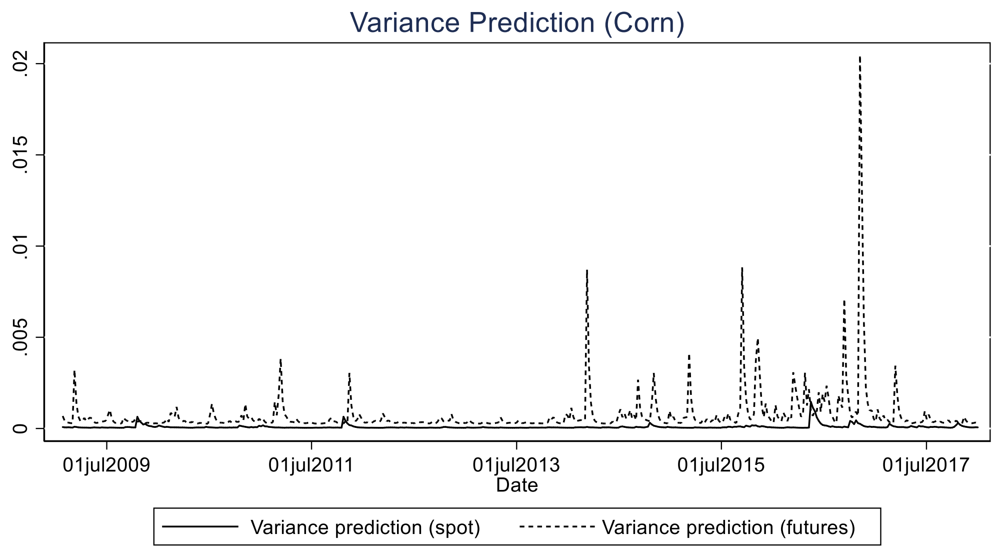

Figure 3.3 Variance Prediction for Futures Price and Spot Price (Corn)

Source: own calculations based on data from DCE and the China Grain Reserves Group, Ltd. using Stata 15.

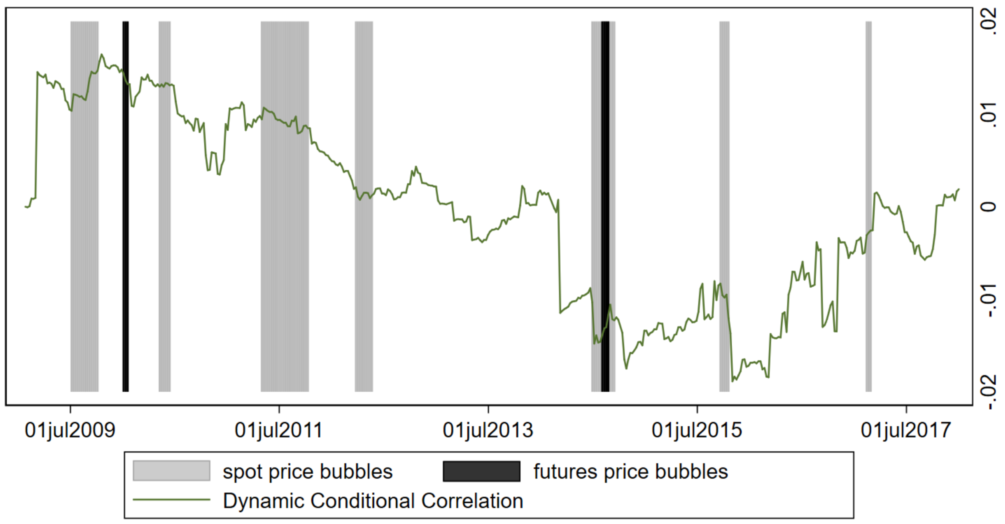

Figure 3.4 Dynamic Conditional Correlation Between Futures Price and Spot Price (Corn)

Source: own calculations based on data from DCE and the China Grain Reserves Group, Ltd. using Stata 15.

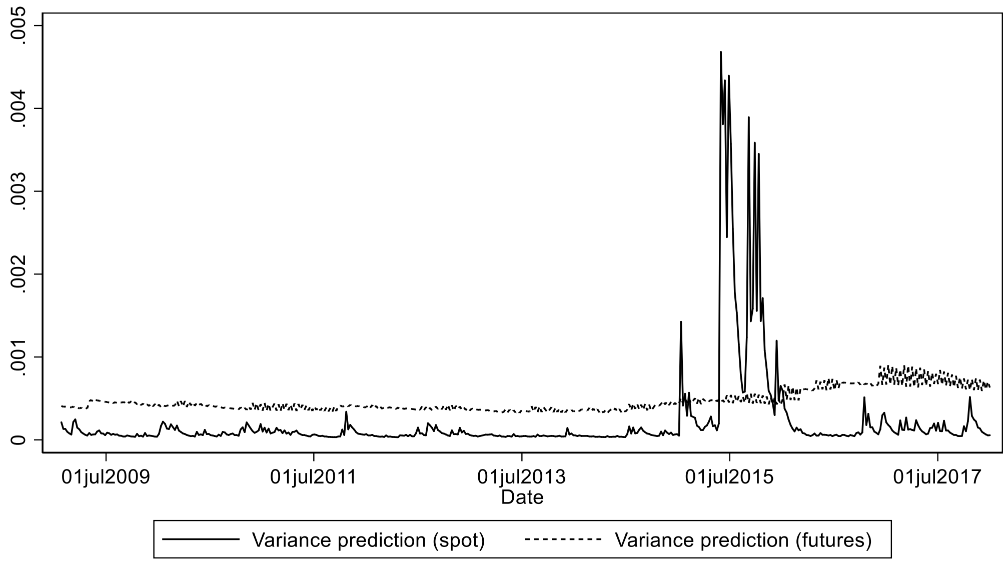

Figure 3.5 Variance Prediction for Futures Price and Spot Price (Soybeans)

Source: own calculations based on data from DCE and the China Grain Reserves Group, Ltd. using Stata 15.

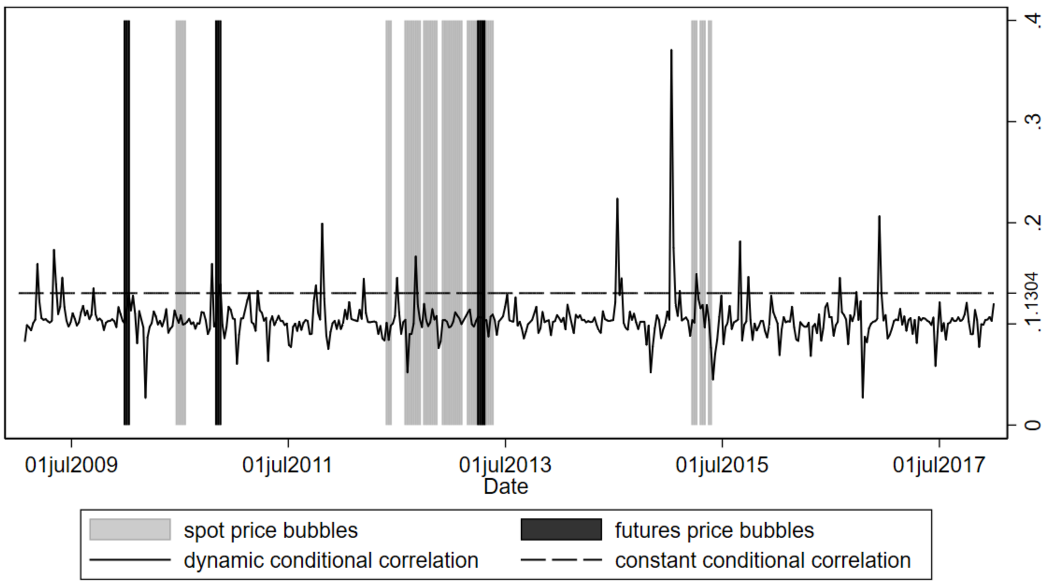

Figure 3.6 Dynamic Conditional Correlation Between Futures Price and Spot Price (Soybeans)

Source: own calculations based on data from DCE and the China Grain Reserves Group, Ltd. using Stata 15.

3.5 Conclusions

In this paper, we first identify the bubble dates for the two highly traded agricultural commodities in China, corn and soybeans. Bubble episodes in the futures and spot price series are compared with each other. We do not find significant transmission or synchronisation of bubbles across the two markets. The spot price series shows more frequent and durable bubbles than the futures prices. This is contrary to the inference that price bubbles are caused by over-financialization in agricultural futures markets and then are transmitted to spot markets.

We proceed to use the MSECM method to capture the nonlinear price transmission across the futures and spot markets, identifying the regime where spot price bubbles are most likely to occur. There is a weak adjustment effect of the spot price towards the long-run equilibrium during that regime. Meanwhile, the spot price indicates a strong self-persistence of its returns. We further adopt the DCC-MGARCH model to analyse the volatility interdependence, the estimation results of which indicate that the futures and spot prices have a very loose dynamic volatility interdependence. Therefore, bubbles occur more easily for the price series with a higher self-persistence of returns and lower volatility. This further implies a poor ability of the spot market to adjust itself to a new equilibrium.

Our results help in understanding the formation of price bubbles in agricultural commodity markets, highlighting the nonlinear transmission across futures and spot markets in the first and second moments of price returns. Previous studies on agricultural price bubbles have mostly ignored spot market factors and agricultural commodity futures markets have been blamed for the potentially negative effects of over-financialization. Our findings are remarkable considering the limited synchronisation of bubbles across agricultural futures and spot markets. The self-persistence of spot price returns during certain regimes may have resulted in more frequent and durable bubble episodes for spot prices. Instead of merely focusing on the over-financialization or speculation in futures markets, the current paper has suggested that the factors with the potential to contribute to the persistence of price returns in the spot market, such as information cascades and market power, should be considered in future relevant studies.

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Appendix

Table 3.7 A-1: Summary of Price Bubbles for Corn

		Bubbles for Spot Price					Bubbles for Futures Price				
Bubble Periods	Length(weeks)	Start	Peak(Trough)	End	%Price Change(Start to Peak or Trough)	%Price Change (Peak or Trough to End)	Start	Peak(Trough)	End	%Price Change(Start to Peak or Trough)	%Price Change (Peak or Trough to End)
2009/07/05-2009/10/04	14	106.51	115.06	115.06	8.03%	0.00%					
2010/01/03-2010/01/17	3						112.69	113	112.97	0.28%	-0.03%
2010/05/09-2010/06/13	6	121.7	127.02	126.1	4.37%	-0.72%					
2011/05/11-2011/10/09	24	137.88	155.55	155.55	12.82%	0.00%					
2012/03/25-2012/05/20	9	149.14	154.07	154.07	3.31%	0.00%					
2014/06/29-2014/09/14	12	157.18	167.02	166.91	6.26%	-0.07%					
2014/08/03-2014/08/24	4						161.97	165.88	165.88	2.41%	0.00%
2015/09/20-2015/10/18	5	140.9	129.11	129.11	-8.37%	0.00%					
2017/02/12-2017/02/26	3	98.42	97.19	97.19	-1.25%	0.00%					
Sum	73 weeks(15.87%)						7 weeks(1.52%)				
Maximum Single Bubble	24 weeks						4 weeks				

Table 3.8 A-2: Summary of Price Bubbles for Soybeans

		Bubbles for Spot Price					Bubbles for Futures Price				
Bubble Periods	Length(weeks)	Start	Peak(Trough)	End	%Price Change(Start to Peak or Trough)	%Price Change (Peak or Trough to End)	Start	Peak(Trough)	End	%Price Change(Start to Peak or Trough)	%Price Change (Peak or Trough to End)
2009/12/27-2010/01/10	3						4054	4162	4162	2.66%	0.00%
2010/06/20-2010/07/18	5	95.57	94.87	94.99	-0.73%	0.13%					
2010/10/31-2010/11/14	3						4092	4244	4164	3.71%	-1.89%
2012/05/27-2012/06/10	3	107.97	108.15	108.01	0.17%	-0.13%					
2012/07/29-2012/09/16	8	111.38	116.96	116.96	5.01%	0.00%					
2012/09/30-2012/11/11	7	116.94	120.59	120.59	3.12%	0.00%					
2012/12/02-2013/05/19	23	120.61	124.5	125.15	3.23%	0.52%					
2013/03/31-2013/04/21	4						4996	5032	5004	0.72%	-0.56%
2015/03/22-2015/05/24	8	104.74	90.62	90.62	-13.48%	0.00%					
Sum	54 weeks (11.73%)						10 weeks(2.17%)				
Maximum Single Bubble Duration	23 weeks						4 weeks				

For the corn, 73 of 460 weeks (15.87 %) indicate bubbles for the spot price, while only 7 of 460 weeks (1.52 %) show bubbles for the futures price. The overlapped episode between corn futures and spot price bubbles is from 08^{th} August 2014 to 24^{th} August 2014 (four weeks). For the soybeans, 54 of 460 weeks (11.73 %) show bubbles for the spot price, while only 10 of 460 weeks (2.17 %) for the futures price. The overlapped episode between soybean futures and spot price bubbles is from 31^{st} March 2013 to 21^{st} April 2013 (four weeks). Regardless of the commodity species, the futures and spot price bubbles seldom synchronise, neither do they indicate a significant lead-lag relationship.

Chapter 4 Economic Growth, Bubbles, and Firm Size Distribution

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Abstract

By introducing a bubbly factor into the growth process of firms, this paper constructs a theoretical model to explain the effect of bubbles on the economy. Our model indicates that, in the presence of financial frictions and productivity differentials, bubbles can act as a financial intermediation to transfer money from investors to productive firms. Hence, the productive firms can expand production and the output of the economy would grow through bubble trades. Moreover, in comparison with previous models based on the framework of overlapping-generations, our model relaxes the assumption of agents' finite survival periods and is useful to interpret the effects of bubbles on the economy in terms of calendar time. Infinitely lived agents rationally hold bubbles in their portfolios because holding the bubbles issued by productive firms could give them higher expected returns.

JEL: E32, E37, G12, G17

Key words: Economic Growth; Bubbles; Firm Size, Yule-Simon distribution

4.1 Introduction

Bubbles have long been considered as the hallmark of market failure (Brunnermeier and Oehmke 2013). During the bubble periods, many countries have witnessed dramatic fluctuations in asset prices and economic output (Jordà et al. 2015, Miao et al. 2015). The origin of bubbles and their effects on economic development have long been discussed and no consensus has been reached. Scholars feel the need to develop new models to explain what drives asset price bubbles and how they affect the macroeconomy (Martin and Ventura 2018).

In this paper, we ask the same questions as previous studies. What is the origin of bubbles? Why they raise the output of the economy? How do they collapse and affect the economy? Current discussions concerning these questions mainly focus on the theoretical model of rational bubbles (Blanchard and Watson 1982, Tirole 1982, 1985, Olivier 2000, Abreu and Brunnermeier 2003, Martin and Ventura 2012, Miao and Wang 2018, Martin and Ventura 2018). Although these models have incorporated many important insights of bubbles and explained possible effects of bubbles on the economy, there are some unsolved issues on the theoretical modelling of bubbles, one of which is the infinite lived periods for agents (Miao 2014).

Our study builds on a series of studies that assume financial frictions and productivity differentials in the economy (Kocherlakota 2009, 2008; Martin and Ventura 2012; Miao and Wang 2012; Miao, Wang, and Zhou 2015; Miao and Wang 2018). In comparison with previous models, our model aims to relax the assumption of finite survival periods for agents, which is commonly shared by the overlapping-generations (OLG) models for bubbles. Our model might also provide a framework for empirical tests of bubbles' origin and their effects on the economy, due to that agents in our model correspond to the investors and firms in the economy. Meanwhile, the introduction of stochastic process could relax the propositions of bubble collapse. This enables us to avoid the criticism of periodically collapsing bubbles by Evans (1991).

In what follows, we provide a literature review on the theoretical models of bubbles in Section 4.2. Section 4.3 gives a brief introduction on the stochastic process of firm growth. In Section 4.4, we present our model of bubbles and explain the dynamic process of bubble trades. We further make a simulation of our model in Section 4.5. Conclusions are summarized in Section 4.6.

4.2 Literature Review

We first make a brief review on the theoretical models of bubbles and then summarize the studies on the effects of bubbles. We confine our attention to the models based on rational bubbles. By using the term of 'rational', we mean agents have rational expectations and maximize their expected revenues by holding bubbles in their portfolios.

The deduction of rational bubbles starts with the present discounted value (PDV) model (Blanchard and Watson 1982, Kamihigashi 2006, Gürkaynak 2008, Miao 2014). The asset price is derived from the customers' dynamic optimization process. In an intertemporal competitive equilibrium without market frictions, the asset price bubbles are ruled out by the Euler equation and transversality condition. The Euler equation means no deviation from the optimal price path at any single period and the transversality condition means that the terminal point of the optimal price path is fixed. In the case of infinite lived agents, any violation of these two conditions would allow the occurrence of bubbles. Detailed mathematical expression of Euler equation and transversality condition is available in the study of Kamihigashi (2006) and Gürkaynak (2008).

Nevertheless, for finite lived agents, scholars use the framework of OLG model and find that bubbles are likely to occur in both exchange economy and production economy (Samuelson 1958, Diamond 1965, Tirole 1985). For instance, the existence of fiat money can be well explained by the OLG model in a pure exchange economy. Fiat money without intrinsic value can be considered as bubbles to store value across overlapping generations. The main advantage of the OLG model is the relax of transversality condition. The finite survival periods of agents fail to eliminate the arbitrage opportunity of bubble holders. Moreover, for a production economy with overlapping generations, Diamond (1965) and Tirole (1985) show that when inefficient investment caused by over capital cumulation occurs, bubbles would absorb the inefficient investment and improve the dynamic efficiency of the economy.

In addition, if the hypotheses of market frictions and/or incomplete markets are incorporated into the model setting, it would be optimal for rational agents to hold bubbles in their portfolios. Santos and Woodford (1997) establish market conditions for pure exchange economy under which asset bubbles cannot exist. These conditions are summarized by Miao (2014) as follows: Each agent is subject to borrowing constraints such that he cannot borrow more than the present value of his future endowments; The present value of aggregate endowments is finite; The asset is either of finite maturity or in positive net supply. If any of these three conditions is violated, an asset bubble might arise in the economy with rational agents.

The economic consequence of bubbles is also critical. Bubbles are often considered as market failure and distort normal market trades and resource allocations (Stiglitz 1990). The models mentioned above show that bubbles could act as a tool of storing value, when there is an inefficient investment chain in the economy (Samuelson 1958, Diamond 1965, Tirole 1985). This means that the implicit interest rate in the bubbleless equilibrium is less than the rate of economic growth, or the bubbleless equilibrium is dynamically inefficient (Gale 1973). Nonetheless, these models cannot explain the associated fluctuations of output and investment with bubbles (Brunnermeier and Oehmke 2013).

More recent theoretical studies on bubbles show that incomplete markets with bubbles could have various effects on the economic output and capital accumulation. Binswanger (1999) proposes a new role of speculative bubbles in the stock market: provided they are sustainable, bubbles may have a positive effect on the market. According to the bubble equivalence theorem proposed by Kocherlakota (2008; 2009), the introduction of a bubble gives agents a windfall, proportional to their initial holdings of the asset, which can lead to a more efficient allocation of physical capital among firms with good projects. Under the assumption of borrowing constraints, Oliver (2000), Martin and Ventura (2012) use the OLG framework to construct new models and explain the bubbles' potential effect on the economic growth.

For more details on the theoretical models of bubbles, Miao (2014) has made a comprehensive review of the models based on OLG framework. In summary, though a lot of insights can be derived from the OLG model with two-period lived agents (Tirole 1985, Olivier 2000, Martin and Ventura 2012), Miao (2014) points out that it is difficult to interpret the period in the OLG framework as calendar time and it is also difficult to do empirical tests with economic data.

Therefore, if infinite-horizons are allowed for agents in the model of bubbles, many other insights can be available. In this paper, we construct a new theoretical model to explain the associated fluctuations of economic output with bubbles. We firstly assume productivity differentials among firms and financial frictions in the economy. Then, we use the stochastic process of firm growth to interpret the effects of bubbles on the economic output.

4.3 Setup

We consider an economy with different industries and let the firm in an industry follow the Gibrat's law, that is the expected value of the individual growth ratio for a firm is independent of the firm size (using output volume to measure firm size).[1] Suppose there is a minimum size S_0, a firm below the size S_0 has an increasing unit cost with its size (Simon and Bonini 1958). The size of firm *i* at the end of the *t*th period is S_{it}. Following Ijiri and Simon (1967), we assume that there are *N* firms in an industry and firm *i* has a growing process:

$$S_{it} = \rho_{it} \cdot \overline{\rho_t} \cdot S_{i(t-1)},\ \text{where } r_{it} = \rho_{it} \cdot \overline{\rho_t}\ and\ t = 1, 2, 3, \dots, T \tag{1}$$

The r_{it} is called the growth rate of the *i*th firm in the *t*th period and can be decomposed into two factors: one is a growth factor applicable to firm *i* only (the individual growth factor), ρ_{it}; and the other one is a growth factor that affects equally all firms in the same industry (the industry growth factor), $\overline{\rho_t}$. ρ_{it} is the residual of the *i*th firm's growth that has taken place in the *t*th period over and above the industry growth factor. Moreover, we define $\overline{\rho_t} = \frac{\sum_i S_{it}}{\sum_i S_{i(t-1)}}$, that is, the industry growth factor is equal to the ratio of the size of the industry in current period to its size in previous period. Then ρ_{it} is a measure of the change in the *i*th firm's share of market in the industry. $\rho_{it} = 1$ means that the *i*th firm has grown just rapidly enough to retain its share of market. When the number of firms in the industry is relatively large, the statistical dependence of the average growth ratio on any individual growth factor will be too slight to bias significantly the estimates of parameters of the model. Equation (1) indicates that the individual growth factor is independent of the size of firm *i* or other firms, which means it follows the Gibrat's law.

Equation (1) iterates backward and the size of firm *i* at period *t* becomes:

$$S_{it} = (\prod_{\tau=1}^{t} \rho_{i\tau})(\prod_{\tau=1}^{t} \overline{\rho_\tau}) S_{i0} \tag{2}$$

Both sides of equation (2) take logarithm:

$$\log S_{it} = \sum_{\tau=1}^{t} log \rho_{i\tau} + \sum_{\tau=1}^{t} log \overline{\rho_\tau} + log S_{i0} \tag{3}$$

From equation (3), the size of the firm *i* in an industry is decomposed into three sets of factors. The first term in the right hand of equation (3) reflects the history of individual growth rate

[1] For the measure of firm size, the output, sales, assets, numbers of employees, value added, or profits could be used as indicators(Simon and Bonini 1958).

(idiosyncratic shocks) for firm *i*. The second term is the history of the industry's growth rate and the final term is the initial size of firm *i* at *t=0*.

Suppose that both the initial size S_{i0} and the industry growth rate $\overline{\rho_\tau}$ are given for $\tau = 1, 2, 3, \dots, \mathrm{t}$. Then the size of firm *i* is determined by the idiosyncratic changes of individual growth rate $\rho_{i\tau}$. The $\rho_{i\tau}$ is further assumed to satisfy the Gibrats' law and a single period Markov process, namely:

$$\rho_{it} = \varepsilon_{it}\rho_{i(t-1)}^{\alpha} \tag{4}$$

where $\alpha \in [0,1)$ is a constant and

$$\rho_{i1} = \varepsilon_{i1} \tag{5}$$

The individual growth rate of firm *i* in the *t*th period is the product of some power of the growth ratio $\rho_{i(t-1)}$ of the same firm in the (*t*-1)th period and a random component ε_{it}. ε_{it} follows an independently and identically distribution in each period for firm *i*, and logε_{it} has zero mean and variance σ^2. In the same industry, ρ_{it} is also determined independently from other firms. Other factors that commonly affect more than one firm are absorbed in the industry growth rate $\overline{\rho_\tau}$. For the parameter α, it is assumed to be in the range [0,1), namely an individual growth rate in one period will have decaying effects on the individual growth rates in the subsequent periods.

Substitute equation (4) and (5) into logρ_{it}, we have:

$$\begin{aligned}\log\rho_{it} &= log\varepsilon_{it} + \alpha log\rho_{i(t-1)} \\ &= \textstyle\sum_{\tau=1}^{t} \alpha^{t-\tau} log\varepsilon_{i\tau}\end{aligned} \tag{6}$$

and

$$\begin{aligned}&\sum_{t=1}^{T} log\rho_{it} = \sum_{t=1}^{T}\sum_{\tau=1}^{t} \alpha^{(t-\tau)}\, log\varepsilon_{i\tau} \\ &= (1+\alpha+\alpha^2 \cdots + \alpha^{T-1})log\varepsilon_{i1} + (1+\alpha+\alpha^2 \cdots + \alpha^{T-2})log\varepsilon_{i2} \\ &\qquad + \cdots (1+\alpha+\alpha^2 \cdots + \alpha^{T-k})log\varepsilon_{ik} + \cdots + log\varepsilon_{iT} \\ &= \sum_{t=1}^{T} \frac{1-\alpha^{T-t+1}}{1-\alpha} log\varepsilon_{it}\end{aligned} \tag{7}$$

Thus, equation (3) becomes,

$$\log S_{it} = \sum_{\tau=1}^{t} \frac{1-\alpha^{t-\tau+1}}{1-\alpha} log\varepsilon_{i\tau} + \sum_{\tau=1}^{t} log\bar{\rho_{\tau}} + logS_{i0} \tag{8}$$

and let

$$x_{it} = \sum_{\tau=1}^{t} \frac{1-\alpha^{t-\tau+1}}{1-\alpha} log\varepsilon_{i\tau} \tag{9}$$

Thus, under the Gibrat's law and a single period Markov process of individual growth rate, the size of firm *i* follows a random process and its growth rate is independent from its current size. In the next section, we would introduce the bubble trades between firms and investors in the economy.

4.4 Economic Growth and Bubbles

We first introduce the conventional form of rational bubbles and then introduce bubbles into the economy described above.

4.4.1 Bubble Trades

A bubble is a situation in which an asset price doesn't reflect its fundamental value and the reason the price is high today is only because investors believe that they could resell at an even higher price tomorrow (Stiglitz 1990, Gürkaynak 2008). Bubbles are akin to pyramid schemes (Ponzi games) and could start randomly without cost, giving the bubble sellers a windfall (Kocherlakota 2008; Martin and Ventura 2012). The mathematical expression of rational bubbles proposed by Blanchard and Watson (1982) is:

$$E(B_{t+1}) = (1+r)B_t \tag{10}$$

where r is the discount rate. The intertemporal no-arbitrage condition always holds for rational bubbles. Based on equation (10), Evan (1991) further developed a model of periodically collapsing bubbles,

$$B_{t+1} = (1+\mathrm{r})B_t\vartheta_{t+1} \quad if\ B_t \le B_0 \tag{11a}$$

$$B_{t+1} = [\delta + \pi^{-1}(1+r)\theta_{t+1}(B_t - (1+r)^{-1}\delta)]\vartheta_{t+1}\ if\ B_t > B_0 \tag{11b}$$

where δ and B_0 are positive parameters with $0 < \delta < (1+\mathrm{r})B_0$, ϑ_{t+1} is an exogenous independently and identically distributed positive random variable with $E_t(\vartheta_{t+1}) = 1$, and θ_{t+1} is an independently and identically distributed Bernoulli process (independent of ϑ) which takes the value one with probability π and zero otherwise. The bubble would have a fast growth rate of $\pi^{-1}(1+r)$, when $B_t > B_0$ and $\theta_{t+1} = 1$. If the θ_{t+1} takes the value of zero, the bubble would collapse.

We assume that firms in the economy are confronted with borrowing constraints. The investors couldn't achieve their optimal asset allocation under financial frictions, but they could earn a low return rate by self-investment on new firms, the size of which is below S_0. Under this circumstance, the bubbles could serve as a financial intermediary to transfer the money from investors to firms.

As aforementioned, there are two stages for a firm's growth process. In the initial stage, firms with the size below the minimum size S_0 are unproductive and have an increasing unit cost. However, for firms above the minimum size S_0, the growth of them would follow the Gibrat's law (equation (1)). The underlying stochastic growth model makes no reference to any feature of the cost curve, other than that unit cost is constant when the firm size is above some minimum point (Simon and Bonini 1958). This means that when obtaining new investments equally, firms below the minimum size tend to have lower expected output than those big firms (above the minimum size) and are at higher risk for investors.

Therefore, investments on the firm with size above the minimum point are more likely to earn a relatively higher return. For a certain level of expected return rate by investors, the growth rate of firms with different sizes follows the binomial probability distribution:

$$\Pr(D_t|D_t > r_t) = \begin{cases} P_s & if\ S_{it} < s_0 \\ P_b & if\ S_{it} \geq s_0 \end{cases} \tag{12}$$

where r_t is the expected return rate required by investors at time t and D_t is the expected return rate of investments on firms. It could be easily derived that $P_s < P_b$, due to that small and new firms are confronted with an increasing unit cost. For firms with different sizes, the probability of the growth rate being larger than the expected return rate r_t is higher for the relatively big firms above the minimum size, as opposed to those small and new companies. For rational investors, they face up with this productivity and probability differentials when aiming to store value through their investments.

Since bubbles start without costs, both big and small firms compete to create and sell bubbles, in order to obtain new investments. Moreover, the return rate of bubbles expected by investors would be linked to the expected growth rate of firms that sell the bubbles (Miao and Wang 2012). As noted above, for a certain level of expected return rate required by investors, the big companies tend to achieve it with higher probability. Thus, the big companies would have an advantage on issuing new bubbles. For instance, when a bubble B_t is sold by firm *i* to investors, the firm will obtain new investment to expand its current size S_{it},

$$S_{i(t+1)} = \rho^B_{i(t+1)} \cdot \rho_{i(t+1)} \cdot \overline{\rho_{(t+1)}} \cdot S_{it} \tag{13}$$

where new investments through bubble trades are considered as a new growth factor $\rho^B_{i(t+1)}$ for firm *i*. It contributes to the firm growth and is independent from individual growth rate $\rho_{i(t+1)}$. We assume that $\rho^B_{i(t+1)}$ follows a single period Markov process with a stochastic component and a new carry-over effect $\lambda, \lambda \in [0,1)$, where λ represents the decaying effect of the new growth factor caused by bubbles. Suppose that the new growth factor ρ^B_{it} and the bubble B_t share the same stochastic component ν_t,

$$\rho^B_{it} = \nu_{it} \cdot \left(\rho^B_{i(t-1)}\right)^\lambda \tag{14}$$

Based on equation (8), we can derive that

$$\log S_{it} = \sum_{\tau=1}^{t} \frac{1-\lambda^{t-\tau+1}}{1-\lambda} log\nu_{i\tau} + \sum_{\tau=1}^{t} \frac{1-\alpha^{t-\tau+1}}{1-\alpha} log\varepsilon_{i\tau} + \sum_{\tau=1}^{t} log\overline{\rho_\tau} + logS_{i0} \tag{15}$$

and let

$$y_{it} = \sum_{\tau=1}^{t} \frac{1-\lambda^{t-\tau+1}}{1-\lambda} log\nu_{i\tau} \tag{16}$$

For an industry with *N* firms, we have:

$$\sum_{i=1}^{N} \log S_{it} = \sum_{i=1}^{N} \sum_{\tau=1}^{t} \frac{1-\lambda^{t-\tau+1}}{1-\lambda} log\nu_{i\tau} + \sum_{i=1}^{N} \sum_{\tau=1}^{t} \frac{1-\alpha^{t-\tau+1}}{1-\alpha} log\varepsilon_{i\tau} + \sum_{i=1}^{N} \sum_{\tau=1}^{t} log\overline{\rho_\tau} + \sum_{i=1}^{N} logS_{i0} \tag{17}$$

Based on equation (11), ρ^B_{it} would experience a periodically collapsing process. Then,

$$\begin{aligned} \log\rho^B_{it} &= log\upsilon_{it} + \lambda log\rho^B_{i(t-1)} \\ &= \sum_{\tau=1}^{t} \lambda^{t-\tau} log\upsilon_{i\tau} \\ &= \sum_{\tau=1}^{t} [\, \mathrm{I}(B_\tau \le B_0) \cdot \lambda^{t-\tau} log\upsilon_{i\tau} + \mathrm{I}(B_\tau > B_0) \cdot \lambda^{t-\tau}\pi^{-1}\theta_\tau log\upsilon_{i\tau}] \end{aligned} \tag{18}$$

where $\mathrm{I}(\cdot)$ is an indicator variable, and it equals to one if the condition is fulfilled, otherwise it would be zero. Substitute (18) into (15), we have

$$\begin{aligned} \log S_{iT} = &\sum_{t=1}^{T} \sum_{\tau=1}^{t} [\, \mathrm{I}(B_\tau \le B_0) \cdot \lambda^{t-\tau} log\upsilon_{i\tau} + \mathrm{I}(B_\tau > B_0) \cdot \lambda^{t-\tau}\pi^{-1}\theta_\tau log\upsilon_{i\tau}] \\ &+ \sum_{\tau=1}^{T} \frac{1-\alpha^{T-\tau+1}}{1-\alpha} log\varepsilon_{i\tau} + \sum_{\tau=1}^{T} log\overline{\rho_\tau} + logS_{i0} \end{aligned} \tag{19}$$

For an industry with N firms, we have:

$$\sum_{i=1}^{N} \log S_{iT} = \sum_{i=1}^{N} \sum_{t=1}^{T} \sum_{\tau=1}^{t} [\, \mathrm{I}(B_\tau \leq B_0) \cdot \lambda^{t-\tau} log v_{i\tau} + \mathrm{I}(B_\tau > B_0) \cdot \lambda^{t-\tau} \pi^{-1} \theta_\tau log v_{i\tau}]$$
$$+ \sum_{i=1}^{N} \sum_{\tau=1}^{T} \frac{1-\alpha^{t-\tau+1}}{1-\alpha} log \varepsilon_{i\tau} + \sum_{i=1}^{N} \sum_{\tau=1}^{T} log \overline{\rho_\tau} + \sum_{i=1}^{N} log S_{i0} \qquad (20)$$

We can see that a possible result of bubble trades is that the relatively productive and big firms can relax their own borrowing constraints and get new investments through selling bubbles to investors. Meanwhile, the investors could get a higher expected return rate, compared with the return rate of the inefficient investments on small and new firms. Consequently, the overall expected output of the economy would grow.

4.4.2 Bubble Collapse and Economic Recession

A key problem for the bubble process is to identify the conditions under which the bubble would boom and bust. For bubbles derived from equation (11), the parameter θ governs the state of bubble's boom and bust. The bubble would increase at a faster rate continuously when θ takes the value one, otherwise the bubble would collapse. Since the industry growth rate is more commonly known by the investors and bubbles usually occur within an industry (Greenwood et al. 2019), it is reasonable to assume that bubbles are attractive to investors when the expected industry growth rate $\mathrm{E}\left(\overline{\rho_{(t+1)}}\right)$ is higher than a certain level of return rate required by investors (ϕ),

$$\theta = \begin{cases} 1, \ \text{if } \mathrm{E}\left(\overline{\rho_{(t+1)}}\right) \geq \phi \\ 0, \ \text{if } \mathrm{E}\left(\overline{\rho_{(t+1)}}\right) < \phi \end{cases} \qquad (21)$$

At the beginning, bubbles occur randomly among the firms in an industry with an upper limit B_0. Once the industry growth rate reaches a certain value (ϕ), the bubbles with size above the upper limit B_0 would enter the stage of booming, namely $\theta = 1$. The bubble would collapse when the expected industry growth rate falls short of ϕ, namely $\theta = 0$.

Then, we explore the possible impact on the industry growth during this dynamic process of bubble trades. One direct result would be that the capital would gradually flow into those industries with higher industry growth rate. At the beginning, bubbles with an upper limit B_0 are created randomly and sold by firms to investors. The bubbles give the firms a windfall and expand their production. This further improves the industry growth rate and facilitates the booming of bubbles. During the booming stage of bubbles, increasing money flows into the industry through bubble trades. Meanwhile, the expected output of the firms in the industry also experience a rapid increase. However, due to the uncertain components of ε_t and ϑ_t, the industry growth rate also has a risk to slow down. The investors would exit the bubble trades, once the industry growth rate falls short of their expectations ϕ. The overall output of the industry during this process would also experience a sudden decline after the bubble's collapse.

So far, the bubble trades we described above would transfer relatively inefficient investment to the productive firms with higher expected growth rate. For the investors, they would expect to receive a higher expected return rate from these productive firms. In this case, the whole efficiency of the economy would increase. However, when the investment becomes highly concentrated in those relatively productive firms of an industry, the risk would concentrate on them, too. Once the bubbles collapse and investments ran away from this industry, the output would also slump in the short term. Worse still, due to that investments are already highly concentrated in these firms, the collapse of the bubbles would result in a huge loss to the whole economy and cause sequent decrease in output in the long term.

4.4.3 Further Discussions

Our model has shown that, during the initial stage of bubbles, the transfer of the investment from investors to the (productive) firms through bubble trading tends to improve the average investment efficiency and increase the average growth rate of output in an economy. Nevertheless, with the concentration of investments on an industry, the whole economy would be in a high risk of bubble collapse. This may further lead to a sudden reduction of the economic output.

Another important implication of our model is that based on the equation (8), the firm sizes in an industry wound follow a highly right skewed distribution, namely the log normal distribution (Ijiri and Simon 1967). The number or frequency of bigger firms decreases with their size class. Simon et. al (1958; 1955) have proven that under the Gibrat's law and meanwhile introducing some new-born firms at the minimum size S_0, the final equilibrium of firm size distribution would be the Yule-Simon distribution. It is also a highly right skewed distribution. The decrease in the birth rate of new companies would lower the left tail and lengthen the right tail of Yule-Simon distribution.

Therefore, when allowing new firms to generate at the minimum size S_0, one possible result of bubble trading is that, the 'birth rate' of new firms whose size just transcend the minimum size S_0 would decrease and few new companies arise in the economy. This is because investors' money mostly flows into those productive firms above the minimum size and less likely to do venture capital investment. This reduction of the new-born firms in the left tail of Yule-Simon distribution would further increase the risk concentration of the economy. In an extreme situation where no new firms are introduced into an industry, a log-normal distribution of firms will form (Simon 1955).

It is noticeable that an underlying hypothesis of our analysis is that bubble's evolvement is linked with the bubble buyer's (investors) expectation on the industry growth rate of the bubble seller (firms). This hypothesis is consistent with recent studies that find positive correlations between fundamental economic factors and bubbles (Frankel 2014, Etienne et al. 2015, Sockin and Xiong 2015b, Sanders and Irwin 2017, Lian et al. 2018). Although the bubbles reflect overpricing phenomenon in the economy, they are associated with fundamental factors to some extent. In this case, the bubble's evolvement is correlated with the performance of corresponding firms in an industry, and bubbles in our model would show a periodically collapsing process. This is often the case in the real economy, compared with those models where bubbles are only allowed to occur from the beginning period and cannot collapse (Evans 1991).

Moreover, the periodically collapsing bubbles and investment flows in our model indicate a possible mechanism of business cycles for the economy. The prosperity of the economy originates from investor' rational expectations on the ongoing development of firms in an industry. They invest in the productive firms through bubble trades, in order to store value and obtain higher return in the future. Along with this process of investment concentration, the risk of the whole industry and economy also increases. Once the industry growth fails to meet the expected return rate required by investors, the economy would face up with a high risk of bubble collapses.

In comparison with Martin and Ventura's model (2012), we can see that a significant distinction is that our model uses the stochastic model of Yule-Simon distribution to replace the absolute productivity differentials and OLG framework in their analysis. We let the firms above the minimum size be the productive agents. This assumption is more realistic, based on the empirical studies on the distribution of firm sizes in the economy (Simon and Bonini 1958, Ijiri and Simon 1967, Stanley et al. 1995, 1996).[2] More importantly, since we don't assume a

[2] The difference with previous studies that assuming competitive economy is that under the Gibrat's law, the final equilibrium distribution of firm sizes is highly right skewed. This has been empirically verified by many studies (Simon 1955, Bain 1956, Simon and Bonini 1958, Ijiri and Simon 1967, Singh and Whittington 1975, Stanley et al. 1995, 1996, Axtell 2001). In the contrast, based on the assumption of perfect competitive economy, distribution of firm sizes in an economy

two-period lived agents, our model allows the investors and firms to survive for infinite periods with a certain probability. Thereby, it would be much easier to implement the empirical test of the bubble's effect on the economic development or business cycles, relative to the OLG framework with the two-period lived agents. In addition, we replace the investors' sentiment shocks with their rational expectations on the industry growth, making the boom and bust of price bubbles depend on the investors' rational expectations.

At last, an expansion of our model is to introduce many industries' (idiosyncratic) growth factors and an average growth rate for the economy. Based on Ijiri and Simon (1967), the firm growth rate can be decomposed into three components, $r_{ijt} = \rho_{ijt} \cdot \rho_{jt} \cdot \overline{\rho_t}$, where $\overline{\rho_t}$ is the average growth rate of the economy, ρ_{jt} is the idiosyncratic growth factor attributable to the *j*th industry, and ρ_{ijt} is the idiosyncratic growth rate of firm *i* in the *j*th industry. Through this generalization of the model, we could further apply the model to the case of international economy and allow bubbles to trade among different countries.

4.5 A Simulation of Bubbles

To illustrate the impact of bubbles on the firm sizes or output in the economy, a simulation of the bubble and output growth is given in Figure 4.1 below. The growth path of firms and bubbles follows the equations as described above[3]. In the beginning, the economy is in the fundamental steady state and the bubble does not enter the stage of booming. In period 4, the bubble starts to boom, and the output of the economy measured by the firm sizes increases, too. The economy then enters a bubbly state. In period 8, shocks to the firms' growth rate end this bubbly episode and the total output suffers a subsequent sharp reduction. In the following periods, the economy would experience a recession. This simulation clearly shows that introducing periodically collapsing bubbles into firm growth's model is a promising strategy to explain the possible effects of bubbles on the economy during a dynamic process.

should be uniform; however, this is not the reality of the economy (Simon 2009).

[3] To produce Figure I, we assume that $N = 2$, $\varepsilon \sim N(1, 0.1)$, $\alpha = 0.8$, $\beta = 0.5$, $S_{i1} = 1, \omega_t \sim N(0, 0.2), \vartheta_t = \exp\left(\omega_t - \frac{\zeta^2}{2}\right)$, $\zeta^2 = 0.2$, $\phi = 0.02$, $B_0 = 1.2$, $\delta = 0.8$, $r = 0$.

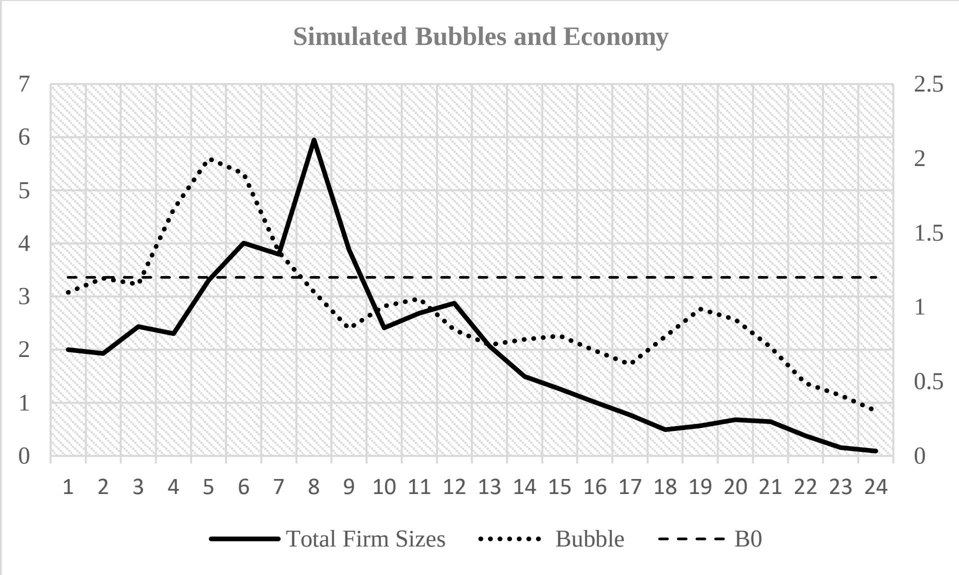

Figure 4.1 Simulated Bubbles and Economy

Source: Own calculations.

4.6 Conclusions

This paper proposes to use the stochastic model of the Yule-Simon distribution to describe the process of firm growth and productivity differentials in the economy. Compared with the model of bubbles based on the OLG framework, the assumptions for the stochastic model of Yule-Simon distribution are relatively weak and allow for a more general analysis of the bubbles and their effects on the economic output in terms of the calendar time.

The assumption of financial frictions is another critical premise for the existence of bubbles in our model. Under the circumstances of productivity differentials and financial frictions, the economy with rational agents could experience periodically collapsing bubbles. As shown above, this could have complicated effects on the economic output.

Our model provides a feasible framework for empirical studies on the bubble's effect on economic output. For example, one possible application is that we can use our framework to analyse the real estate market in China. The over-prosperity of the real estate market in China has raised concerns about its negative effect on other industries and the economic development. The long lasting and increasing housing price has raised public worries that too much money has flown into the real estate industry, while the money ought to have flown into other industries. Although the real estate industry has contributed a lot to China's economic success during the last decades, it is now a highly risk factor for China' economic development.

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Chapter 5 Price Discovery and Volatility Spillovers in Chinese Apple Futures Market

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Abstract

The Red Fuji apple futures contracts introduced in China at the end of 2017 marked the first fresh fruit trade at a futures exchange. This paper models the relationship between the futures and spot prices for apples. Evidence based on daily price data reveals that apple futures contracts function poorly in terms of price discovery and spot prices show no improvements in synchronisation among major apple spot markets. The volatility analyses from GARCH and BEKK-MGARCH models indicate that futures markets do not lead to higher spot price volatility and even reduce the spot price volatility in the short term. The findings of this study question the efficiency of the Red Fuji apple futures market. In order to facilitate the exchange of information between the futures and spot markets, regulators should consider measures to attract more commercial traders into the futures market.

Key words：apple; futures market; price discovery; volatility

JEL Codes: G13 Q11 Q13 P22

5.1 Introduction

Agricultural commodity futures markets have become increasingly important for price discovery, hedging and risk transfer (Hernandez & Torero, 2010; Yang et al., 2001). At the end of 2017, the trade of fresh Red Fuji apple futures contracts started at the Zhengzhou Commodity Exchange (ZCE) in China. In this paper we analyse the main function of the new futures market, which is the first futures market for fresh fruits worldwide.

The law of one price and no-arbitrage opportunities suggests a long-run equilibrium price for the futures and spot markets of one commodity (Listorti & Esposti, 2012). Every trader can hedge against or speculate on the price provided by the apple futures market if the futures price is an unbiased predictor for spot price at the time of maturity. To test this connection, a linear co-integration relationship has to be observed between apple futures and spot prices at the time of maturity (Brenner & Kroner, 1995). Meanwhile, in a market where no one has all the information on supply and demand, auction theory implies that a trader would adjust his or her price expectation based on others' quotations (Milgrom, 2017). Thus, the basis between the futures price and each regional market's spot price may motivate local traders to access new information and adjust their price expectations accordingly. This would improve the synchronisation level of spot price changes among different regions if nationwide apple traders became actively involved in the futures trade and shared their private information through futures markets.

Moreover, traders' disagreements on the same market information and their heterogeneous priors could result in high price volatility (Hong & Stein, 2007; Gizatulina & Hellman, 2019). The futures market is expected to reduce spot price volatility because it could speed up the homogenisation of traders' common expectations (Porter & Smith, 2003). Nevertheless, the public tends to believe that the apple futures market has led to higher volatility because it attracts too many speculators into the market who distort price formation.

Following the discussion above, the primary function of the apple futures market is to facilitate information exchange and price formation. This study investigates three different aspects of the operation of this new futures market for fresh fruit. (1) We check whether futures prices can predict spot prices at the time of maturity. The futures price is expected to provide an unbiased predictor for the spot price, so this is a precondition of the futures market. (2) We check whether the operation of the futures market improves the synchronisation level of price changes among major apple spot markets. If nationwide commercial traders obtain more information through futures trade, the timing of individual spot price changes across different markets tends to synchronise. (3) Finally, we test whether the apple futures market increases its spot price volatility. A detailed empirical analysis of the effects of the apple futures market is important not only for the market under study but also for establishing futures market contracts for other fresh fruits.

In the following analysis, we first describe the data source of apple futures and spot prices in Section 5.2. Then, in Section 5.3, we implement the co-integration tests to analyse the long run equilibrium relationship between apple futures and spot prices. Moreover, we test the synchronisation degree of price changes among major apple markets before and after the introduction of the apple futures market. At last, the change of spot price volatility and the volatility spillovers effects are investigated. Section 5.5 summarises the paper and gives our conclusions.

5.2 Data and Methodology

Being the largest producer, consumer, and exporter of apples worldwide, China produced 57% of the global apple harvest (43.88 million tons) in 2016 (ZCE, 2018). The main apple species in China is the Red Fuji, with a harvest of more than 70% of the country's total apple production. Therefore, it is reasonable that China established a futures market for Red Fuji apples. After the harvest season, which occurs around October, some of the apples will enter the market for consumption and the rest will be stored in cooling warehouses for consumption over the year. Correspondingly, the futures contract offers seven delivery months, namely January, March, May, July, October, November, and December. The trading unit of an apple futures contract is 10 metric tons/lot, which is physically delivered. The quality of apple should meet the Chinese national standard 'GB/T 10651-2008': fresh apples with fruit width greater than or equal to 80mm, a fruit width tolerance no greater than 5% and quality tolerance no greater than 10% (ZCE, 2018).

For the futures price of apples, we use the nearby futures contract price obtained from ZCE, which covers the period from 22nd December, 2017 to 12th December, 2019. The daily open interest data from ZCE serves as an indicator of speculative activity. For the spot price, since the futures price aggregates the information from traders nationwide, we use the Qianhai wholesale price index (QW index) for Red Fuji apples[1]. China's Ministry of Commerce uses this index as an official price indicator for Red Fuji apples because it captures the trend of apple prices in major markets nationwide. The sample period of the QW index is from 1st January, 2016 to 12th December, 2019; both the periods before and after the introduction of futures markets are around two years. We also use the individual price components contained in the QW index to calculate the degree of synchronisation of the price changes across major apple markets. These individual price series, representing thirty-five large wholesale markets across eighteen Chinese provinces, keep constant for some periods and often change by discrete amounts**.** We take the logarithms of all price series under study.

We first conduct a co-integration analysis by applying Johansen's test, then gauge the synchronisation level of spot price changes. Specifically, we compare the standard deviation of the actual proportion of price changes in each period with the standard deviations of perfect synchronisation and/or staggering (Loy & Weiss, 2002). If prices are perfectly staggered, the proportion of price changes in any period would be equal to the average proportion of price changes over time and the standard deviation should be close to zero. If prices were perfectly synchronized, the proportion of price series in any period would be either 0 or 1 and the standard deviation should be close to 0.5. We then compare the synchronisation levels before and after the establishment of the apple futures market.

We further estimate volatility spillovers between apple futures and spot market prices. Engle and Kroner (1995) present a detailed introduction about GARCH and BEKK-MGARCH model, so we use the GARCH model with additional exogeneous variables to gauge whether there is a structural break of price volatilities after introducing the futures market. Finally, we use the BEKK-MGARCH model to analyse spillovers across futures and spot markets.

5.3 Estimation results

5.3.1 Co-integration Analysis

The difference of the log prices is stationary, though the log price series shows non-stationary results (See Table 5.1). The QW index has a common trend with futures prices, but there is no tight correlation between them (see Figure 5.1). After an initial period that features price divergence, the futures and spot prices tend to have a common process; however, around 1st July, 2019, these two prices deviate from each other again. The futures price jumped down on

[1] Another prosaic reason for the usage of the QW index is that it is the only time-variant price series available to us. Other price series all present discrete changing behaviour, which is not suitable for volatility analysis.

1st July, 2019, while the spot price continued to increase. This price divergence reflects that the apple contracts from July to October correspond to different harvests and the inventory was running out during this period. The July contract corresponds to apples harvested in 2018 and the October contract corresponds to apples harvested in 2019. The harvest reduction caused by poor weather in 2018 resulted in an inventory shortage between July and October 2019. With this low inventory, arbitrage may not work effectively and there is no other force that links futures and spot prices together (Yang et al., 2001). Once inventories run out, no stocks can be released into the market to dampen the soaring price. Analysing the Johansen test in Table 5.1, no co-integration relationship is found between apple futures and spot prices, suggesting that futures prices have no long-run adjustments on spot prices and cannot be considered as unbiased predictors for spot price.[2] Thus, the futures market functions poorly in discovering spot prices.

Table 5.1 ADF and Johansen tests

	Futures Price:	Spot Price (QW):
ADF Test	-1.68	-1.54
P-value	0.44	0.52
	Futures Price Returns:	Spot Price Returns (QW):
ADF Test	-21.21	-38.73
P-value	0.00	0.00
Johansen test:	R_0	R_1
	23.60	4.65
	(15.41)	(3.76)

Source: personal calculations with Stata 15.

[2] We further use separate co-integration tests before and after 1st July, 2019 and find no cointegrated relationship between apple futures and spot prices.

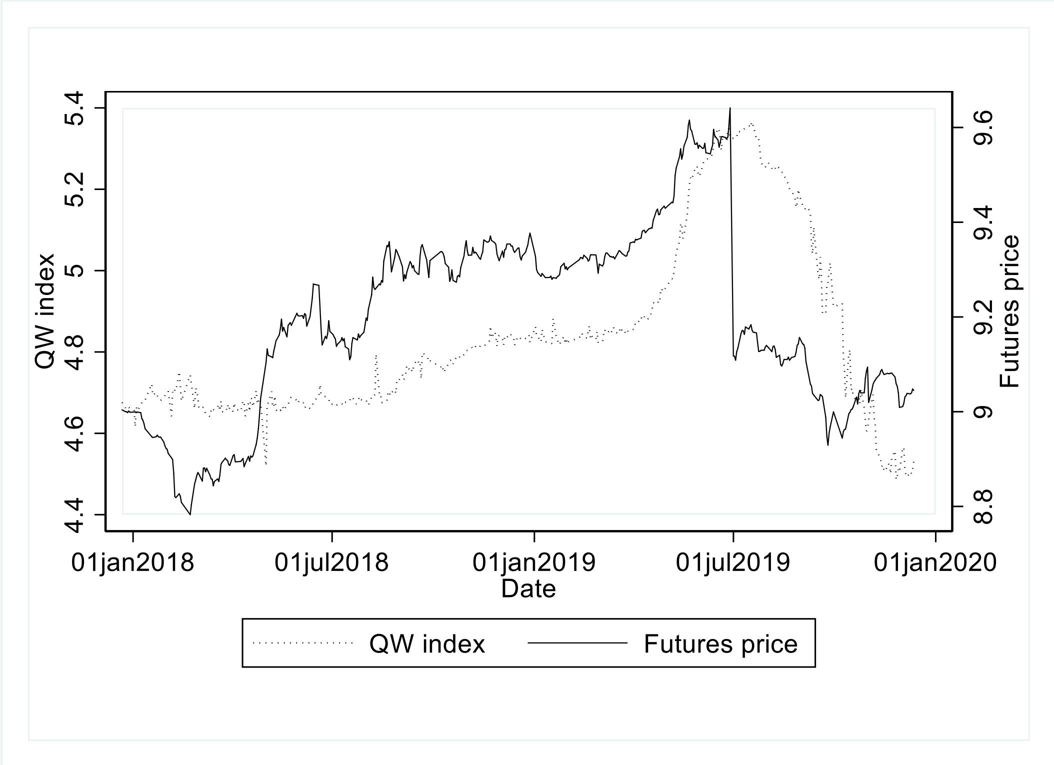

Figure 5.1 Futures price and QW index

Source: personal calculations based on data from ZCE and China's Ministry of Commerce using Stata 15.

5.3.2 The Synchronisation Level of Price Changes

One of the main purposes for establishing apple futures market is to provide a unified platform for traders from different regions. However, if the fresh apple market is segmented into many regional markets, price changes tend to be staggering among different regions. This is due to that each local market has its own specific conditions and prevents the spatial arbitrage. The synchronisation degree of price changes should increase if the apple futures market has functioned well as the role of price discovery and gathering information for all traders from different regions.

We use the individual wholesale price series from QW index. They are collected from 35 important wholesale markets for apples around China. We then estimate the synchronisation level of price changes among different regions. Results in Table 5.2 show that the actual standard deviations before and after the introduction of futures markets are much closer to that obtained under the assumption of price staggering. The standard deviation even decreases from 0.06 to 0.05 after the introduction of apple futures markets. The futures market hasn't significantly improved the synchronisation level of apple price changes nationwide, further suggesting that more commercial traders need to be involved in the futures market. Segmented markets of apple trades remain even after the introduction of futures market.

Table 5.2 Comparing the mean and standard deviations of different cases

Standard Deviation	Before (01Jan2016-21Dec2017)	After (22Dec2017-20Dec2019)
In actual data	0.06	0.05
Assuming perfect staggering [a]	0.04	0.04
Assuming perfect synchronisation	0.34	0.32
Difference from perfect staggering [b]	6.67%	3.57%
Observations	709	688

[a] The standard deviations are calculated from the actual number of price changes.
[b] Calculated as $(\sigma_{st} - \sigma_d)/(\sigma_{st} - \sigma_{sy}) * 100\%$, where σ_d, σ_{st} and σ_{sy} are the standard deviations in the data, the standard deviation under the assumption of perfect staggering, and the standard deviation under the assumption of perfect synchronisation, respectively.
Source: personal calculations with Stata 15.

So far, we have found limited effects of the fresh apple futures market on its spot market. Neither can it act as an unbiased price predictor, nor improve the synchronisation level of price changes among major apple markets. One possible reason is that not enough commercial traders have participated in the futures trade or hedged their risks through futures trade. This may result in the disconnection between the apple futures and spot prices. Another possible reason is the difference between commodity cash and futures markets in the ability of incorporating relevant price information (Crain and Lee 1996, Yang and Leatham 1999). The commodity spot market is for immediate delivery, traders in which may not have time to respond to new information. The results of price synchronisation further prove that different spot markets fail to respond to the information simultaneously. Some of them react to the information shocks and some not, exhibiting a sluggish movement for price changes.

5.3.3 Price Volatility Spillovers Effect

The spot price volatility changes before and after the introduction of the apple futures market is investigated using the GARCH model with exogeneous variable. Afterwards, the volatility spillovers across the apple futures and spot prices is analysed through a BEKK-MGARCH model.

The estimated results of GARCH-model with exogeneous variables are shown in the second and third columns of Table 5.3. The significant Arch and GARCH-coefficients in both specifications suggest a volatility cluster effect for the spot price series. In the second column, we use a dummy variable, ‘Futures’, to indicate the period when the apple futures market has been operating. The coefficient value of the dummy variable is 1.04 and highly significant because it means the apple spot price has become more volatile since the introduction of the futures market. However, this cannot directly prove that it is the futures market that caused the more volatile spot price. In the third column of Table 5.3, we use the daily open interest to represent the impact of speculation from the futures market and find significant negative effects from the open interest on the spot price volatility.

Table 5.3 GARCH model with dummy variable or open interest

	Apple Spot Price (01Jul2016 – 12Dec2019)	
	GARCH with a Dummy Variable ‘Futures’	GARCH with ‘Open Interest’
Cons	-10.28	-10.16***
	(0.57)	(0.41)
Arch (1)	0.23***	0.27***
	(0.06)	(0.06)
Garch (1)	0 .61***	0.54***
	(0.11)	(0.09)
Futures	1.04***	1.73***
	(0.34)	(0.41)
Open Interest	--	-0.17***
		(0.05)
Quarter 2	0 .44	0.22
	(0.61)	(0.53)
Quarter 3	0.23	0.71*
	(0.46)	(0.42)
Quarter 4	-0.80	-1.17***
	(0.49)	(0.43)
obs	967	967

Standard errors are in parenthesis. *** p<0.01, ** p<0.05, * p<0.1

Source: personal calculations with Stata 15.

We proceed to analyse the volatility spillovers between these two markets through the BEKK-MGARCH model. The results are listed in Table 5.4.[3] The coefficient a_{ij} measures the direct effect of lagged innovations originating in market i on the conditional return volatility in market j in the current period, whereas the b_{ij} captures the direct dependence of the conditional volatility in market j on that of market i. When only considering these direct cross effects, the innovations in the futures market tend to have a negative effect on the conditional

[3] Treating the price jump-down as missing in July 1st, 2019 has virtually no impact on the estimation results of BEKK-MGARCH model.

volatility in the spot market ($a_{21} = -0.15$), while the volatility dependence of the spot market on the futures market reveals a limited positive effect ($b_{21} = 0.07$).

Table 5.4 The results of BEKK-Mgarch Model

	Apple (01jul2018 – 01jul2019)	
	Spot (*i=1*)	Futures (*i=2*)
c_{i1}*100	0.48*** (0.15)	0.01 (0.25)
c_{i2}*100	——	0.83*** (0.16)
a_{i1} (arch)	0.37*** (0.05)	-0.15*** (0.04)
a_{i2} (arch)	0.43*** (0.07)	0.27*** (0.10)
b_{i1} (garch)	0.85*** (0.03)	0.07* (0.09)
b_{i2} (garch)	-0.16** (0.08)	0.76*** (0.10)
Log likelihood function:	2388.94	
Obs.	479	479

Standard errors are in parenthesis. *** p<0.01, ** p<0.05, * p<0.1

Source: personal calculations with Stata 15.

5.5 Conclusions

This paper investigates the operation of the newly established fresh Red Fuji apple futures market. Futures markets are supposed to facilitate information exchange and price formation. Based on the law of one price and no-arbitrage conditions, the efficiency of the futures market suggests a long-run equilibrium price for futures and spot markets; however, through various tests, we find limited effects from the apple futures market on its spot market. The futures price can neither act as an unbiased price predictor nor does it improve the synchronisation level of price changes among major apple spot markets. The inventory shortages and limited information exchange across the futures and spot markets may result in a disconnection between apple futures and spot prices. Commercial traders may not have fully participated in the futures market or revealed their own information on supply and demand through futures trading. The fresh apple market is more likely to be locally oriented than nationally. We find that the apple futures price tends to alleviate its spot price volatility in the short term, which illustrates that the futures market accelerates the homogenisation of traders' common expectations to some extent. Our study suggests that the regulators should take measures to attract more commercial traders from different regions in China into the futures market in order to improve the efficiency of the new fresh Red Fuji apple futures market.

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Chapter 6 Further Introductions of the Methods and Theories

In this chapter, we make a detailed introduction on the theories and methods which are used but are not fully explained in previous chapters.

6.1 Rational Bubbles under the OLG Framework

We use the theoretical model of bubbles proposed by Martin and Ventura (2012) as an example. The core idea of their model is that under the assumption of rationality and financial frictions, productive investors would sell bubbles to the unproductive investors. This trade transfers the money from the unproductive agents to the productive agents and raises the average productivity of the whole economy. In this case, the inefficient investment chain will be replaced by a more efficient investment chain, which thus enhance the overall output of the economy.

They base their analysis on the OLG model and consider a production economy. In the model, each agent only survives two periods: the youth and the old. For the young agents, they can use their human capital to produce and earn wages. Part of the wages will be consumed during their young period, and the rest will be saved or invested for future consumption. For the old agents, they can only consume what they obtain from their savings or investment income during their youth.

Specifically, the production economy in their model is consisted of an OLG model and a Cobb-Douglas production function: $F(l_t, k_t) = l_t^{1-\alpha} \cdot k_t^{\alpha}$ with $\alpha \in (0,1)$, where l_t and k_t are the labor force and capital stock, respectively. Assuming that only young agents have one unit of labor ($l_t = 1$) in the economy, markets are competitive, and factors of production are paid the value of their marginal product,

$$w_t = (1-\alpha) \cdot k_t^{\alpha} \quad \text{and} \quad r_t = \alpha \cdot k_t^{\alpha-1} \tag{1}$$

where w_t and r_t are the wage and the rental rate, respectively.

The stock of capital in period $t + 1$ depends on the investment made by young generation t during its youth. Martin and Ventura (2012) assume that some individuals are better at investing than others, whose fraction of the whole investors is $\varepsilon \in [0, 1]$. They can produce one unit of output with one unit of capital (productive investors), while the rest can only produce δ<1 units of output (unproductive investors). Assuming that the young use all their savings to invest, and the savings consist of their labor income, whose fraction is $s \equiv 1-\alpha$ of output. If financial markets worked well, productive investors would borrow money from the unproductive ones and pay them reasonable returns. A key assumption of Martin and Ventura's model is the financial frictions, which prevent this effective borrowing behavior and the unproductive investors have to make their own investments. Thus, the average investment efficiency is determined by the population weights of both types of investors and equals: $A \equiv \varepsilon + (1-\varepsilon) \cdot \delta$. Under these assumptions, the dynamics of the capital stock of the economy are given by

$$k_{t+1} = \mathrm{A} \cdot \mathrm{s} \cdot k_t^{\alpha} \tag{2}$$

namely, $s \equiv 1 - \alpha$ of output at time t is used to produce the new capital with efficiency of $A \equiv \varepsilon + (1 - \varepsilon) \cdot \delta$.

Martin and Ventura (2012) then pick a non-negative stochastic process for the bubbles and the bubbles have three forms: (i) b_t is the market price of the portfolio that contains all old bubbles, i.e. already existing before period t or created by earlier generations; (ii) b_t^P is the market price of the portfolios that contains all new bubbles created by productive investors at time t; (iii) b_t^U is the market price of the portfolios that contains all new bubbles created by unproductive investors at time t. The process of these bubbles can be indicated by $h_t = \{b_t,\ b_t^P, b_t^U\}_{t=0}^{\infty}$.

Under the setup described above, bubbles can be traded between different investors and result in different economic results. The process of bubbles' trading is as below:

$$E_t\left\{\frac{b_{t+1}}{b_t+b_t^P+b_t^U}\right\}\begin{cases} = \delta \cdot \alpha \cdot k_{t+1}^{\alpha-1} & if\ \frac{b_t+b_t^P}{(1-\varepsilon)\cdot s\cdot k_t^{\alpha}} < 1 \\ \in [\delta \cdot \alpha \cdot k_{t+1}^{\alpha-1}, \alpha \cdot k_{t+1}^{\alpha-1}] & if\ \frac{b_t+b_t^P}{(1-\varepsilon)\cdot s\cdot k_t^{\alpha}} = 1 \\ = \alpha \cdot k_{t+1}^{\alpha-1} & if\ \frac{b_t+b_t^P}{(1-\varepsilon)\cdot s\cdot k_t^{\alpha}} > 1 \end{cases} \tag{3}$$

$$0 \le b_t \le s \cdot k_t^{\alpha} \tag{4}$$

where the left hand of equation (3) is the growth (return) rate of bubbles at *t+1* and the right hand is the rental rate of capital for unproductive investors and productive investors. Specifically, $(1-\varepsilon)\cdot s\cdot k_t^{\alpha}$ is the savings of unproductive investors at time *t*. $\delta\cdot\alpha\cdot k_{t+1}^{\alpha-1}$ is the rental rate of unproductive investors' savings at time *t+1*. When the bubble is small, the marginal buyer is an unproductive investors and the capital accumulation equals the savings of the productive investors times their efficiency (the value is one), i.e., $\varepsilon\cdot s\cdot k_t^{\alpha}+b_t^{p}$; plus the savings of the unproductive investors minus the value of the bubbles they purchase times their efficiency (the value is δ), i.e., $\delta\cdot[(1-\varepsilon)\cdot s\cdot k_t^{\alpha}+b_t^{U}-b_t-b_t^{P}-b_t^{U}]$. When the bubble becomes large, the marginal buyer is a productive investor. Unproductive investors do not build capital and capital accumulation equals the savings of the productive ones, i.e., $\varepsilon\cdot s\cdot k_t^{\alpha}+b_t^{P}$; minus the bubbles they purchase, i.e., $[b_t+b_t^{P}+b_t^{U}-(1-\varepsilon)\cdot s\cdot k_t^{\alpha}-b_t^{U}]$. More importantly, the dynamics of the capital stock in this case would be:

$$k_{t+1}=\begin{cases}A\cdot s\cdot k_t^{\alpha}+(1-\delta)\cdot b_t^{P}-\delta\cdot b_t & if\ \frac{b_t+b_t^{P}}{(1-\varepsilon)\cdot s\cdot k_t^{\alpha}}<1\\ s\cdot k_t^{\alpha}-b_t & if\ \frac{b_t+b_t^{P}}{(1-\varepsilon)\cdot s\cdot k_t^{\alpha}}\geq 1\end{cases}\tag{5}$$

Two possible outcomes of bubbles can be seen from equation (5). The first one is the classic crowding-out effect: when the old people sell bubbles to the young, consumption grows and investment falls. This is why b_t slows down capital accumulation. It is worthy of attention that the unproductive investments are crowded out first. It is only when there are no unproductive investments, the bubble would start to crowd out productive investments. During this process, the average investment efficiency would improve. The second macroeconomic effect of bubbles is a new reallocation effect. The unproductive investments can be replaced by productive investments through bubbles' trading between different investors. This further explain that why b_t^{P} speeds up capital accumulation. The relative magnitudes of these two effects determine the final effect of bubbles on the economy.

Furthermore, Martin and Ventura (2012) contend that the ratio of bubbles over savings at each period should lay in the interval [0,1]. They deduce that the bubble occurrences are possible if and only if,

$$\alpha<\begin{cases}s\cdot\frac{A}{\delta} & if\ A>1-\varepsilon\\ s\cdot\frac{A}{\delta}\cdot max\left\{1,\frac{1}{4\cdot(1-\varepsilon)\cdot A}\right\} & if\ A>1-\varepsilon\end{cases}\tag{6}$$

So far, we can see that the advantage of Martin and Ventura's model is that it can explain the changes of output, consumption, and capital stock in the economy. The inefficient self-investment of unproductive investors is replaced by the efficient investment of productive investors, so that the overall efficiency of the economy will improve through bubble trades. However, they still limit their model to the OLG framework, where agents could only survive for two periods. Moreover, in their simulated result of bubbles, the origin of bubbles is determined by the investors' sentiment shock. This tends to be contradictory with their assumption of ration agents.

6.2 Univariate GARCH Model

We first introduce the autoregressive conditional heteroskedasticity model (ARCH) proposed by Engle (1982). Let ε_t be the innovations in a linear regression,

$$\varepsilon_t = y_t - x_t'b \tag{7}$$

where y_t is the dependent variable, x_t is a vector of explanatory variables, and b is a vector of unknown parameters. Let ψ_t be the information set (Sigma field) of all information through time *t*. The linear univariate ARCH model can be written as

$$\varepsilon_t | \psi_{t-1} \sim N(0, h_t) \tag{8}$$

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \cdots + \alpha_p \varepsilon_{t-p}^2 \tag{9}$$

This model is called ARCH of order *p*, or ARCH(*p*).

Bollerslev (1986) further generalized the ARCH model by allowing past conditional variances to appear in the current conditional variance equation, namely the general autoregressive conditional heteroskedasticity model (GARCH). The GARCH (*p*, *q*) process is given by

$$h_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j h_{t-j} \tag{10}$$

where $p \geq 0$, $q > 0$, $\alpha_0 > 0$, $\alpha_i > 0$, $i = 1, \dots, p$, $\beta_i \geq 0$, $j = 1, \dots, q$. Moreover, exogeneous variables could also be incorporated into the conditional variance equation of GARCH (*p*, *q*) process.

6.3 BEKK Multivariate GARCH Model

The BEKK Multivariate GARCH model (BEKK MGARCH) is proposed by Engle and Kroner (1995), which is used to estimate the volatility spillovers among different price series. The extension from a univariate GARCH model to an *n*-variate model requires allowing the conditional variance-covariance matrix of the *n*-dimensional zero mean random variables to depend on elements of the information set Ψ_t. Letting H_t be measurable with respect to Ψ_{t-1}, the BEKK MGARCH model can be written as

$$\boldsymbol{\varepsilon}_t | \Psi_{t-1} \sim N(0, H_t) \tag{11}$$

$$H_t = C + \sum_{i=1}^{p} A_i' \varepsilon_{t-i} \varepsilon_{t-i}' A_i + \sum_{j=1}^{q} G_i' H_{t-i} G_i \tag{12}$$

where *C*, A_i and G_i are $n \times n$ parameter matrices.

Take a bivariate GARCH (1,1) model as example, it becomes

$$H_t = \begin{bmatrix} c_{11} & c_{12} \\ c_{12} & c_{22} \end{bmatrix} + \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}' \begin{bmatrix} \varepsilon_{1,t-1}^2 & \varepsilon_{1,t-1}\varepsilon_{2,t-1} \\ \varepsilon_{2,t-1}\varepsilon_{1,t-1} & \varepsilon_{2,t-1}^2 \end{bmatrix} \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} + \begin{bmatrix} g_{11} & g_{12} \\ g_{21} & g_{22} \end{bmatrix}' H_{t-1} \begin{bmatrix} g_{11} & g_{12} \\ g_{21} & g_{22} \end{bmatrix} \tag{13}$$

The coefficient a_{ij} measures the direct effect of lagged innovations originating in market *i* on the conditional return volatility in market *j* in the current period, whereas the g_{ij} captures the direct dependence of the conditional volatility in market *j* on that of market *i*.

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Chapter 7 Conclusions

The abnormal agricultural price movement and its impact on the livelihood of the poor have gained considerable public attention and research interests, since the food crisis around 2007/08. As the most populous country, China would suffer welfare losses during the volatile food price period. To avoid the shock on the people's livelihood, China has implemented many measures to stabilize its agricultural commodity markets. However, the mechanism behind the agricultural price bubbles is still under discussion among scholars and no consensus is achieved in this field.

In order to enhance our understanding of the fundamental mechanism behind the agricultural price bubbles, this dissertation consisting of four contributions examines the origins of agricultural price bubbles and their possible effects in China, and further constructs a theoretical model to explain business cycles with price bubbles. These studies not only provide the empirical evidence for agricultural price bubbles, but also contribute to economic implications and recommendations for farmers, commodity traders, commodity exchange regulators and policy makers. Since each chapter focuses on a specific research issue regarding agricultural price bubbles, a comprehensive review is drawn in this chapter and each contribution is summarized separately as following.

Price Bubbles in Agricultural Commodity Markets and Contributing Factors: Evidence for Corn and Soybeans in China

Through a recently developed rolling window right-side augmented Dickey-Fuller (GSADF) test by Phillips et al. (2012, 2015), this study first detects the exact dates of price bubbles in China's two highly traded agricultural commodity markets, namely corn and soybeans. Then, we continue to use a penalized maximum likelihood estimation of a multinomial logistic model to estimate the contributing factors of price bubbles in each commodity futures market.

The results of bubble detection illustrate that bubbles only occur in a very low proportion of our sample period (2006-2017), namely 5.48% for corn and 3.91% for soybeans. Negative bubbles are most frequently observed in the corn market, while positive bubbles are more prominent in the soybeans market. 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. This is counterintuitive and bubbles often occur when prices suddenly increase or crash.

The different dates and types of bubbles in the corn and soybeans futures markets suggest a separate investigation of the potential factors contributing to price bubbles for each commodity. The results of the multinomial logistic model show that higher market liquidity and speculation reduce the likelihood of positive bubbles for corn, while they increase the likelihood of positive bubbles for soybeans. 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 soybeans 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., 2017). The commodities with higher self-sufficiency rate have shown less volatile price movements in China, such as corn, rice and wheat (Li, et al., 2017; Yang et al., 2008). In the contrary, Chinese soybeans 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 soybeans market is more vulnerable to speculative attacks, while corn market is more stable under higher market liquidity and speculation.

For the fundamental economic factors, domestic and world stocks-to-use, and external bubble shocks (from corresponding USA futures markets) exhibit different effects on these two commodity markets. Again, we find that Chinese corn market is relatively stable, while the soybeans price bubbles are more likely to be affected by its domestic and world stocks-to-use, and external bubble shocks. This may reflect the different levels of market openness for corn and soybeans. Unlike the corn market, Chinese soybeans market is highly connected with the 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 (Wu et al. 2011, Adämmer and Bohl 2015). 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.

In conclusion, we find complicated effects of specific factors that contribute to agricultural price bubbles. Unlike previous studies, we find crucial differences for bubbles of different commodities. This further suggests that policy makers should adopt commodity-specific measures to curb bubble occurrences in different commodity markets.

Agricultural Price Transmission between Futures and Spot Markets during Price Bubbles

In this chapter, we first examine the degree of bubble synchronisation between agricultural commodity futures and spot markets in China, using the weekly price data for corn and soybeans over the period 2009-2017. Afterwards, using the Markov Switching Error Correction Model (MSECM) and the Dynamic Conditional Correlation GARCH Model (DCC-MGARCH), we investigate the dynamic interdependence between futures and spot prices in terms of their first moments and second moments. Particularly, we concentrate on the price interdependence during the price bubble episodes.

The results indicate that the bubble occurrences tend to be staggered between agricultural commodity futures and spot markets. This does not support the deduction from the hypothesis that the speculation in futures markets mainly contributes to price bubbles. Moreover, it is noticeable that we find only a few bubbles for futures prices, regardless of the commodity species, even though there is a co-integration relationship between agricultural futures and spot prices. This raises our suspect about the effectiveness of commodity spot markets and there may be a nonlinear transmission effect between agricultural futures and spot prices.

We continue to use the MSECM and DCC-MGARCH methods to estimate the nonlinear transmission effect. The results of MSECM support that the co-integration relationship becomes weak and the adjustment effect of spot prices toward the long-run equilibrium is the lowest during the regime where bubble occurs the most frequently. The spot price returns are more likely to be affected by its own lagged terms. This suggest that the commodity spot markets may fail to respond to the new market information as effectively as futures markets. Meanwhile, we find a loose dynamic volatility interdependence between futures and spot prices. The lack of sensitivity to new market information may have resulted in more bubbles episodes of spot prices.

Economic Growth, Bubbles, and Firm Size Distribution

Under the assumptions of productivity differentials and financial frictions, the economy with rational agents could experience periodically collapsing bubbles and business cycles (Santos and Woodford 1997, Martin and Ventura 2012). When the financial market is inefficient, bubbles could act as a tool for capital reallocation. Nevertheless, the instability of bubbles could result in huge economic losses.

This study constructs a new theoretical framework for the economy with periodically collapsing bubbles. It attempts to incorporate rational bubbles into the stochastic model of firm growth behind the Yule-Simon distribution. The Yule-Simon distribution has been used to describe the distribution of firms in the economy and could be deduced from certain assumptions on the process of firm growth (Ijiri and Simon 1967, Simon and Bonini 1958, Simon 1955). Compared with previous models of bubbles embedded in the Overlapping Generations (OLG) framework, our model does not impose finite lived periods for agents and allows for infinitely lived agents. This enables a better interpretation and empirical examination on bubble's effect on the economy in terms of the calendar time. Moreover, our model can be easily generalized into a model for many industries or many countries.

Our model shows that bubbles could enhance the economic growth through transferring the money from the unproductive agents to the productive ones. As a result, the output, capital cumulation, and social welfare improve, as well. However, once there is a negative shock on the productivity of firms, the industry growth would fail to meet investors' expected return rate and the economy faces a high risk of bubble collapses and recession.

For policy implications, our model supports that the government should take measures to prevent hot money from overly flowing into the industries with high expected returns. Otherwise, the industry would absorb too much money and the whole economy would be in a danger of collapse.

Price discovery and volatility spillovers in Chinese apple futures market

The global first fresh fruit futures market for apple (Red Fuji) was established in the end of 2017 in China. This paper examines the effects of apple futures market on its spot prices from different perspectives. Based on daily price data from Zhengzhou Commodity Exchange (ZCE), we analyse the price discovery, synchronisation, and volatility spillover effects.

Through the co-integration analysis, we find no long run equilibrium relationship between apple futures and spot prices. This reveals that apple futures market has a limited function for price discovery and cannot be considered as an unbiased predictor for its spot price. The failure of price discovery further undermines the hedging effectiveness of apple futures market for commercial traders.

Furthermore, we adopt the method that gauge the synchronisation degree of price changes among different price series. We compare the standard deviations of the actual proportion of price changes in each period with the standard deviations of perfect synchronisation and/or staggering (Fisher and Konieczny, 2000; Loy and Weiss, 2002). The result indicates that the operation of apple futures market does not improve the price synchronisation among major apple markets in China.

At last, we implement the volatility analyses through GARCH and BEKK-MGARCH models. The result of univariate GARCH model indicates that the apple spot price volatility has increased a lot in the last two years, but we find that the increase of spot price volatility cannot be attributable to the speculation in the apple futures market. The result of BEKK-MGARCH even shows that futures price tends to reduce the spot price volatility in the short term.

Our study reveals that apple futures market does not serve well for the price discovery and may reduce the spot price volatility to some extent. This causes a doubt about whether fresh fruit is suitable for futures trading. So far, the regulators of ZCE have taken measures to restrict the positions of speculators. Our results show that these measures may not be useful for a more effective futures market. To improve the efficiency of apple futures market, the regulators should consider measures to encourage more commercial traders from different regions in China into the futures trading.

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Planning: Planning of experiments/analyses and formulation of investigative methodology, including choice of method and independent methodological development, in such a way that the scientific questions asked can be expected to be answered	C
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