Essays on the Agricultural Commodity Price

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Submission for the degree of

Doctor of Philosophy

in

Economics

Newcastle University Business School

September 2020

Abstract

Interests in commodity price dynamics are not new phenomena. Booms and slumps in recent decades have renewed the interest in understanding the factors behind agricultural commodity price movements. This thesis includes a collection of empirical chapters concentrate on critical aspects concerning the movement behaviours of selected grains prices in the United States. In particular, this thesis contributes to studies in applied commodity price analysis.

The agricultural commodity price is characterised as being highly volatile and the factors lying behind these fluctuations are characterised by a significant complexity. Chapter 2 discusses the agricultural commodity price developments and main factors associated with agricultural commodity price dynamics in the United States. This chapter leads the subsequent chapters with the motivations for the selected factors discussed in this thesis and the technical methods.

Using data on energy markets and agricultural commodity export prices, chapter 3 identifies the long-term co-movements between diesel prices and corn export prices in the U.S., considering diesel powers the U.S. economy in exporting agricultural commodities and offering long-term productivity gains in the fundamental sectors. The analysis provides evidence of a positive connection between diesel prices and corn export prices in the long-term. Besides, by employing the quantile-based analysis, this study also finds the long-run relations between corn and diesel prices vary over different market conditions. The findings in chapter 3 imply that the response of corn export prices to changes in diesel prices is generally much steeper when corn export prices at normal levels than in extreme levels.

Considering the threats of climate changes on agricultural commodity production, chapter 4 analyses the effects of extreme climate events on the movements of agricultural commodity price. Particularly, the chapter explores the extent by which changes in an important climate phenomenon, El Niño Southern Oscillation (ENSO), have contributed to the dynamics of grains prices in the United States. Previous works contribute to the belief that the dynamic relation of ENSO events on grain prices should be nonlinear in nature. To take the climate volatility information and nonlinear feature into account, this analysis fits an interval-based threshold model. This chapter finds that the warm condition increases the prices of soybeans

and corn, and the cooler condition has an impact on wheat and corn. These results can help form policies on storage and production decisions.

Chapter 5 provides evidence for the agricultural commodity market efficiency of the United States on the causal effects of agricultural commodity futures prices on cash prices. Applying three time-varying methods, with placed on grains markets including wheat, soybean and corn, chapter 5 finds that the causal effects between futures and cash prices change over time and depend on agricultural commodity markets. This chapter has proved that the cash and futures prices linkages behave differently in wheat and soybean, corn markets, implying a time-varying bidirectional causality in the wheat markets but unidirectional causal effects in the soybean and corn markets.

The joint theme and main contribution of this thesis lie on providing new evidence in relevant issues in applied agricultural commodity prices analysis by employing econometric methods in a novel way.

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Acknowledgement

I would like to take this opportunity to express my huge and boundless gratitude to my distinguished supervisor, Atanu Ghoshray, for your constant guidance, support and encouragement throughout my PhD journey. Atanu, you are an absolute inspiration for my research life. Being always available for my questions and providing constructive comments, criticism and feedback, I am able to finish my PhD and complete this thesis. In addition to the academic supervision, thank you for hours spent patiently guiding me to explore the main ingredients to become an independent researcher. I have learnt lessons from you, and your attitude for conducting research will always remain as an excellent example for my future academic career. A special thanks to Markus Jochmann, who has supervised me with econometrics and R coding during my first-year PhD study.

Furthermore, I must express my heartfelt thanks to my parents for their priceless love, encouragement and motivation. Without your support, I would not have been able to get through the difficult times. Although you both live far away from me, your daily greets and messages are my spiritual anchor. I also extend thanks to my boyfriend, Zhengyu, for accompanying me and encouraging me when I feel depressed. In particular, we exchange research ideas, work together and face the difficulty coronavirus period. I am blessed to have met you during my PhD journey and traversed the ups and downs with you. My appreciation is extended to my colleagues and friends who always stand by me and share the stress moments during my PhD study.

I am also grateful to researchers from other universities and institution, who have provided generous and valued supports to my research projects. Last but not least, I would like to acknowledge all the supports from Newcastle University Business School. All these make my PhD study valuable and interesting.

Declaration

I hereby declare that this thesis is my original work under the guidance and supervision of Professor Atanu Ghoshray. Atanu has provided comments and feedback on drafts of all chapters of this thesis. Chapter 3 and chapter 4 in this thesis have been enriched with feedback collected in seminars and conferences.

The early version of chapter 3 has been poster presented at the Annual Conference of the Agricultural Economics Society (AES) 2019 and orally presented at the First Newcastle University Business School Conference 2019. The comments and suggestions received in these two conferences have helped to improve this chapter with empirical analysis and discussion parts.

Chapter 4 has been online presented in a seminar at Newcastle Economics Research Development (NERD) group, and it has received valuable comments of Matt Walker, Robert Anderson, Smriti Sharma, Scott Kirkman as well as other participants. In addition, this chapter has been selected as the discussion paper and originally scheduled to orally presented at the Annual Conference of the Agricultural Economics Society (AES) 2020, which has been cancelled because of the pandemic.

Chapter 1. Introduction

This thesis analyses the dynamic behaviour of agricultural commodity prices movements, with relation to factors that are known to influence such behaviour. The focus is on U.S. prices, and this thesis deals with three main research topics: The relation between energy prices and agricultural commodity prices; the impact of global climate changes on agricultural commodity prices; and the role of financial derivatives and physical agricultural commodity prices.

The interest in the commodity price dynamics is not a new trend. Large price fluctuations in recent decades have renewed interest in understanding the factors behind agricultural commodity price dynamics. It is widely acknowledged that agricultural commodity prices have experienced booms and slumps over the years. Specifically, there is a significant surge in agricultural commodity prices in both 2007-2008, but the prices of commodities increase decelerated in the second half of 2008 and then drop sharply during the midst of the financial and economic crisis. Booms and slumps in agricultural commodity prices are inevitable in the following decades. Understanding the transmission mechanism between the different factors and agricultural commodity prices is helpful for forecasting and risk management. In the United States, programmes such as the Farm Commodity Programme and the Direct Payments Programme tend to protect farmers against adverse price shocks (Ghoshray, 2019). However, the previous mixed findings make it unclear to predict how the different shocks affect prices. With looming federal budget deficits, the considerable variability in predicting the cost of risk management policies has induced discussions on the efficiency of such policies. As a result, it is necessary to know the relations between factors and agricultural commodity prices. The work of this thesis is built upon three research questions and concerned with three aspects that affect the agricultural commodity prices giving special attention to the grains including, wheat, soybean and corn.

The thesis is organised in five chapters. Chapter 2 provides the background regarding each chapter. Chapter 3, 4 and 5, make a contribution to this research in the form of three essays that cover the three research topics as outlined earlier. In particular, given the importance of transporting grains from the prairies of the U.S to the ports for exports, Chapter 3 investigates the swings of energy prices on the agricultural prices. Since extreme climatic events can cause changes in temperature and precipitation, Chapter 4 is concerned with the effects of climate changes on agricultural prices. Finally, chapter 5 analyses the effects of changes in the financial derivative instruments prices to the variations in the agricultural commodity prices.

The recent strong co-movements between energy prices and agricultural commodity prices have renewed interest in exploring the transmission mechanism between oil prices and agricultural commodity prices (Dimpfl *et al.*, 2017; Nazlioglu, 2011). Energy prices are considered fundamental in increasing agricultural commodity prices. The direct causal link between energy and agricultural commodity prices is made with production and transportation costs (Reboredo, 2012, Tothova, 2011). The oil price transmission to agricultural commodity prices suggests that the increasing energy prices drive up the agricultural commodity prices by adding the production costs including the fertilizer, chemicals, transportation and other inputs (Nazlioglu, 2011). In the United States agricultural sector, there is no cost-effective substitute for diesel engines with the same combination of energy efficiency, power and performance, durability and reliability. Diesel engines power most of the farm equipment in the United States (EIA, 2018). In addition, 90 per cent of agricultural products are transported by trucks and trains with diesel engines. Compared to other oil derivatives, diesel prices should be closely related to agricultural commodity prices. An increase in diesel prices could increase the input costs and transportation costs, and a corresponding rise in agricultural commodity prices. Diesel prices and agricultural commodity prices are expected to co-move in the long-run.

Chapter 3 builds on the studies that analyse the long-term co-movements between energy prices and agricultural commodity export prices. The variability of energy prices has a direct impact on agricultural commodity prices through a range of aspects such as farm production inputs and transportation costs (Cabrera and Schulz, 2016; Nazlioglu, 2011; Nazlioglu and Soytas, 2012; Nazlioglu *et al.*, 2013). We focus on the U.S. as it is the leading producer and exporter of several important agricultural commodities. The motivation of this chapter is to analyse the long-run relationship between diesel and corn export prices, given the central role that diesel plays in transporting corn (EIA, 2018; Wensveen, 2016). The empirical evidence on the long-run relationship so far is mixed. A potential reason may be the response of agricultural commodity prices to energy prices that could vary at different market conditions (Pal and Mitra, 2017b). Corn is a storable commodity. Exporters could increase or decrease the storage of the corn. This leads to the changing demand for diesel. Exporters are not sensitive to the diesel price changes when they only need less diesel. These features prove that the long-run relationship could change according to the corn export prices levels. The contributions of this chapter to the studies are on two counts. First, this chapter reveals the dominant role of diesel in the U.S. agricultural sector. Second, we contribute to identifying the long-run linkage between corn export price and diesel prices in the United States. In particular, this chapter deviates from past studies and provides a timely contribution by identifying that the long-run relationship between diesel and corn export prices varies according to the market conditions.

Climate change is set to have a major impact on the agricultural sector because agriculture is among the more climate-sensitive human activities that most rely on climate conditions (Hertel *et al*., 2010). The agricultural sector is more vulnerable to growing conditions. Climate changes are characterised as significant sources for agricultural commodity price changes (Gilbert and Morgan, 2010). Agricultural production has been affected by climate changes from several different conditions, including dryness, excess precipitation, and even more hazardous manifestations like wildfires and hurricanes (Tack and Ubilava, 2015). Considering global climate changes could lead to production variability and therefore affect market fundamentals and commodity prices (Tothova, 2011). Specifically, Climate change is likely to trigger weather variability and the occurrence of extreme conditions that potentially generates weather shocks on agricultural prices. Climate variations and increasing global mean temperature (GMT) create significant threats to the global natural systems as well as socioeconomic well-being (Smith *et al*., 2009). For instance, small changes in GMT could lead to serious adverse effects on agricultural productions, especially for tropic regions (Müller *et al*., 2011; Rosenzweig *et al*., 2014). Weather conditions play a crucial role in all aspects of commodity prices, which includes commodity access, utilisation and commodity price stability. As such, the climate conditions, compared to other factors, are considered to be the major factor in the food prices (Headey and Fan, 2008).

Chapter 4 is on the relationship between climate changes and agricultural commodity prices and places attention on the grains farm prices, which are most likely to be impacted by variable climate conditions. For quite some time there have been warnings about increasing temperatures and declining precipitation related to global warming having a profound impact on agricultural production and prices, especially grains (Lobell *et al*. 2008). El Niño Southern Oscillation (ENSO) is one of the most important climate phenomena that exists over the tropical Pacific and shows a close correlation to global weather implications (Chen and McCarl, 2000; Collins *et al*., 2910; Dai 2013; Timmermann *et al*., 1999). ENSO exerts impacts on crop prices in several ways (Marlier *et al*., 2013; Cashin *et al*., 2017). This chapter contributes by exploring to what *extent* and *how* such climate phenomenon has impacted the grains farm received prices, including wheat, soybean and corn. Recent studies contribute to the belief that the dynamic relation of ENSO events on grain prices should be nonlinear in nature (Ubilava and Holt, 2013; Ubilava, 2017a; Ubilava, 2017b). Typically, ENSO itself is characterised as asymmetric cyclical variations with turbulent periods (An and Jin, 2004; Hall *et al*., 2001; Kohyama *et al*., 2018; Ubilava and Helmers, 2013). The findings of this chapter indicate that the warm phase of ENSO drives the prices of soybeans and corn. In comparison, the cooler phase of the ENSO has an impact on wheat and corn. The contribution of this chapter is to identify the asymmetries in the transmission of climate extreme events and explore how these asymmetries behave differently in various grains. Unlike most existing works examining the climate variations in levels, this study adopts a novel approach to measure climate changes by means of a range to cover both level and volatility information.

Over the last decade, the recorded fluctuated agricultural commodity prices are attributed to the growing role played by financial instrument trading, especially financial derivatives trading (Ouyang and Zhang, 2020). Beforehand the year of 2000, hedgers are the major participants in the commodity futures markets and they mainly engage in leveraged trading (Hirshleifer, 1988). Besides, commodity markets have a low or negative relation to other external financial markets such as stock and bond markets. Therefore, commodities are commonly used by institutional investors for portfolio diversification (Gorton and Rouwenhorst, 2006). However, the past decade has witnessed large capital inflows into commodity markets and the increasing popularity of commodity investing leads to an unprecedented inflow of institutional funds into commodity futures markets (Basak and Pavlova, 2016). The scale of the speculative positions in the commodity futures markets increases rapidly and over the commercial traders who participate in the business activities in the underlying spot markets; the commodities become a popular asset class for portfolio investors, a process known as ‘financialisation of commodity markets’ (Basak and Pavlova, 2016; Bohl and Stephan, 2013). Traditionally, futures markets are introduced for commodity suppliers and demanders to mitigate later cash prices risks and control costs. Given futures market is considered fundamental in facilitating and price discovery and risk sharing, the emerging financialisation of commodity markets raise the general question of the functioning and interaction of commodity futures and cash prices

(Mayer *et al*., 2017). The issues of the abilities of agricultural commodity futures and spot market to discover price has broad implications for varying horizons of traders such as producers, hedgers, consumers and speculators. In this regard, understanding the spot-futures lead-lag relationship for the special asset class of agricultural commodities assumes particular importance.

Chapter 5 reconsiders the lead-lag relationship between spot and futures agricultural commodity prices in the United States, with particular interests in wheat, soybean and corn, because they are the top three popular agricultural futures contracts in the United States. Past studies tend to lend support to the leadership role of the futures prices over cash prices because of the lower transaction costs, higher liquidity and transparency (Herbst *et al*., 1987; Xu, 2018). However, less is known about the time-varying relations between agricultural commodity cash and futures markets. The pattern of the lead-lag is sensitive to the choice of the sample period. The direction of causality could vary with the new information received alongside the time and price movements (Kawaller *et al*., 1987). At certain periods of time, the flow of information may be relatively sluggish, thereby affecting the lead-lag relationship. This implies that the relationship between futures and spot prices can be sensitive to the chosen time period (Alzahrani *et al*., 2014; Balcilar *et al*., 2015; Bekiros and Diks, 2008; Polanco-Martínez and Abadie, 2016; Silvapulle and Moosa, 1999). The time-varying features incorporated in the lead-lag relationship has received limited attention, which motivates this chapter to explore the potential time-varying nature of the lead-lag relationship. The empirical results from this chapter show a time-varying causality in the case of wheat, and unidirectional effects are revealed in the cases of soybean and corn. The core contribution of this chapter consists of providing new additions on the issues of market efficiency in the agricultural commodity markets and revealing the lead-lag causality for the selected grains. Knowing the time-varying lead-lag relationship between spot and futures prices is useful for producers. Producers could fix sales prices according to the spot or futures prices ahead of production and adjust supply decisions for the chosen time. Besides, the lead-lag relations change at different time periods, which is important for hedges to predict the possible movements in spot and futures prices to minimise the risks. This chapter also contributes by applying a novel time-varying Granger causality test that based on a recursive evolving window procedure. This method allows for potential heteroscedasticity in the testing process and no need for data transformation.

Chapter 2. Agricultural Commodity Price Movements

2.1 Introduction

Following the seminal paper of Samuelson (1965), there is now widely acknowledged that commodity prices often change randomly (Brooks and Prokopczuk, 2013). Agricultural products prices are considerably more volatile than are the prices of most non-agricultural commodities and services. It is broadly known that commodity prices could decrease by 75 per cent or jump by 100 or more per cent during only some months (Tomek and Kaiser, 2014). The persistence in volatility in agricultural commodity prices reveals the continued uncertainty in terms of how market fundamentals have unfolded and how they are likely to develop (Tothova, 2011). Producers usually voice concerns about the increased price fluctuations because they make production decisions partly based on expected prices (Tomek and Kaiser, 2014). Large swings in agricultural prices introduce difficulties in forecasting the price (Piot-Lepetit and M'Barek, 2011). To the extent that their expectations are not realised, prices and yield risk occurs (Tomek and Kaiser, 2014). In addition, agricultural prices are important for consumers' access to food. High volatility in prices may restrict the ability of consumers to secure supplies and manage input costs. Rising uncertainties in agricultural prices indicate that buyers and sellers of commodities will face large price risks (Tomek and Kaiser, 2014).

The price volatility of most commodity prices, including agricultural prices, appear to have moderated and currently are much lower than in 2011. However, price volatility and ways to solve its impacts on producers and consumers still worry both market participants and policy-makers. Policies to solve perceived and real problems related to agricultural commodity price uncertainties could be misconceived if they are not based on the comprehensive understanding of price movement factors (Baffes and Haniotis, 2016). Therefore, it is crucial to understand the nature of these stochastic movements and underlying causes (Brooks and Prokopczuk, 2013). This chapter introduces the factors and the motivations for the selected factors in this thesis.

This chapter first reviews the performance of volatile prices and discusses the dynamics of agricultural commodity prices. Next, section 2.2 moves to review the typical factors that have caused the changes in the agricultural commodity prices within the current economic environment. Section 2.3 emphasises three key issues that are of key significance to agricultural prices. The logistical issues of transportation of grains from the prairies to the ports of exports call for the relation of diesel prices and agricultural prices. Climatic change has been hogging the limelight in recent years and is likely to have an impact on agricultural prices by affecting the production. We concentrate on the certainly most discussed climate anomalies, ENSO, and its impacts on grains prices. Last, we investigate the financial side of commodities by analysing the lead-lag relationship between cash and futures markets in a dynamic environment. This thesis is empirical in nature, and therefore the final part of each subsection in section 2.3 describes how the econometric procedures add to new knowledge about the price dynamics of agricultural prices. To this end, a contribution of this thesis consists of applying the newly developed econometric methods that could shed further light on the contentious issues that are dealt with in this thesis and inform policy-makers related to agriculture. In addition, section 2.3 briefly illustrates the key contribution of each chapter and answering the question of new additions provided by this thesis.

2.2 Agricultural commodity price performances

The first decade of the new millennium has witnessed a longest and broadest boom in commodity prices and widespread financialisation of commodity products since World War II (Baffes and Haniotis, 2016). Sharp booms and slumps in agricultural commodity prices are common, and the current price spike is still evolving. According to Peters *et al*. (2009), there are six spikes in agricultural commodity prices since 1970. In each price spikes period, the large growth in agricultural prices are followed by a dramatic drop, and the prices rocket to the record highs before decreasing. Typically, the declines in prices are as much as the rises after the conditions that drive the increase was reversed. Between the spikes in the 1975 and 2008, the agricultural commodity prices only decrease to a new plateau that higher than the historical average values. Particularly, agricultural commodity prices have experienced substantial spikes from 2002 with significant spikes in 2007-2008 and again in 2010-2011 (Borychowski and Czyżewski, 2015).

Figure 2.1 reports the performance of the food commodity price index and crop price index over the period of 2002-2011. The overall agricultural commodity prices show particularly marked run-ups during 2002-2008 and reverse to decline rapidly after reaching the highest level in the mid-2008. Compared to the overall food commodity price index, the four basic crops price index, including wheat, soybean, corn and rice, show especially greater price fluctuations in the recent decade. To show the performance of the crop prices, the Economic Research Service (ERS) in the United States Department of Agriculture (USDA) has constructed a four-crop index, which also applies the International Monetary Fund (IMF) monthly prices weighted by global trade shares. **Figure 2.1** shows that the four-crop price index begins increasing in 2002, reversing the 20-year downward trend. The index of monthly-average world prices for these four basic crops rises accelerated and reaches a peak in nearly thirty years, with 226 per cent jumping from January 2002 to June 2008. Then the four-crop index upswing decelerates and decreases sharply with 40 per cent in the following half-year, the midst of the financial and economic crisis period. Wheat and corn prices tripled in this period (Von Braun, 2008a). A similar price movement's pattern occurs between June 2010 and March 2011, where the four-crop index slowly began to climb once again and increased by 70 per cent in 2011. The largest price swings are found in the wheat and corn prices.

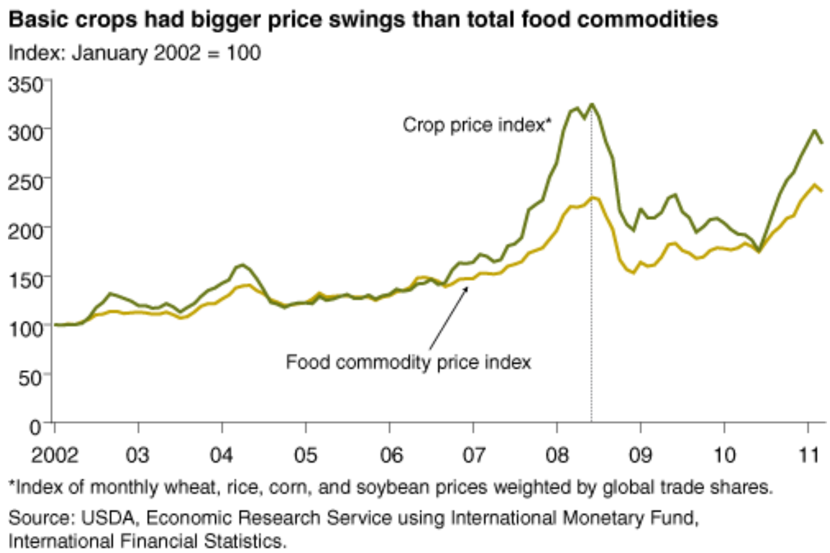

Figure 2.1: Food commodity price index and crop price index, 2002-2011

Agricultural commodity prices have now decreased significantly after the peaks in early 2011. However, the prices in real terms are still with 40 per cent higher than the lows in 2000 (Baffes and Haniotis, 2016). Increasing agricultural commodity prices and related rising food prices have received much press and led to aroused concerns, given the effects of two major price spikes in 2007-2008 and 2010-2011 are still on the minds of producers, consumers, agricultural businesses and governments (Trostle, 2011a). In both developed and developing countries, consumers suffer the effects of increasing food prices, especially during the periods of overall inflationary pressures. Producers also face pressures from the rising costs. Meanwhile, all individuals feel the effects of the agricultural commodity price spikes, which is commonly recognised as 'perfect storm', which last persistently even when the immediate effects of the Great Recession gradually subside (Baffes and Haniotis, 2016). The rising food prices have drawn the attention of the United Nations' Food and Agricultural Organisation (FAO), who have called for additional research on the rapidly increasing food prices. These sharp increases in agricultural commodity prices disproportionately affect global consumers in an adverse manner, especially those who are living in low-income and food-importing countries.

2.3 Factors explaining agricultural commodity dynamics

Not every commodity market experiences price fluctuations. They tend to be markets where the supply and demand conditions of the products are relatively stable every year, and where both the supply elasticity and demand elasticity are high. Only the markets with unstable supply and demand conditions on products will experience price changes year by year (Piot-Lepetit and M'Barek, 2011). For agricultural commodity markets, agricultural prices change because of the variabilities in production and demand consumption (Gilbert and Morgan, 2010). As introduced above, agricultural prices are very volatile over 2006-2011. Studies on exploring the sources of agricultural commodity price movements have shifted the focus from the topics of 'yesterday' towards more pertinent today because of the more volatile current prices (Baffes and Haniotis, 2016). This implies more studies have concentrated on the factors that are typical for current economies, especially during and after the price spikes of 2007-2008 and 2010-2011 (e.g. Meyers and Meyer, 2008; Tothova, 2011; Trostle, 2010). A number of factors and their interactions can be identified as lying behind the movements in these grains prices. The typical supply-side factors in current economies include (1) production costs or the production factors prices (from macroeconomic perspective), in which the energy and energy resources prices such as oil, natural gas and coal prices account for the large part; (2) the availability of arable land for agricultural purposes; (3) the developments in agricultural techniques and biological progress; (4) climate changes and adverse weather conditions with their related effects. The typical demand-side prices factors include (1) population; (2) economic development degree, demand scale as well as the changing structure of consumption; (3) alternative possibility of the arable land usage and competition for agricultural land between food market and bioenergy sector; (4) financial speculation and activity in commodity markets (Gilbert and Morgan, 2010; Borychowski and Czyżewski, 2015). The purpose of this thesis is to investigate certain factors – that are distinct in their own right - which contribute to the agricultural commodity price dynamics. We try to explain the transmission mechanisms. The motivations for the certain factors discussed in this thesis are introduced below.

2.3.1 Energy price

Energy prices, along with agricultural commodity prices, are two vital determinants of the global economic performance. Typically, energy, as a crucial commodity worldwide, affects different economy sectors either through direct or indirect channels (Nikkinen and Rothovius, 2019). It may be expected that there is a feedback effect between energy and agricultural prices. On the one hand, given crude oil is a considerable input for transportation and processing in the agricultural sector, rising oil prices raise crop prices by pushing up production costs (Cabrera and Schulz, 2016). On the other hand, increased energy prices lead to energy policies that tend to be towards renewable and cheaper energy sources. In this regard, energy policies develop to support biofuel production and alternative energy sources. The increases in biofuel production raise the demand for agricultural commodities and boost their prices (Chen *et al.*, 2010; Nazlioglu, 2011).

In a dominant part of the literature on agricultural commodity price dynamics, the energy market is conceived to play a critical role in affecting the agricultural price behaviour (Baffes, 2011; Tothova, 2011). In the past 15 years, the global economy has experienced a two-surge in commodity prices. Agricultural commodity prices have witnessed several booms and slumps after 2000, and they tend to relate to trends in energy commodities because oil prices have been volatile. For example, oil prices have embarked on a bull run from September 2004 and peaked at $145 per barrel in 2008, but this surge stopped because of the Global financial crisis, and by the end of 2008, the oil prices plunge to $40 per barrel (Fowowe, 2016). This volatile behaviour has been reflected in agricultural commodity prices. In particular, the movements of agricultural commodity prices have matched with those of energy prices (Nazlioglu *et al.*, 2013). The co-movement among most prices, especially between energy and non-energy commodities, is one key feature of the commodity price surges from the beginning of 2006 to the end of 2011. Such co-movement behaviour is often identified in conjunction or attributed to the agricultural commodities (Baffes, 2011). Particularly, during the global food crisis period, around the beginning of 2006 until the middle of 2008, the prices of the major crops including wheat, soybean and corn show dramatic growth compared to other agricultural commodities, and rise in concurrence with oil prices and reach the highest level. The joint swings are further observed to drop at the end of 2008 and restart to steadily increase to around $124 a barrel in April 2011 (Pal and Mitra, 2017a). Consistent with this argument, crude oil and grains return co-move with increased correlations between two markets for years. The increased correlations are related to a rise in the direct pass-through between energy markets and grains markets (Serra, 2011; Tyner, 2010). The concurrent movements in energy and agricultural commodity prices, as well as the increase correlations between two markets, indicate world oil price is a primary factor for the volatile agricultural commodity prices (Nazlioglu and Soytas, 2012). Given the observed co-movements between energy and agricultural markets have renewed interest in identifying price transmission from energy prices to agricultural commodity prices, the issue of knowing the relationship between these two markets continues to attract attention over the years (Nazlioglu *et al.*, 2013). In particular, this observed co-movement have attracted widespread attention to examine the factors of energy prices to agricultural prices, and identify the possible transmission mechanism between energy and agricultural markets.

Two important transmission mechanisms have been identified for explaining the pass-through from energy prices to agricultural prices. The first linkage is based on the cost-push effects from energy prices to agricultural commodity prices. For a long time, it is argued that the farm input, production, storage and transportation of agricultural commodities have been affected by energy prices (Nazlioglu *et al.*, 2013). A large amount of energy has been consumed for agricultural production which consumed directly for the use of the combustion of fossil oils, such as gasoline, diesel and petroleum for operating equipment, or indirectly used as necessary energy-intensive inputs, particularly fertilizer. Between 2005 and 2008, the averaged direct energy use expenses and fertilizer expenses account for approximately 6.7 and 6.6 per cent of entire production expenses in the United States farm sectors, respectively. However, these average values cannot reflect much greater energy intensities for major field crops. Therefore, the agricultural production becomes sensitive to the energy price movements, whether the movements are caused by global oil markets, policies related to the environmental objectives or policies for improving energy security (Sands *et al.*, 2011). Secondly, it is argued that the rising energy prices lead to increased agricultural commodity prices through rising demand for the agricultural commodities applied for biofuel production to respond to the increased biofuels demand (Ciaian, 2011a; Nazlioglu and Soytas, 2012). United States Department of Agriculture (USDA) points an accelerating process of biofuel production since 2003 in the United States. In the European Union, the biofuel production increased in 2005. The conventional anecdotal evidence indicates that energy and agricultural correlation is relatively low and negative. However, in addition to the cost-push effects, the stronger positive correlation between two prices is partially related to the increased production of biofuel from agricultural commodities (Beckman *et al*., 2012).

The above transmission mechanism between energy and agricultural commodity prices suggest the energy costs are the essential component of the inputs for agricultural production. Therefore one of the recent tendencies in agricultural price determination is to identify the dependency for long periods between them. A large volume of empirical studies have examined the presence of a long-run relationship between energy and agricultural commodity prices but the findings in the literature are polarised. One the one hand, it is found that the energy and agricultural prices co-move in the long-run (e.g. Balcombe and Rapsomanikis, 2008; Pal and Mitra, 2017a; Paris, 2018; Serra *et al*., 2011). On the other hand, there are several empirical studies unable to conclude long-term energy-agriculture linkage (e.g. Koirala *et al*., 2015; Natanelov *et al*., 2011; Nazlioglu, 2011 and Zhang *et al*., 2010). As this literature review shows, there leaves a gap in understanding the long-run relationship because of no consensus with respect to the energy-agricultural commodity prices nexus.

After the 2008 world food crisis, surges in agricultural prices have added additional risks to producers and consumers, resulting in tremendous pressure to the world food insecure issues (Nazlioglu and Soytas, 2011). Surges in agricultural commodity prices add additional stress on the family budget of poor household, which is expected to exacerbate world hunger problem. These combined effects pose a series of challenges in policymaking (Xu *et al*., 2018). Therefore, for policymakers, it is essential to be aware of the connection between the energy and agricultural sectors for the purpose of adopting an effective set of policy tools to maintain price stability and provide significant implications for policy adjustments that based on the dynamic market condition (Su *et al*., 2019).

The upshot from these discussions suggests that, given the following properties, energy price is an important factor and should be revisited when understanding the agricultural commodity price dynamics based on the following reasons: (a) the tendency of the basic agricultural commodity prices has roughly followed the same pattern as oil prices over the years. (b) energy is directly linked to agricultural commodity prices as it is a fairly significant input for transportation and processing in the agricultural sector. (c) increasing energy prices related accelerating process of agricultural fuel production has induced the movements in agricultural commodity prices. (d) while there are a growing number of studies that propound the issue of energy-agricultural commodity prices linkage, the empirical evidence is not clear-cut. Further analysis is required to handle the issue within the context of different methods. Finally, (e) information about energy-agricultural nexus can be useful for policymakers, especially to maintain price stability and design policy adjustments. These considerations have motivated chapter 3 of this thesis to examine the factor of energy prices to address a gap in the extant works of agricultural commodity price dynamics.

The long-run relationship may vary among different market conditions. The linear relationship between energy prices and agricultural prices may not always hold (Pal and Mitra, 2017b).For example, when oil prices decrease farmers instead supplying soybean as feedstock may sell soybean to feed processing plants or may choose to export. Besides, some agricultural commodities such as wheat, soybean and corn are storable agricultural commodities. Market participants such as exporters may choose to store these commodities in the situation that beneficial for them to increase storage. On this condition, they will reduces the demand for energy for transport purpose and become less sensitive to the energy price changes. Moreover, it is widely known that commodity prices including energy prices and agricultural commodity prices are known to be highly volatile. Both energy and agricultural commodity prices are characterised by negative skewness and excess kurtosis (Deaton and Laroque, 1992). This chapter argues that the underlying properties of commodity prices have been overlooked in past studies which can potentially affect the conclusion of long-run co-movement between these variables. Chapter 3 contributes to the existing literature by employing the quantile cointegration procedures to examine the long-run relations between energy prices and agricultural commodity prices. This method is introduced by Xiao (2009) that allows for the long-run relations affected by the shocks received in each period, and vary over the innovation quantile. Namely, the model proposed in chapter 3 assists in capturing the long-run relationship between energy prices and agricultural commodity prices under different market conditions. The potential nonlinearity in the long-run relationship is revealed from the data based on the level of the individual prices. This allows to identify the response of agricultural prices to energy prices, if agricultural prices are high and vice versa. Moreover, chapter 3 uses this quantile-based modelling framework to determine the linkages between these variables considering this is appropriate given the nature of the prices data.

2.3.2 Climate change

Climate refers to the changes in temperature, humidity and precipitation of the atmosphere in a certain area for long periods. Weather is what arises at a particular moment in time, which is the variations in the atmospheric conditions over a short period of time. By contrast, the climate is a long-term interpretation of weather conditions in a particular region (Pandey, 2020; Rotem, 2012). Weather describes a group of meteorological conditions at an exact time and place, for instance, wind, rainfall, snowfall, daylight, temperature, humidity, pressure, etc. (Trenberth, 2006). The climate is the long-run summary of the average values of these weather conditions. The distribution of vegetation, the types of ecosystem, the diversity of animals and plants, livelihood and the settlement of people in the region and their agricultural practices are determined by the climate of the area. When the climate of a certain area shows a long-term, gradual and stable change, which is the consequences of a long-term average daily weather change, it refers to climate change. Climate change could be caused by both anthropogenic and natural resources. The observed climate changes are periodic and unstable changes in weather conditions, which connected to the emergence of El Niño or La Niña, volcanic eruptions, or the variations in the earth's dynamic system. In addition, climatic variations include the annual variations and the existence of the extreme events as well, for example, the violent storms, unprecedented precipitation and abnormal hot seasons (Pandey, 2020).

Over the past few decades, researchers from worldwide have noticed the remarkable increased global average temperatures (Bhattacharya, 2019). There is widespread evidence supports this argument of rising global average temperatures and ocean temperatures, melting snow and ice in permafrost area, and increasing average sea levels (Bandara and Cai, 2014; Lobell *et al.*, 2011). The 2007 Fourth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC) indicates that global warming is not an occasional conjecture, but an apparent and continuous phenomenon (IPCC, 2007). Over the previous five centuries, the average temperature of the atmosphere and the ocean has been at the highest level in history, and this tendency has been dominant for over a century now (Jones *et al.*, 1999; Pandey, 2020). With the increasing temperature over the South and North Poles, and accelerating ice cap melting, as well as the reducing icebreaking period in polar lakes, global warming becomes evident and leads to a remarkable rise in the sea level. The intensive global warming could result in extreme climatic conditions, including flood, drought and heatwaves, which increases the possibility of natural disaster over the world (Pandey, 2020). In addition to the warming temperature, the climate changes also affect the hydrology, which indicates direct impacts on the underground water level, water temperature, river flow and water quality of lakes and marshes (Bandara and Cai, 2014). The precipitation, evaporation and soil moisture content are sensitive to the impacts of warming air. For instance, the changing precipitation pattern caused by climate changes increase the precipitation and the outflow, but the rising temperature reduces the outflow through more evaporation (Parry, 1990). These effects pass to the river flows and available underground water (Trenberth, 2011). Besides, the seasonal changes in precipitation and temperature are the results of climate variations as well. The consequences of climate change can be seen in the form of melting polar ice, retreating glaciers, melting permafrost, flooding and drought in rivers and lakes, erosion in coastal areas, sea-level rise, and extreme phenomena in nature, not only the physical system of the earth but also biological systems (Pandey, 2020). Namely, the phenomena related to climate change, such as wildfires, fauna and flora migration, and even the death of sensitive fauna and flora species caused by extreme weather conditions, directly or indirectly affect biological systems. For example, rising ambient temperature could hurt the crops yield or even causes the death of the crops.

Agriculture is known to be vulnerable to weather changes and arguably the most directly exposed economic sector. Hence it seems more likely to be affected by climate change (Adams *et al*., 1995). Agricultural production is highly dependent on local actual climatic conditions, and the damage caused by climate change is real. It has long been confirmed by scientists from all over the world that the changing patterns of precipitation and temperature systems of the atmosphere affect agricultural production. Especially, the unprecedented changes in the climate are disrupting the economic and social sectors worldwide. The effects could be worsened for the tropical regions and the less developed countries of this region (Pandey, 2020).

Since 1950, the global average temperatures have increased by approximately 0.13 °C every ten years (Lobell *et al*., 2011), and the effects of this phenomenon have had on agriculture is not fully revealed (Lobell and Field, 2007). In the next two to thirty years, the pace of global warming is expected to be even faster with roughly 0.2 °C growth per decade, especially with considerably larger trends for cultivated land regions (Lobell *et al*., 2011). The IPCC report has confirmed the realness of the global climate change and indicates the global warming is occurring rapidly. Regardless of changes in greenhouse gas emission, by 2030, global warming is expected to be about 1 °C relative to the late 20th century (Hertel *et al*., 2010). Lobell *et al*. (2008) predict that, over the next two decades, the rising temperatures and declining rainfall over the semiarid area are likely to hurt the yield for grains such as wheat, corn and rice, and other primary crops, which could cause a severe impact on global food security. According to the study of Stevanović *et al*. (2016), due to climate changes, the estimated global economic losses in the production of wheat, corn and barley reach at 5 billion dollar per year over the past three years. By the end of 2010, global undernourished people reach 925 million. It is expected that the world with 2.3 billion more people and peak at over 9 billion by 2050, to meet the needs of the ever-growing and urbanized population, agricultural production is required to increase substantially, approximately 70% in the first 50 years of this century (Aiking, 2011; Hochman *et al*., 2017). Given the pressure of surging agricultural productions, any factor that drives agricultural outputs has become a serious threat to humanity (Pandey, 2020). It is predicted that local and global changes in climatic conditions will not only result in long-term climate change but will also become more frequent and severe, accompanied by more recurrent and destructive extreme events (Field, 2014). The climatic variations and related extreme conditions spread over the world and pose severe challenges for agricultural productions to satisfy the food and nutrition demands of the growing world population (Rötter *et al*., 2018).

The climate matters argument is of particular interest as it leads to a potential discussion as to how climate changes could be linked to agricultural commodity prices. Climate and agriculture are intrinsically connected. This statement is commonly accepted. In particular, crop yields have long been found to be closely tied to growing environments (Ubilava and Holt, 2013). Following the same reasoning, crop prices are bound to be sensitive to global climate shocks (Ubilava and Holt, 2013; Ubilava, 2017a). Some supporting statistics are described below. Spikes in agricultural commodity prices during the period of 2010-2011 are attributed to a series of the global adverse weather events (Trostle, 2011b). The reduction in agricultural commodity production from adverse climate conditions is more severe in 2010-2011. Russia and parts of Ukraine, as well as Kazakhstan, have experienced severe drought in 2010, which reduces the production of all crops, especially wheat. At the end of the summer in 2010, precipitation on almost mature wheat across Canada and northwest parts of Europe downgrade the quality of the wheat to feed grade. Nearly the same period, the increasing temperatures and its related dryness during the grain-filling months result in the reductions in corn yield prospects in the United States. The abnormal climate conditions continue and cause effects on the crops in 2011. The drought conditions triggered by the adverse weather threats the crop productions, leading to significant reductions in winter wheat plantings in Russia for the 2011 crop. In November 2010, the La Nina condition caused higher temperature and drought overspread in Argentina lower the expectations of soybean and corn crops. Besides, similar to Canada and north-western Europe in the late summer of 2010, the precipitation during the end of 2010 and the beginning of 2011 hurt the quality of eastern Australia's wheat by downgrading the food quality to feed quality, which decreases the worldwide supplies of the food quality wheat. The rare freeze condition in early February of 2011 has destroyed the standing corn for Mexico. Focusing on the United States, the largest producer and exporter of grains, the dry autumn, winter and spring conditions in the United States is harmful to the hard red winter wheat yields, which lowers the prospects of 2011 wheat productions in the south-western Great Plains. The regions of Corn Belt and Northern Plains in the U.S. as well as Canada have been hit by the heavy and persistent spring rainfall, which delays the planting of 2011 corn and wheat, therefore, lowers the production expectations (Trostle, 2011b).

The changes in agricultural production patterns and commodity prices result from climatic anomalies would convey to both producers and consumers, changing the profitability of production and the portion of income spent on food (Hertel and Rosch, 2010). Facing the increased product prices triggered by the climate changes, households have to take more from their income on consuming food, more worsen, they may expose to the risks of nutritional shortage and insufficient food access (Stevanović *et al*., 2016). The better understanding and estimating of the climate effects transmission mechanisms, especially agricultural commodity price behaviours, can assist in implementing effective policies at both the national and international levels to cushion the potential influences (Ciscar *et al*., 2011). Besides, the identification of the effects of previous trends helps to evaluate the importance of near-term climate changes for crucial commodity supplies (Lobell *et al*., 2011).

Climate change is expected to last. Future variations in climate may cause substantial effects on agricultural productivity and food supply worldwide, warned by some leading scientific and environmental organisations (Porter *et al*., 2017). However, studies attempting to evaluate the sensitivity of agriculture to climate, in expectations of gaining insights into the impacts of future climate change have yielded different consequences. For example, the warming conditions may lead to the long dry areas suffer further losses, but advantageous the cooler areas and increase agricultural yields. Therefore, it is perhaps expected that climate change influences on agriculture are not always the same. The climate change effects could range from negligible to serious (Butler and Huybers 2013; Schlenker and Roberts 2009). In addition, although a growing body of research on this topic, there remains some uncertainties as to the nature and timing of the climate changes on the agriculture, and also the implications of these effects for human wellbeing in the world (Hertel *et al.*, 2010; Schmidhuber and Tubiello, 2007). Addressing this uncertainty is one of the top priorities for improving the understanding of climate change effects (Lobell and Burke, 2008).

To summary the preceding discussions, the motivation for adopting and analysing the factor of climate change is as follows: First, climate change and rising global mean temperature is the apparent and continuous phenomena, and they are emerging and occurring at an extremely rapid rate over the world. In the coming decades, it is predicted that climate would become more variable than at present, with increases in the frequency and severity of climate-related natural disasters including cyclones, floods, droughts and heatwave. Second, in the 21st century, climatic uncertainties are considered as posing the most significant threats to agriculture and food security. Changes in climate affect all sectors of the natural and human ecosystem. However, agriculture is the industry that is most vulnerable because it is highly sensitive to climatic factors. Third, the ever-growing population put pressures on the food supply. Climate is the principal determinant of agricultural productivity. With prospects of continued global warming, the implications of climatic variations could be substantial for four dimensions of food supplies, which are availability, stability, access and utilisation. The global agricultural will need to confront the increasing food requirements and respond to climate change challenges. Fourth, agricultural production is one way through which climate change may affect agricultural commodity prices. Crop growth and yield could be interrupted by excessive heat or insufficient water. Besides, the extreme events, particular flooding and dryness, could destroy the harvest. If, as predicted, agricultural commodity prices are exposed to further upward risks because of the continues reduction in agricultural yields caused by climate variations. Last, many of the past research provides mixed and uncertainty information, regarding the nature and timing of the climate changes on agriculture. Motivated by these facts, chapter 4 places particular attention to the effects of climate changes on agricultural commodity prices.

Chapter 4 studies the different phases of climate anomalies and analyses the impacts of the different stages of climate anomalies on the agricultural commodity prices. Recently studies have documented the dynamic relation of climate events on grain prices is nonlinear. The climate effects are known to be asymmetric because different phases of adverse climate events can affect crop production in different ways. For example, the hot conditions and cold conditions triggered by climate anomalies have different effects on temperature and precipitation. Besides, the effects of most extreme episodes climate phenomenon are likely to be more pronounced compared to the moderate phases. In addition to the asymmetry, the climate - price transmission has been broadly assessed with agricultural prices using point-based nonlinear models. This means the average values of the prices and climate index are employed to reflect the changes within a month or quarter. Unfortunately, such point-value models fail to capture the extreme and volatility information of the price data, as well as the climate indicators, because the data collected at a specific time point during a period is unable to record valuable interval information. In particular, climate events and related weather conditions can vary significantly within a period. It is vital to account for the volatility information in the regression settings to facilitate a comprehensive analysis of the relationship between climate change and agricultural commodity prices. The contribution of this chapter is based on the idea that the volatility of both the climate indicators and agricultural commodity prices is not exploited in point-valued based nonlinear models, thereby failing to make a complete analysis of the dynamic linkages between price spikes and climate anomalies. The recently developed threshold autoregressive interval (TARI) model proposed by Sun *et al.* (2018) is useful to classify the different phases of climate changes and analyse the asymmetric effects. Besides, TARI model is an interval-based modelling framework, which is superior to conventional point-based approaches such as threshold autoregressive (TAR) model, smooth transition autoregression (STAR) model and vector smooth transition autoregression (VSTAR) model which not only capture more information about both the level and volatility.

2.3.3 Financialisation

Over the past few years, agricultural commodity prices have undergone remarkable fluctuations. Recent claims have linked commodity financialisation and commodity derivative prices to volatile world commodity prices (Basak and Pavlova, 2016; Tothova, 2011). As early as 1848, the Chicago Board of Trade (CBOT) is established, which is the first futures exchange. However, major changes emerge in the market environment of commodity markets in the 21st century (Mayer *et al*., 2017). With a series of developments linked to the growing dominance of financial markets, institutions and interests in the United States economy since 1970, the term financialisation is introduced. It becomes widely used in the political economy literature to describe these developments loosely. Subsequently, the concept of financialisation becomes prevalent and extended to the commodity markets (Pradhananga, 2016). In the context of modern portfolio theory, research of Greer (2000) and Gorton and Rouwenhorst (2006), the understanding of the diversification properties of commodities is enhanced, and it can be observed growing popularity of commodity investments (Mayer *et al*., 2017). For example, the stock market collapse motivates investors to explore the safe assets for their portfolio, which results in the increasing interest in commodity futures. The financial industry and some academic economists have marketed commodity futures as the assets. The weighted index of commodities has comparable returns to the S&P 500 index but not correlated with stocks and bonds (Kat and Oomen, 2007). Commodity derivatives are effective to diversify investment and hedge against inflation. Therefore, investments in commodity derivatives increase rapidly, either through exchanges and over-the-counter (OTC). Over the last decade, especially since the early 2000s, commodity investing has become popular, which leads to an unprecedented inflow of institutional funds such as hedge funds and commodity index traders into commodity markets (Basak and Pavlova, 2016; Cheng and Xiong, 2014). This process is referred to as the financialisation in the context of the commodities futures market, which indicates the rise of commodities is applied as a popular investment asset class, similar to the stocks and bonds (Cheng and Xiong, 2014; Ouyang and Zhang, 2020). Financialisation of the commodity market is one of the potential explanation of the persistent and at times sharp jumps in the agricultural commodity prices. The upward price trend and most of the anomalies recorded after 2005 is related to the growing application of financial instruments and the effects of financialisation (Baffes and Haniotis, 2016). In 2008, Commodity Futures Trading Commission (CFTC) estimated and reported the total investment inflows of various commodity futures indexes increases from \$13 billion to \$260 billion from the beginning of 2003 to the first half of 2008. Simultaneously, commodities across agricultural, energy and metal sectors show the concurrent cycles of prosperity and depression during 2007-2008. Meanwhile, commodity prices become extremely volatile. The coincident occurring price spikes and volatility level increases within major commodity markets have attracted growing attention from both market participants as well as public and the policy community, to identify if financialisation of commodity has distorted their prices, and attribute this abnormal behaviour of commodity prices to speculations (Cheng and Xiong, 2014; Mayer *et al*., 2017).

The examination of the potential impacts of financialisation on commodity markets raises a general question of the functioning and interaction between spot and futures markets (Fattouh *et al*., 2013; Mayer *et al*., 2017). Futures trading is frequently claimed to accentuate price movements in the spot markets. The underlying belief is that commodity futures prices lead the spot prices but not vice versa (Silvapulle and Moosa, 1999). This relative ability to lead prices knows as price discovery can provide significant insights into the nature of prices discovery mechanism between spot and futures markets. The importance of futures markets in providing a price discovery mechanism has been a broad field of extensive empirical research (Bekiros and Diks, 2008). Financial derivatives are important to assist information dissemination, price discovery and resources allocation (Chan, 1992; Schwarz and Szakmary, 1994). According to the theory of asymmetry information and price discovery function, futures prices should respond more quickly to new information in the markets and signal the spot prices movements within markets. The considerable support for the information imbalance between spot and futures markets stems from the fact that futures markets show a lesser amount of friction than physical spot markets. Therefore, better-informed participants in futures markets promote the price discovery mechanism, leading to new information regarding fundamentals will be factored faster (Mayer *et al*., 2017). Especially, severe informational frictions threats the commodity market participants. Increasing globalised trading in extensive industrial and agricultural commodities prompt market participants confront the information frictions related to the supply, demand and inventory of these commodities across the world (Cheng and Xiong, 2014). In the occurrence of informational frictions in worldwide commodity supply, demand and inventory, the centralised futures markets centralised futures market complement the normally dispersed spot market in the field of information discovery and assists in aggregating the information (Grossman and Stiglitz, 1980). Therefore, futures prices become the important price in signalling the commodity demand and reflecting the impacts of futures market trading on commodity demand and spot prices.

However, many scholars have recognised price discovery changes with time and attempted to estimate the lead-lag relations over different subsamples (Foster 1996; Moosa 2002; Narayan and Sharma, 2018; Oellermann *et al.*, 1989). They argue that the price discovery or the lead-lag relations between futures and spot prices is not time-invariant but sensitive to the choice of the sample period (Foster, 1996). Here are two main reasons. First, at any time, market participants filter the new information that is related to either spot or futures markets. This may induce the spot-futures lead-lag interaction change over time (Kawaller *et al.*, 1987). Second, at certain periods of time, the flow of information may be relatively sluggish, thereby affecting the lead-lag relationship. Despite several attempts in the literature to identify the causal linkage between commodity futures and spot prices, limited empirical evidence acquired for agricultural commodity markets. In particular, the time-varying lead-lag relations between agricultural futures and spot markets needs to be brought into focus. Price discovery theory suggests a direction for causality between spot and futures markets. The issue of price discovery is undoubtedly still one of the specific problems to be resolved when evaluating the ability to assimilate and transmit information of the agricultural futures markets (Alzahrani *et al.*, 2014; Dimpfl *et al.*, 2017). Motivated by these considerations, the last chapter in this thesis aims to address a gap in the extant studies regard the price discovery perspective and examine the time-varying lead-lag causality between agricultural spot and futures prices.

Chapter 5 uses three time-varying causality procedures to identify the lead-lag causal effects of futures prices on the cash prices in the agricultural commodity markets. The time-varying approach used in this chapter is based on the belief that the lead-lag pattern between cash and futures markets can alter with the new information received and varies with time. These time-varying form tests are inspired by several empirical applications in the energy markets (e.g. Chang and Lee, 2015; Polanco-Martínez and Abadie, 2016), which find the changing pattern of the causal relations between cash and futures prices. However, the tests of the changing pattern of leads and lags over time are less found in the context of the agricultural commodity markets. The chapter adopts both the traditional Granger causality methods, forward expanding window causality test (Thoma, 1994) and the rolling window causality test (Swanson, 1998), and newly presented recursive evolving window Granger causality test from Shi *et al.* (2020). This chapter contributes to reveal the time-varying lead-lag causality between agricultural futures and spot markets and identify the exact dates of the origination and end dates of any causality periods. The understanding of the time-varying causality is a benefit for market participants to avoid inaccurate prediction.

Chapter 3. Examination of the U.S. Corn Export Price Behaviour

3.1 Introduction

The volatility of commodity export prices has led to mounting interest in the dynamics of the export price behaviour. One of the key variables that can cause shifts in export prices has been documented to be energy prices (e.g. Hanson *et al*., 1993; Nazlioglu and Soytas, 2012; Piesse and Thirtle, 2009; Trostle, 2010). International agricultural commodity trade relies on oil to ship agricultural products to the ports for export and final importing countries. The increasing oil prices and surcharges result in costly shipping, which shrinks the profits for the regional agricultural exporters and motivate these traders to adjust commodity export prices, especially for the long-distance supply of the agricultural products (Curtis, 2007; Nazlioglu and Soytas, 2012; Von Braun, 2008b). The fact that the agricultural commodity export prices and the growth of oil prices both experienced sharp jumps from 2006 to 2008. Some studies indicate that food crisis during this period is expected to be caused by the rise of oil prices (Nazlioglu and Soytas, 2012; Wang *et al*., 2014). The oil and agricultural commodity prices are believed to exhibit a co-movement behaviour, which motivates interest in studying the transmission mechanisms for oil and agricultural commodity prices (Nazlioglu and Soytas, 2012). Existing work examines the possible linkage between oil and agricultural commodity prices through the direct supply-driven mechanism, and they suggest the high-priced fuel has direct symptoms regarding the cost-push effects by raising the production and transportation costs (Nazlioglu, 2011; Nazlioglu and Soytas, 2012). In other words, a rise in oil prices is considered directly related to the increased agricultural commodity export prices through the increased cost of producing and transporting grains to world markets (Nazlioglu and Soytas, 2011).

Oil prices are a major cost to agricultural exporters, which involve the cost of moving agricultural commodities between points of production, export and import (Nazlioglu, 2011; Nazlioglu and Soytas, 2012). In the case of the U.S., diesel powers the transportation of agricultural. Over four-fifths of products exported from and imported to the U.S. are employing diesel technology. Owing to the lower cost and higher volume advantages, diesel-powered surface transportation containing road, rail or combinations thereof are the preferred modes for moving the agricultural goods from farm to port in the U.S. (Wensveen, 2016). The energy usage details from the U.S. Energy Information Administration (EIA) document that most of the consumer products including agricultural commodities are transported by diesel engines in trucks, trains, boats and barges (EIA, 2018). Diesel engines power over two-thirds of the farm equipment and transport nearly 90% of the agricultural products in the United States. As a transportation fuel, diesel is popular because of its superiority in efficiency and safety features[1]. In the agricultural industry, the similar cost-effective substitutions of diesel engines that could provide the same performance, durability and reliability are rare. Diesel dominates the entire farm supply chain from planting the seeds, tending the grains, harvesting the products and transporting the commodities to markets at home and abroad. A fact which reflects this is that approximate 96% of the large trucks powered by diesel is employed to deliver the agricultural products to the railheads and warehouses[1]. In addition, the Diesel Technology Forum (DTF) in the U.S. reports that the freight locomotives, marine river grain barges and ocean-going vessels used to move the agricultural commodities to domestic and international markets are diesel engines. The energy costs for agricultural production vary significantly for various crops. According to the report from United States Department of Agriculture (USDA), on the per-care basis, the energy-related expenses for corn are considered to the highest among eight selected major agricultural commodities (Sands *et al*., 2011). Given the importance of diesel as a transportation cost for exporters, price changes in diesel are likely to have an impact on corn prices. Diesel has been popularly used for corn transportation since the 1990s, making diesel becomes an important long-run input cost for exporting corn for a considerable length of time. Agriculture is considered to be an energy-intensive sector (Reboredo, 2012). A change in diesel prices results in the movement in transport and input costs and a corresponding fluctuation in producer prices. In the short-run, the producer prices and export prices could drift apart because of the agricultural policy changes or seasonal factors. However, if they continue to move far apart in the long-run, the economic forces, for example, the market mechanisms, may act to bring them together (Palaskas, 1995). Therefore, one would expect that within the integrated commodity markets, diesel and corn export prices would move together over time. In econometric methodology, this suggests that the corn export prices and diesel prices are cointegrated.

Interest in oil stems from the fact that large amounts of corn were being siphoned off to produce biofuels as a result of the energy policy mandate in the U.S. around the mid-2000s. Hence the large volume of studies of oil-corn linkages. Considering the importance of diesel prices to

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[1] Source: https://www.dieselforum.org/about-clean-diesel/agriculture

transport agricultural commodity prices in the U.S., little research has been conducted to examine the relationship from the transportation perspective. This research considers diesel instead of oil to analyse the long-run relation with corn prices. We focus on the diesel-corn price linkage through the channel of transportation, which has been largely overlooked. Cointegration methods are the most commonly employed econometric tools to identify the long-run relationships for economic variables, such as the oil – corn comovement (Koirala *et al.*, 2015; Pal and Mitra, 2017a; Zhang *et al.*, 2010). These tests determine whether there is a long-run relationship. For example, if oil prices are found to be cointegrated with the agricultural commodity prices, there is co-movement between oil and corn prices, or the prices share a common trend (Goodwin and Schroeder, 1991). Employing the cointegration methods, some studies have identified a long-run relationship to exist between oil and agricultural prices (Pal and Mitra, 2017a; Serra *et al.*, 2011), while some find no such relation (Koirala *et al.*, 2015; Nazlioglu, 2011; Zhang *et al.*, 2010). Although a body of literature has evolved that characterises the long-run relations between oil prices and agricultural commodity export prices, the empirical studies in understanding the influences of energy prices on agricultural prices are mixed. The mixed results open up questions of the nature of the so-called long-run relationship between oil and agricultural commodity prices.

Pal and Mitra (2017b) examine the long-run relationship between diesel and soybean price and find the cointegration changes when soybean prices at different levels. They point out that farmers have the choices to supply soybean as feedstock, sell soybean to feed processing plants or opt for export in the face of diesel price changes. Hence, a linear relationship between soybean prices and diesel prices does not hold true, implying soybean prices should respond differently to the changing diesel prices. Similar to soybean, corn is also an important storable agricultural commodity for both domestic and export markets in the United States. Exporters could adjust export or storage volume in anticipation of higher revenue and profits. Their demand for diesel varies according to their export decisions. Export prices may not be sensitive to the diesel prices movements when exporters do not need to use much diesel to transport corn. But become sensitive when exporters need more diesel. The potential nonlinearity in the long-run relationship between corn export prices and diesel prices is expected to occur. This study conjectures that corn export prices do not uniformly respond to diesel price changes when corn export prices at different levels. This study, therefore, is attempting to examine the corn-diesel long-run relationship by applying a quantile cointegration model. This approach uses the quantile indicates the different level of corn export prices, which allows us to test the corn-diesel cointegration at different levels of corn export prices. It is of considerable interest to corn traders to know how export prices react to the movements in diesel prices under different market situations. Because more real decisions depend upon current market states and prices (Lee and Zeng, 2011), especially for the extreme market conditions and prices. Understanding the long-run relationship between diesel and corn export prices in the U.S. market may be used for predicting purposes for policymakers. In addition, if the corn traders know the co-price movements for different level corn export prices, they could predict how the corn export prices will move with changing diesel prices based on current corn export prices. This is helpful for corn traders to design the inventory holding strategies and demand.

This study aims to make a contribution to the diesel-corn price linkage. We consider diesel, as it is the primary fuel for transportation of grains in the U.S.. By focusing on diesel rather than other oil prices, this study shed lights on revealing the facts of the dominant role of diesel in the agricultural industry. Secondly, we contribute to identifying the long-run co-movements between diesel and corn export prices using cointegration methods. However, we depart from the traditional cointegration regression used in recent studies, by adopting the quantile–based cointegration method, which allows us to identify the long run corn-diesel price linkage measured at different market conditions. To this end, we bring new insights into the literature on the fuel-food nexus. The remainder of the paper is organised as follows: The next section provides a literature review, followed by a description of the novel econometric methods in section 3.3. The data to be used in the analysis are described in Section 3.4. Section 3.5 presents empirical results and discussion. The final section concludes.

3.2 Literature review

The joint upward and downward drifts between energy and agricultural prices is not a new concern. Supply-side views attribute changes in agricultural export prices to changes in crude oil prices, which is of particular interest as it leads to the explanations as to why an increase in fuel prices caused growth in input transport costs that can, in turn, exert upward pressure on agricultural commodity export prices in the long-run. A body of literature exists that examines the long-run co-movements of oil and agricultural commodity export prices relying on cointegration procedures. These are helpful to address the topic and to further empirical analysis with novel econometric estimation.

Several studies have applied cointegration methods to oil prices and grain export markets relations using the traditional cointegration framework such as those of Engle and Granger (1987) and Johansen (1988; 1991). Studies including Zhang *et al.* (2010), Koirala *et al.* (2015) and Pal and Mitra (2017a) have tested the cointegration over the full data samples. The study from Zhang *et al.* (2010) characterises the cointegration between oil and global agricultural commodity prices. Using the Johansen (1988; 1991) procedure, they find no long-run relationships between fuel and agricultural commodity prices for three fuel-price series (ethanol, gasoline, and oil) and five agricultural commodity prices (corn, rice, soybeans, sugar, and wheat) from March 1989 through July 2008. Applying the Engle-Granger test, Koirala *et al.* (2015) fail to identify cointegration relations between oil prices with soybean and corn prices, using the daily futures prices. Corresponding to these studies, Pal and Mitra (2017a) obtain varying results relying on using the Johansen (1991) cointegration trace test. They confirm the oil prices and world food price indices will move together in the long-run with monthly data on crude oil prices and the world food price index and its sub-categories including dairy, cereals, vegetable oil and sugar, over the period January 1990 to February 2016.

A drawback of the above studies is that they ignore the possible presence of structural breaks in the price series, which has been found in several studies (Harvey *et al.* 2010; Kellard and Wohar 2006). This has been addressed in several studies which include Nazlioglu (2011), Natanelov *et al.* (2011), Harri *et al.* (2009) and Ciaian (2011b). Nazlioglu (2011) conducts Johansen trace (1988) cointegration tests between oil and three agricultural prices. These include natural logarithms of weekly prices, spanning from the first week in 1994 to the 29th week in 2010 of corn, soybeans and wheat prices. To test for the cointegration for subsamples, he uses the unit root test proposed by Lee and Strazicich (2003) to determine the breakpoints. The results indicate no cointegration relation exists for soybean-oil and corn-oil for the three subsamples (1994w4-1998w12, 1998w13-2004w37, and 2004w38-2008w37) as well as the full sample. However, for the fourth subsample (2008w38–2010w29), soybean, corn and oil are found to be cointegrated. In contrast, the wheat-oil prices are found to be cointegrated over the full samples with the exception of one subsample 1998-2004. Further, the residual-based cointegration test with the presence of the structural change could occur in the intercept and trend introduced by Gregory and Hansen (1996), is applied. The empirical results conclude that corn-oil and wheat-oil price pairs are cointegrated from 2007 onwards, while no evidence supports the cointegration relations for soybean-oil. Natanelov *et al.* (2011), employing the

Johansen (1988) trace and maximum eigenvalues cointegration tests with the U.S. data used in the empirical analysis comprises monthly futures prices of crude oil, gold and a series of agricultural commodity prices starting July 1989 until February 2010. To account for the problem of structural change, they break down the full sample into two subsamples by choosing January 2002 as the break point. Reasons behind the structural break of price movements in 2002 include the depreciation of U.S. dollars, global inflation, OPEC oil supply manipulation and geopolitical events (Zhang and Wei, 2010). The results suggest that the co-movement of commodity prices is temporal and contrast in two subsamples. Regarding the cointegration tests in two split periods, in the first period, they find cocoa, soybeans, soybean oil, wheat and corn prices co-move with crude oil future prices. But in the second period, they only notice coffee prices besides cocoa and wheat prices to be cointegrated with fuel prices. Many papers have also concentrated on the structural break effects in the cointegration relationships between oil and agricultural commodities, and they acquire the similarly mixed cointegration results, such as Harri *et al*. (2009) and Ciaian (2011b).

In light of these conflicting findings, different econometric methods have been introduced to analyse the cointegration with the asymmetric adjustments which involve applying nonlinear cointegration procedure; these include Balcombe and Rapsomanikis, 2008; Natanelov *et al*., 2011; Serra *et al*., 2011 and Paris, 2018. For example, Balcombe and Rapsomanikis (2008) propose the generalised bivariate error correction models which allow for investigating the nonlinear adjustment toward long-run price equilibrium relations between sugar, ethanol and oil prices. They use these methods on the weekly prices for crude oil, ethanol, and sugar in Brazil, expressed in Brazilian Real, covering the period from July 2000 and May 2006. They argue that the asymmetric vector error correction (VEC) approach outperforms the linear models. Their findings reveal that oil prices co-move with sugar and ethanol prices in Brazil in the long-run. Serra *et al*., (2011) assess price cointegration relations within the U.S. ethanol industry by employing a smooth transition vector error correction (VEC) model with ethanol, corn, oil and gasoline prices on a monthly basis, spanning the period of 1990-2008. Their findings show the existence of a long-run relationship through two cointegration relations among four prices analysed, which provides strong evidence between energy and agricultural commodity prices, with the nonlinear adjustment process of ethanol prices depending on the deviation of the equilibrium. Natanelov *et al*. (2011) consider whether asymmetric cointegration exists for crude oil, gold and a series of agricultural commodity prices. Beyond employing the Johansen (1988) cointegration test, they give an in-depth focus on studying the oil-corn, oil-soybeans and oil-soybean oil relations by using the threshold cointegration approach proposed by Hansen and Seo (2002). The findings indicate a long-run relationships prices between corn and oil prices in the U.S. In the recent study, Paris (2018) adopts the cointegrating smooth transition regression model due to Saikkonen and Choi (2004), to study the long-run relation of oil and agricultural commodity prices using the daily prices of oil, corn, soybean, wheat, sunflower oil and rapeseed oil. The empirical results underline that, in the long-term, rising oil prices have an impact on the prices of agricultural products used in biofuel production.

The above literature suggests that there is no clear consensus regarding the presence of cointegration between fuel and agricultural product prices. While relying on conventional cointegration tests, it is clear that there is a growing body study that conducts estimating the equilibrium process. Though the existing studies have considered the structural break and asymmetry problems in commodity data price series, the highly volatile features of commodity prices has received limited attention in understanding the cointegration relationship. Volatility is an acknowledged characteristic in commodity prices (Deaton and Laroque 1992). Testing cointegration only focus on the average of the oil and agricultural commodity prices is not appropriate because the cointegration coefficients could be affected by the shocks received in each period and vary over different innovation quantiles (Lyon and Olmo, 2018). As such, the speed of adjustment may differ from the different magnitudes of deviations from the equilibrium (Tsong and Lee, 2013). Allowing for additional volatility of the dependent variables in addition to the regressors and permitting the cointegrating coefficients to be affected by the shocks received in each period (Xiao, 2009), this paper is an important supplement to investigate the long-run relationship between oil and agricultural commodity prices by employing a novel quantile-based cointegration tests.

3.3 Econometric methodology

Engle and Granger (1987) originally introduced a seminal framework to evaluate the cointegration between two-time series data, and his method has been widely employed in different disciplines over several decades. However, recent literature identifies although the concept of cointegration has been defined for the conditional distribution, the majority of previous papers identify the cointegration based on estimated conditional mean behaviour. For the cases of fat tail distribution data, the conditional mean-based approach fails to describe the complete cointegrating relationships between economic time series indicators (Ding *et al.*, 2016). Quantile regression approach refers to modelling the relations between a set of predictor variables and specific percentiles of the response variable. By supplementing the conditional mean function estimations with techniques for estimating an overall range of conditional quantile functions, quantile methods allow us to perform complete statistical analysis of the stochastic relations between random variables (Koenker and Xiao, 2004). The quantile inference is robust in estimation compared to the least squares approach if the data is non-Gaussian or heavy-tailed. Compared to the traditional models, we could test for different persistence patterns relying on the size and location of the shocks.

3.3.1 Quantile autoregression unit root

When conducting the empirical analysis on the hypothesis, researchers are required to characterise the nature and distribution of the data since the conclusions acquired to rely on econometric methods. Non-Gaussian conditions and non-stationarities in commodity price series argue that the estimation and inference procedures based on mean value are not robust. One way to achieve robustness is to utilise the quantile-based approach and associated inference apparatus. Quantile autoregression model enjoys power gains over the augmented Dickey-Fuller (ADF) test in exploring the stationarity of the series at quantile levels of the conditional distribution. To be precise, their framework allows for identifying the mean-reverting behaviours by explicitly testing the unit root at various quantiles rather than exclusively focusing on the single measure of conditional central tendency. We first consider the ADF autoregression model (Dickey and Fuller, 1979) on the price series.

$$y_t = \alpha_1 y_{t-1} + \sum_{j=1}^{q} \alpha_{j+1} \Delta y_{t-j} + u_t \tag{3.1}$$

Where the autoregressive coefficient α_1 measures the persistence in y_t. Under regularity conditions, the $\alpha_1 = 1$ represents y_t has a unit root and is persistent, while $|\alpha_1| < 1$ indicates y_t shows mean reversion pattern. To acquire complete estimates for studying persistence in the tails of the conditional distribution of y_t, the equation (3.1) could be estimated with quantile autoregression approach. The τ th conditional quantile of y_t refers to the value $Q_{y_t}(\tau | y_{t-1}, \dots, y_{t-q})$ which implies the probability that y_t conditional on its recent history will be less than $Q_{y_t}(\tau | y_{t-1}, \dots, y_{t-q})$ is τ. For instance, if the diesel price is higher (lower) than recent diesel price realisations, which suggests a large positive (negative) shock has existed and y_t stays at above (below) the mean conditional on past information somewhere in the upper (lower) conditional quantiles. Following the methodology proposed by Koenker and Xiao (2004) and based on the ADF autoregression, the τ th conditional quantile of y_t, conditional on the past information set $\mathcal{F}_{t-1} = (y_{t-1}, \dots, y_{t-q})$ could be functionally presented by the following quantile autoregression model:

$$Q_{y_t}(\tau|\mathcal{F}_{t-1}) = \alpha_0(\tau) + \alpha_1(\tau)y_{t-1} + \sum_{j=1}^{q} \alpha_{j+1}\Delta\, y_{t-j} \tag{3.2}$$

Where $\alpha_0(\tau)$ denotes the τth quantile of u_t. Letting $\alpha_j(\tau) = \alpha_j, j = 1, \dots, q+1$, and define

$$\alpha(\tau) = (\alpha_0(\tau), \alpha_1, \dots, \alpha_{q+1})'$$
$$x_t = (1, y_{t-1}, \Delta y_{t-1}, \dots, \Delta y_{t-q})'$$

Thus, we have

$$Q_{y_t}(\tau|\mathcal{F}_{t-1}) = x_t{}'\alpha(\tau) \tag{3.3}$$

It is worthy of notice that $\alpha_1(\tau)$ measures the reversion speed of y_t, which varies within each quantile. Estimation of the linear quantile autoregression model requires minimising the sum of asymmetrically weighted absolute deviations:

$$min \sum_{t=1}^{n} (\tau - I(y_t < x_t^{'}\alpha(\tau))) \left| y_t - x_t^{'}\alpha(\tau) \right| \tag{3.4}$$

Where I represents an indicator taking the value of unity if $y_t < x_t^{'}\alpha(\tau)$ and zero otherwise. Given the solution of equation (3.4) is indicated by $\hat{\alpha}(\tau)$, Koenker and Xiao (2004) consider testing the behaviour of y_t for each quantile with the t-ratio statistic:

$$t_n(\tau) = \frac{\hat{f}\left(F^{-1}(\tau)\right)}{\sqrt{\tau(1-\tau)}} \left(Y_{-1}^{'} P_X Y_{-1}\right)^{\frac{1}{2}} (\widehat{\alpha_1}(\tau) - 1) \tag{3.5}$$

Where $\hat{f}\left(F^{-1}(\tau)\right)$ is a consistent estimator of $f(F^{-1}(\tau))$, with f and F denoting the density and distribution function of u_t. Y_{-1} is the vector of lagged dependent variables y_{t-1}, and P_X indicates the projection matrix onto the space orthogonal to $X = \left(1, \Delta y_{t-1}, \dots, \Delta y_{t-q}\right)$. In addition to the t-ratio statistic $t_n(\tau)$, Koenker and Xiao (2004) construct the Kolmogorov–Smirnov (KS) test to generally examine the unit root property based on the quantile method across a range of quantiles, which is a complete inference of the unit root process and given as

$$\mathbf{QKS}_t = \operatorname*{Sup}_{\tau \in \Gamma} |t_n(\tau)| \tag{3.6}$$

Where $t_n(\tau)$ is the t-ratio statistic of the autoregressive coefficient defined in equation (3.5) and $\Gamma = (0.05, 0.10, 0.15, \dots, 0.95)'$ in the later applications. In order to evaluate the overall non-stationarity, we need to test the null hypothesis of $\widehat{\alpha_1}(\tau) = 1 \forall \tau \in \Gamma$ using the $\mathbf{QKS}_t$ statistics. If such a null hypothesis is rejected, then we conclude our series is not a constant (homogeneous) unit root process. The critical values for the QKS test are acquired by implementing the bootstrap approach (number of bootstrap=1000 in our case) of Koenker and Xiao (2004).

Although the quantile autoregression methods introduced by Koenker and Xiao (2004) provides a framework that is robust to departures from Gaussian conditions and allows for exploring a range of conditional quantiles exposing a variety of forms of conditional heterogeneity. However, such model only accounts for the intercept but ignores the linear time trend and covariates. Galvao (2009) generalised their test by including related stationary covariates and the linear trend in the Koenker and Xiao (2004)'s framework, which leads to gains in power. Additionally, containing a deterministic time trend in the model is powerful since the time series data presents trend reversion properties under the alternative hypothesis of stationarity (Galvao, 2009). In this case, we perform the quantile autoregressive unit root test by adding the trend term and then rewrite the equation (3.2) as

$$Q_{y_t}(\tau|\mathcal{F}_{t-1}) = \mu_1(\tau) + \mu_2 t + \beta_1(\tau) y_{t-1} + \textstyle\sum_{j=1}^{p} \beta_{j+1} \Delta y_{t-j} \tag{3.7}$$

Where $\mu_1(\tau)$ and t are the drift term and deterministic trend item, respectively. Estimating equation (3.7) at each quantile $\tau \in \Gamma$ gives us a set of estimates of the persistence parameter $\beta_1(\tau)$. Then we test the null hypothesis H_0: $\beta_1(\tau) = 1$ for each quantile to investigate the persistence using our dataset. Despite including more covariates would enhance the unit root test power, adding correlated stationary covariates in the regression relies on examining variables from the same regime and exploiting the economic relations between these variables. Besides, the test results can be very misleading once the covariates are non-stationary. As such, this study excludes the stationary covariates in the regression equation (3.7).

Setting $\beta_j(\tau) = \beta_j, j = 1, \dots, p+1$, then define

$$\rho(\tau) = (\mu_1(\tau), \mu_2, \beta_1, \dots, \beta_{p+1})'$$

$$z_t = (1, t, y_{t-1}, \Delta y_{t-1}, \dots, \Delta y_{t-p})'$$

thus we acquire

$$Q_{y_t}(\tau|\mathcal{F}_{t-1}) = z_t{}'\rho(\tau) \tag{3.8}$$

Note that the asymptotic distribution for Galvao (2009)'s t-ratio statistic is the same as Koenker and Xiao (2004)'s QAR unit root test when there is no information in the stationary covariates. We employ the t-ratio statistic proposed by Koenker and Xiao (2004) and generalised by Galvao (2009), which is given as

$$t_G(\tau) = \frac{\hat{f}\left(F^{-1}(\tau)\right)}{\sqrt{\tau(1-\tau)}}\left(Y_{-1}^{'}M_Z Y_{-1}\right)^{\frac{1}{2}}(\widehat{\beta_1}(\tau) - 1) \tag{3.9}$$

Same as the definition given by Koenker and Xiao (2004), $f(.)$ and $F(.)$ are the probability and cumulative density function of residuals, respectively, and $\hat{f}\left(F^{-1}(\tau)\right)$ is a consistent estimator of $f(F^{-1}(\tau))$. Y_{-1} denotes the vector of lagged dependent variables y_{-1} and M_Z represents the projection matrix onto the space orthogonal $Z = \left(1, \Delta y_{t-1}, \dots, \Delta y_{t-q}\right)$. Under regularity conditions, the null hypothesis of $\beta_1(\tau) = 1$ implies y_{t-1} contains a unit root and is persistent for different quantiles $\tau \in \mathcal{T}$. For different quantile levels, we estimate the $t_G(\tau)$ and reject the null hypothesis when the t-statistic is numerically smaller than the calculated critical value which has been reproduced by Galvao (2009) for both demeaned and detrended cases. The test extended by adding the trend components completes the tests of Koenker and Xiao (2004), which is essential for testing unit roots of drifting time series data (Hosseinkouchack and Wolters, 2013).

3.3.2 Quantile cointegration

The traditional methods to test the economic variables have the cointegrated relations are to employ Engle and Granger (1987) or Johansen (1988, 1991, 1995) cointegration frameworks. Although their approaches have gained great popularity, a large number of applications fail to discover the cointegration on the data that are seemingly cointegrated by visually inspecting the data. One interpretation for these findings suggests the occurrence of time-varying cointegrating parameters, namely, the persistence coefficients that indicate the long-term relations would change over time, despite these series perform to move together in the long term. Xiao (2009) addresses this issue by proposing a new cointegration test with quantile-varying coefficients, in which the values of cointegrating parameters differ over the innovation quantile, to measure the impacts of conditioning variables on the location and shape of the response variables' conditional distribution. In solving the endogeneity in traditional cointegration models, Xiao (2009) decomposes the error term into lead-lag terms and a pure innovation component. Consider the following bivariate regression model

$$y_t = \sigma + \gamma x_t + \epsilon_t \tag{3.10}$$

Where y_t is the corn export prices and x_t is the diesel prices, respectively. By decomposing ϵ_t into the sum of the lead and lag terms of Δx_t and a pure innovation ε_t to avoid the second-order bias generated by the correlation between x_t and ϵ_t, we reparameterise the equation (3.10) as

$$y_t = \sigma + \gamma x_t + \sum_{i=-K}^{K} \pi_i \Delta x_{t-i} + \varepsilon_t \tag{3.11}$$

Following Xiao (2009)'s work, the quantile cointegration method accordingly incorporates the standard cointegration specification of Engle and Granger (1987) as particular conditions in which $\gamma(\tau)$ remains constant γ as described by equation (3.11). And the general form of the quantile cointegration model is given by

$$Q_{y_t}(\tau|\mathcal{F}_t) = \sigma(\tau) + \gamma(\tau)x_t + \sum_{i=-K}^{K} \pi_i(\tau)\Delta x_{t-i} \tag{3.12}$$

where $\mathcal{F}_t$ denotes the information accumulated up to time t and $\sigma(\tau)$ is the τ th conditional quantile of ε_t. Note the $\gamma(\tau)$ in equation (3.12) represents the cointegrating coefficient which depends on the new information (or shocks) received in the period and therefore varies over quantiles. We are interested in investigating if the $\gamma(\tau)$ are constant over several specific quantiles. Estimation of the coefficients in equation (3.12) involves solving the issue

$$Min \sum \rho_\tau(y_t - \sigma(\tau) - \gamma(\tau)x_t - \sum_{i=-K}^{K} \pi_i(\tau)\Delta x_{t-i}) \tag{3.13}$$

Where $\rho_\tau(u) = u\big(\tau - I(u < 0)\big)$, the check function (Koenker and Bassett, 1978) with I denoting an indicator function. Following Xiao (2009), the null hypothesis of $\gamma(\tau) = \hat{\gamma}$ can be tested overall quantiles through applying a supremum norm of the absolute value of the difference $\widehat{V_n}(\tau) = n|(\hat{\gamma}(\tau) - \hat{\gamma}|$ as the test statistic, where $\hat{\gamma}$ is the least square estimate for γ in equation (3.11) and $\hat{\gamma}(\tau)$ is the estimated parameters in equation (3.12). Then we use the statistic of $\sup_\tau\left|\widehat{V_n}(\tau)\right|$ to facilitate comparison with the critical values acquired by performing 1000 Monte Carlo simulations. In this model, the null hypothesis is constant cointegrating coefficient while and the rejection of the null displays evidence of varying coefficient behaviour.

3.4 Data and preliminary tests

The time series analysed are diesel price and corn export price using monthly observations over the period April 1994 to February 2019. Although the transformation of time series data is common, the expected analysis results and related explanations can differ according to the types of data (Tomek, 2000). For instance, the time series properties for the deflated and nominal commodity prices can vary. The nominal prices could present a stationary trend, while the real prices may exhibit a random walk characteristic. As such, this paper deflates the nominal diesel and corn export prices by employing the CPI (U.S. Consumer Price Index, CPI) as the deflator. All variables are taken in their natural logarithm counterpart before analysing.

The price data for diesel was sourced from the open data published by the U.S. Energy Information Administration (EIA). The monthly U.S. No.2 yellow corn (maize) free on board (FOB) Gulf of Mexico quotation (FOB) of the export prices of corn reported by the U.S. Department of Agriculture has been chosen to conduct the analysis. Indicating 'FOB port' implies that the seller is responsible for the costs of transporting the commodities to the shipment port and the loading costs. The purchaser pays the costs associated with moving the goods from the arrival port to the final destinations. Examples of these costs include marine or air freight transport, insurance fee and unloading costs. The term 'FOB Gulf of Mexico' indicates that the exporter pays the fee of delivering corn to the port of the Gulf of Mexico, and the buyer affords all the costs beyond this port. For this reason, the FOB quotation is appropriate to identify the sensitivities of the corn export prices to the volatilities of the transporting oil prices.

Table 3.1: Descriptive statistics of the data

	Diesel	**Corn export**
Skewness	0.135	0.700
Kurtosis	1.779	2.656
Jarque-Bera	19.477***	25.868***
Probability	0.000	0.000

Note: For diesel and corn export prices case, the data consist of 299 monthly observations on diesel price and corn export (fob), from April 1994 to February 2019. ***, **, and * denote significance at the 1%, 5% and 10% levels, respectively.

The corn export price series start from the different year for constructing the balanced pairs. **Table 3.1** shows the descriptive statistics for all variables and their respective results of the Jarque-Bera (JB) normality test. The values of kurtosis indicate all series exhibit the leptokurtic distribution. It is clear that the distributions of the diesel prices and corn export prices experience some form of asymmetry since the JB test rejects the null hypothesis of normality at the 1% and higher significance level. The marked evidence of non-normality suggests that it would be more fruitful to employ the quantile methods to consider each quantile separately instead of modelling for the mean in this paper.

Non-stationary and trending characteristics could be witnessed in economic time series data. Pre-testing for unit roots becomes necessary before deciding the most appropriate form and approach to employ (Hatanaka, 1996). As a prelude to the test of quantile autoregression unit roots, this paper employs four conventional unit root tests to verify the stationarity of the data and serve as a baseline test to compare our results, which are the Augmented Dickey-Fuller (ADF) test of Dickey and Fuller (1979) and Phillips and Perron (1988) (PP) test. These tests also performed to be verified as a precursor to testing for cointegration. The Augmented Dickey-Fuller (ADF) test is the most common unit root test for ascertaining whether the stationarity of the series. The Phillips-Perron (PP) test is non-parametric with respect to nuisance parameters, which improved in allowing for the weakly dependent and heterogeneously distributed series. The results of these benchmark standard unit root tests are reported in **Table 3.2** below.

Table 3.2: Conventional unit root tests

Unit root test	Diesel	Corn export
ADF Test: level	-1.921	-2.263
ADF Test: 1^{st} diff.	-10.599***	-13.267***
Phillips-Perron: level	-1.667	-2.067
Phillips-Perron: 1^{st} diff.	-10.648***	-13.296***

Note: ***, **, and * denote significance at the 1%, 5% and 10% levels, respectively.

The preliminary results at this stage are consistent and have strong evidence of containing a unit root indicated by all unit root tests. According to the results in **Table 3.2**, both the ADF and PP tests cannot reject the null hypothesis of non-stationarity for all level series at 10% significance level or higher. But the first differences of all data series reject the null of a unit root at all conventional levels of significance, which confirms the variables are integrated of order one.

3.5 Empirical analysis and discussion

We first conduct the Engle and Granger (1987) cointegration test as our benchmark because their test is the special case for the quantile cointegration test. The ADF and PP tests have tested that the diesel and corn export prices series are integrated of the same order, say I(1). We proceed to investigate the issue of cointegrations in cases of transportation-export. The results of the Engle-Granger cointegration test are presented in **Table 3.3**. We are unable to reject the null hypothesis of no cointegration at any significance level, which is consistent with Koirala *et al*. (2015).

Table 3.3: Engle-Granger cointegration test

Cases	Tau-statistic	MacKinnon P-value
Diesel and Export	-2.9100	0.1364

Note: The critical value calculated from the MacKinnon tables for variable levels at 10% significance is -3.0599 for the Diesel and Export case. The absolute value of the Tau-statistic is smaller than the absolute value of critical value. It indicates we cannot reject the null hypothesis of no cointegration at 10% significance level. Besides, the MacKinnon p-values represent we cannot reject the null hypothesis of no cointegration.

The results of the preliminary exercise confirm evidence of leptokurtosis and non-normality in each case, supporting the application of quantile autoregression model. We reassess the persistence of these series applying the quantile autoregression framework and present the results in **Table 3.4 – Table 3.5**. We utilise the following two tests to our data series: (1) the Kolmogorov–Smirnov (KS) test (QKS_t) proposed by Koenker and Xiao (2004), and calculate the bootstrapped critical values by applying simulation procedure; (2) Galvao (2009)'s quantile unit root test which modified by considering both the intercept and time trend. By including the presence of time trend, Galvao (2009)'s framework becomes more effective as it is a generalisation of the quantile unit root test by allowing for researchers to add trend term according to data performance. Therefore, this study concentrates on the results of Galvao (2009) for the following analysis. Schwarz information criterion (SIC) is used to determine the appropriate lags of the dependent variables. The first test offers a general examination of the unit root properties over a range of quantiles, while the second test is detailed to reveal the unit root behaviour at each decile. We estimate the QKS_t statistic for all $\tau \in [0.05, \dots, 0.95]$. In the context of accepting the null hypothesis of the QKS test implies constant (or homogeneous) unit root process. The 10%, 5% and 1% level critical values calculated based on the resampling procedure are presented in **Table 3.4**.

Table 3.4: Quantile unit root tests (QKS test)

	Diesel	Corn export
QKS statistic	2.244	1.556
p-value	0.753	0.994
CV10%	3.276	3.237
CV5%	3.534	3.519
CV1%	4.269	4.153

Note: The bootstrapped p-values (1000 replications) are calculated by using the pair-wise bootstrap approach for the Kolmogorov-Smirnov (QKS) test, over the whole quantiles $\tau \in \Gamma$, where $\Gamma = (0.05, 0.95)$. CV10%, CV5%, and CV1% denote QKS test critical values at the 10%, 5% and 1% levels, respectively.

For the diesel-corn case, the null hypothesis of constant (or homogeneous) unit root process is failed to be rejected at all significance level. As discussed above, the QKS test, by excluding the trend term and loses the power in testing the variables which have a trend. The Galvao (2009) method allows us to generalise the QKS model by allowing for a linear time trend. For the following quantile cointegration tests, the quantile respective individual tests can be informative in understanding the detailed persistence behaviour of our variables. Accordingly, we rely on the Galvao (2009) approach and take the QKS test as a reference. The Galvao (2009)'s quantile unit root tests results at 10% level of significance are displayed by pair cases in **Table 3.5**. In the case of diesel and export, we cannot reject the null hypothesis of a unit root for diesel prices for all the deciles. Besides, it is possible to reject the null for corn export prices (starts from 1994) only for the first quantiles, at 10% significance level. Supplementing the estimation of conditional mean functions with techniques for estimating an entire family of conditional quantile functions allows us to reveal the full range of stationarity for diesel prices and corn export prices by decile.

Table 3.5: Quantile unit root tests (Galvao, 2009)

τ	Diesel			Corn export		
	$\hat{\alpha}$	t-statistic	CV	$\hat{\alpha}$	t-statistic	CV
0.05	0.9610	-1.0146	-2.4665	**0.8844**	**-2.2946**	**-2.0821**
0.10	0.9635	-1.4262	-2.5700	0.9154	-2.2378	-2.2658
0.15	0.9645	-2.0521	-2.5700	0.9447	-2.0955	-2.2995
0.20	0.9897	-0.8047	-2.5700	0.9572	-2.0293	-2.4207
0.25	0.9945	-0.5274	-2.5700	0.9683	-1.9694	-2.3966
0.30	0.9957	-0.5039	-2.5700	0.9727	-1.9692	-2.4353
0.35	0.9951	-0.7425	-2.5700	0.9742	-2.0867	-2.4267
0.40	0.9924	-1.2363	-2.5700	0.9821	-1.4967	-2.4745
0.45	0.9908	-1.4268	-2.5516	0.9855	-1.2750	-2.4631
0.50	0.9915	-1.1182	-2.5270	0.9879	-1.0567	-2.4685
0.55	0.9920	-0.9921	-2.4641	0.9777	-1.9151	-2.5700
0.60	0.9924	-0.9046	-2.4640	0.9856	-1.1348	-2.5700
0.65	1.0018	0.1915	-2.5503	0.9849	-1.1438	-2.5700
0.70	1.0105	1.0811	-2.4856	0.9960	-0.2860	-2.5700
0.75	1.0084	0.8100	-2.4068	0.9934	-0.4464	-2.5700
0.80	1.0040	0.3507	-2.2698	1.0109	0.7233	-2.3775
0.85	1.0031	0.2336	-2.1028	1.0090	0.4711	-2.2333
0.90	1.0022	0.1307	-1.9422	1.0119	0.3880	-2.1996
0.95	1.0061	0.2157	-1.9419	1.0111	0.2518	-2.1371

Note: The t-statistic values in red represent the rejection of the null hypothesis of non-stationary or $H_0: \alpha(\tau) = 1$.

We further examine the stability of the cointegrating coefficients in equation (3.12) and report the results in **Table 3.6**. The quantile-varying cointegrating coefficient behaviour is strongly supported by the fact that the test statistic $\mathbf{sup}_{\boldsymbol{\tau}}\left|\widehat{\boldsymbol{V}_{\boldsymbol{n}}}(\boldsymbol{\tau})\right|$ is higher than the bootstrapped critical values for all cases, leading us to reject the null hypothesis of constant cointegrating coefficients in favour of varying-coefficient behaviours. These findings are in sharp contrast to the counterparts in **Table 3.3** where no cointegrating equilibrium is observed employing the Engle-Granger approach, implying the traditional cointegration model can lead to misspecified and erroneous conclusions. We turn our attention to discover such varying cointegrating coefficients and analyse the effects of quantile cointegrating relations. **Table 3.7** reports the estimated quantile-dependent cointegrating coefficients for the case of diesel-export. In the following, closer scrutiny delivers further insight that of the cointegrating relations for the individual case.

Table 3.6: Quantile cointegration test

Relationship	**Coefficient**	$\mathbf{sup}_{\boldsymbol{\tau}}\left\|\widehat{\boldsymbol{V}_{\boldsymbol{n}}}(\boldsymbol{\tau})\right\|$	**CV (1%)**	**CV (5%)**	**CV (10%)**
Diesel - Corn export	γ	**62.665**	30.885	22.013	19.086

Note: This table summarises the results of the quantile cointegration test (Xiao, 2009). CV (1%), CV (5%) and CV (10%) are the critical values of statistical significance at 1%, 5% and 10%, respectively. The critical values have been created through 1000 Monte Carlo simulations. We use an equally spaced grid of 11 tail quantiles, [0.10; 0.95], to calculate the test statistic of the quantile cointegration model between diesel and corn export (fob) price. The sup-statistic values in bold form represent the rejection of the null hypothesis of no quantile cointegration at all conventional significance level.

Table 3.7: Quantile cointegration test estimated coefficients

τ	**Diesel and Corn export** $\gamma(\tau)$
0.05	-
0.10	0.311***
0.15	0.409***
0.20	0.473***
0.25	0.515***
0.30	0.530***
0.35	0.539***
0.40	0.531***
0.45	0.530***
0.50	0.516***
0.55	0.481***
0.60	0.507***
0.65	0.561***
0.70	0.568***
0.75	0.659***
0.80	0.623***
0.85	0.642***
0.90	0.595***
0.95	0.427**

Note: This table reports the estimated coefficients of the quantile cointegration model (3.12), where ***, **, and * denote rejection of the null hypothesis at the 1%, 5%, and 10% significance level, respectively.

Table 3.7 reports the most striking results of the estimated values of $\gamma(\tau)$, which are significant to reflect the elasticity and confirm the long-run co-movements for by quantiles. For the diesel-corn case, the estimated results for cointegrating parameters $\gamma(\tau)$ are significant at all significance levels, except for the 95% quantile. To be precise, we could identify the cointegrating relationship between diesel and corn export prices and it occurs over the whole available quantiles, which is opposite to the recognition of no cointegration using the mean-based Engle-Granger method.

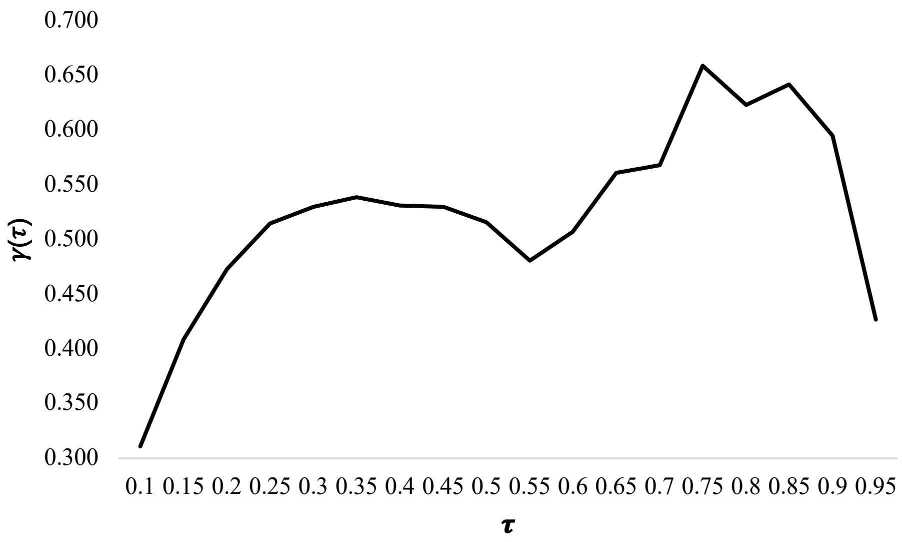


Figure 3.1: Coefficients of quantile cointegration with diesel and corn export prices

Figure 3.1 reports the quantile cointegrating results for the diesel-corn case. With rough eye inspection, they approximately constitute an increasing tendency but with some fluctuations depending on the quantiles. Generally, this upward pattern implies that the values of $\gamma(\tau)$ are much larger in the upper quantiles compared to the lower quantiles. A closer scrutiny in the model of diesel and corn export delivers further insight. The values for $\gamma(\tau)$ increase from 0.311 at 10% quantile and peak at 0.539 at 35% quantile, then slowly drop to 0.481 at 55% quantile. Take the higher quantiles such as 60%, 65%, 70% and 75% quantiles, the estimated values are 0.507, 0.561, 0.568 and 0.659, respectively, implying that in such quantiles, the responses become much stronger with quantiles increasing and reach the highest at the quantile of 0.75. The higher the quantiles are, the larger the estimated values of $\gamma(\tau)$ until they present a sudden downward trend within the extreme high quantiles (0.80-0.90), but the values of $\gamma(\tau)$ are still higher than the lower quantiles. For the 95% quantile, the estimated cointegrating coefficient further reduces to 0.427 and only significant at 5% significance level. When the corn export prices at the extreme high level, shifts in diesel prices convey less pressure to push the corn export prices up. These results could also explain the fact that the standard Engle-Granger cointegration test shows no cointegration whereas in the median quintile of the quintile cointegration test the cointegrating parameter is statistically significant. The traditional cointegration test relies on the mean value, which fails to consider the effects of extreme values. In our case, the cointegrating coefficients are statistically significant over both the median and extreme quantiles. However, the cointegrating test results of the traditional Engle-Granger cointegration approach will be affected by extreme values.

Diesel is widely used for transporting corn since the 1990s and plays a key role in the corn supply chain from planting, harvesting and transporting (Reboredo, 2012). The price of diesel is a large and significant component affecting the price of corn. As mentioned before, $\gamma(\tau)$ is the cointegrating coefficient and represents the diesel-corn price elasticity in each quantile. The cointegrating coefficients increase with quantiles and decrease at the extreme high quantile. Therefore, the long-run relations between corn export prices and diesel prices are best characterised as nonlinear and more – specifically state-dependent, where states are defined as high or low corn prices. This finding is consistent with the study of Pal and Mitra (2017b). Our results show, when corn export prices are at a low or high level, or alternatively low or high quantile, the response of corn export prices to diesel prices is small. While a stronger response of corn export prices to diesel price changes when corn export prices are closer to the average level or alternatively in the mid-quartile range. What might suggest that when the corn export prices are at the extreme low and extreme high levels, corn export prices are less sensitive to the changes in the diesel prices? A possible explanation is as follows: An excess supply/production of corn can cause low corn export prices. For example, in the United States, income support policies could provide economic incentives for farmers to increase corn acreage. Besides, producers adopt favourable production practices developed through research, which increases the corn yields and causes the excess supply. Alternatively, a fall in demand but a stable corn production could also lead to the lower corn export prices. Abundant corn in the importing countries could reduce U.S. corn export demand, lowering U.S. corn prices (Westcott and Hoffman, 1999). Under such circumstances, exporters become less responsive to diesel price changes as they tend to lose the incentive to export corn. At the other extreme, when corn export prices are at a high level, the response of corn export prices to diesel prices turns out to be weak. High corn prices are a result of excess demand relative supply. The global demand for U.S. corn has been strong when competitors like Brazil and Argentina struggling with dry weather. A shortfall in these corn-producing countries leads to the U.S. corn become more attractive to global purchasers, increasing the U.S. corn demand. Alternatively, the higher corn prices are the result of a fall in corn production but the demand for corn is stable. In the United States, the reduces in beginning stocks and production are the main reasons for the corn supply shortage. For example, small stocks can provide lower corn supplies in a low production year (Westcott and Hoffman, 1999). The extreme climate anomalies and weather condition could damage the planted area of corn. The corn yields will decrease (Tack and Ubilava, 2013). If corn exporters assume that such excess demand or reduce supply is going to be persistent, then they will store corn anticipating future demand. But according to the storage theory, the commodity inventory level and convenience yield are inversely related (Working, 1949). The convenience yield is the benefit of physically holding commodities for a period. The convenience yield falls as corn inventories pile up, making it gradually more costly to store more corn. Once the convenience yield is negative, exporters do not take more corn. At this stage, exporters are reluctant to demand corn in spite of the higher price it can fetch on exporting the commodity. This leads to a decrease in the demand for diesel to transport corn to ports. Hence, high corn export prices can become less sensitive to the changes in diesel prices. When corn export prices are in the median range, corn exporters find the prices to be within their expectations. Therefore the positive relationship that we expect to prevail between corn prices and diesel prices holds, as higher corn prices (within the range) would lead to higher profits for the exporter. As more corn is exported in anticipation of higher revenue and profits to the exporter, more corn is demanded to arrive at the ports. Exporters need more diesel and gradually become more sensitive to diesel price changes. These features prove that the movement in corn export prices in the United States varies over quantile in response to the changes in diesel prices, highlighting the importance of quantile methods of cointegration. The nonlinearity in long-run relations between corn export and diesel prices could lead to non-rejection of the null hypothesis of no cointegration (Michael *et al*., 1997). This result is of significance as we can mistakenly conclude that there is no cointegrating relation between diesel and corn using the traditional cointegration test. In general, we conclude that the diesel price evolves independently and that the corn export prices adjusts to maintain a long-run relation with diesel prices, depending on the level of corn prices, whether they are too high or low, or whether they are within a range that is within a specified interval of the central distribution of corn prices.

3.6 Conclusion

This article utilises a novel quantile cointegration methods of Xiao (2009) to investigate whether a long-run relationship between corn export prices and diesel prices exists. Corresponding to the traditional estimation conditional on mean distributions of dependent variables, this method allows us to identify cointegrating relations conditional on quantiles in the distributions of corn export prices. The consequences of this study are different from the previous empirical investigations that focus on the long-run relationship between prices using the overall mean levels. These previous studies neglect the possibility that the dependence structure between energy prices and agricultural commodity prices could vary under different market circumstance. This work addresses this gap. Using traditional cointegration methods, we fail to find a long-run relationship between diesel and corn prices. However, when applying the quantile-based cointegration measures of Xiao (2009), we estimate an entire family of conditional quantile functions, to assess the corresponding-dependence structures. Analysing for the long-run co-movements provides compelling evidence of cointegration between corn export prices and diesel prices. The immediate implication of this work is that the effect of quantile cointegration indeed occurs in the relationship between corn export prices and diesel prices. This condition could lead to the standard linear cointegration measure fail to capture the long-run relation. Studies may move beyond the traditional cointegration framework, and explore the nonlinear price transmission from energy to the agricultural commodity as the results of the quantile cointegration model has found that the diesel-corn relation is quantile-dependent.

Our empirical analysis finds quantile-dependent behaviour for the cointegration relationship between the prices of diesel and corn. More specifically, the findings of this study support that changes in corn export prices vary over quantiles in response to the movements in diesel prices. The long-run equilibrium relation becomes stronger in the case of upper tail quantiles, which implies that corn export prices respond strongly to the diesel price changes as compared to that in the lower quantiles. However, the dependence between corn and diesel prices tends to drop for extreme quantiles. These findings have important implications for corn traders as it reflects the nonlinear performance among different market states (lower corn export prices and higher corn export prices) and in addition to nonlinear effects of diesel prices changes. This nonlinear linkage is less considered in agricultural and energy markets, especially for the cointegration between corn and diesel prices. We employ a more accurate model to analyse the nonlinear relationship and hence enabling a better forecast of the future movements of the corn export prices. We hope our empirical results could offer different aspects to policymakers when building the estimation and prediction models. They should consider the nonlinear behaviour of the corn export prices to changing diesel prices when conduct predictions. Finally, if the corn importers want to make the optimum decisions of importing corn, then they should make the decisions according to the market conditions to avoid imprecise predictions. For instance, they could predict how the corn export prices will move with changing diesel prices based on current corn export prices.

Given the summary findings of the existence of quantile-varying cointegration, this paper explains the phenomenon of the absence of cointegration between energy prices and corn prices that are seemly cointegrated, which provides the explanations of the mixed conclusions in the existing literature. This study provides a timely contribution to explain the mixed literature evidence of this topic. Unfortunately, this study presents a limitation with regards to the adjustment behaviour. Quantile cointegration method provides more efficient estimations but yet does not allow to analyse the adjustment behaviour of corn export prices in more detail. Further avenues of study consist of exploring quantile-dependent adjustment behaviour.

Chapter 4. Climate Anomalies and their impact on Cereal Grain Prices

4.1 Introduction

For quite some time, there have been warnings about increasing temperatures and declining precipitation having a profound impact on agricultural production, especially grains (Lobell *et al*. 2008). More recently, the strongest El Nino events during 2015-2016, have led to concerns of possible global food shortages and agricultural commodity price spikes (Ubilava, 2017b). This concern is reasonable because agriculture is a vulnerable industry in the face the weather fluctuations as uncertainty and risk affects agricultural production (Kennett and Marwan, 2015). According to the Intergovernmental Panel on Climate Change (IPCC) report, climate change could affect all aspects of food security, including food access, utilisation and food price fluctuations (Porter *et al*., 2017). Given the importance of staple grains that are one of the primary sources of calories (Cranfield *et al*., 2002), and the increases in food prices could lead to global worsen poverty (Ahmed *et al*., 2009), the agricultural commodity price fluctuations motivate a need for better studying of the climatic fluctuations and their linkage to prices.

Global warming is an important climate phenomenon related to the frequency and intensity of extreme weather events, and it has been discussed that the Pacific area climate would experience significant variations under global warming conditions (Collins *et al*., 2010). Within the climate phenomenon associated with global warming, the El Niño Southern Oscillation (ENSO) phenomenon describes the climate anomalies by irregular periodic volatiles in the wind and sea surface temperatures over the central and eastern tropical Pacific Ocean, which triggers various extreme weather conditions to much of the tropics and subtropics (Chen and McCarl, 2000; Dai 2013). The El Niño is defined by the occasional return behaviour of the abnormal warm water in the normally cold-water area along the Peruvian coast, and the La Niña describes the cooler-than-normal sea surface temperatures in the central and eastern tropical Pacific Ocean (Ashok and Yamagata, 2009). The Southern Oscillation is an accompanying global-scale atmospheric component measured by the atmospheric pressure-field difference fluctuations between the area of the eastern and western tropical Pacific coupled with the sea surface temperature so that El Niños and La Niñas are accompanied with high and low air surface pressure over the tropical western Pacific, respectively (Aceituno, 1992). This coupled atmosphere-ocean systems together named ENSO, which is a nature interannual climate fluctuation that impacts entire global ecosystems, freshwater supply, hurricanes, agricultural industry and severe climate events (Timmermann *et al*., 1999; Collins *et al*., 2010). El Niño and La Niña are, therefore, the two extreme phases of the ENSO cycle, which are also characterised as warm tropical Pacific surface sea temperatures (SSTs) and cold tropical Pacific SSTs, respectively. Between El Niño and La Niña is the third phase termed as ENSO-neutral (Hanley *et al*., 2003) where the trade winds blow west crossing the tropical Pacific area and the tropical Pacific SSTs to keep at the average level. In contrast, under El Niño conditions, the weak trade winds in the central and western Pacific lead to abnormal SSTs increasing in the central and western Pacific area and form a warning of the ocean surface (Ashok and Yamagata, 2009); and La Niña, which is strongly related to the trade winds and the causes a cooling of the ocean surfaces. Generally, the warmer (cooler) the ocean temperature anomalies, the stronger the El Niño (La Niña) (Timmermann *et al*., 1999).

ENSO exerts impacts on agricultural commodity prices in several ways (Marlier *et al*., 2013; Cashin *et al*., 2017). First, the primary channel is arguably weather-driven supply shocks. The link between global climate events and the local weather phenomenon in some regions of the world is termed ‘teleconnection’, which in turn orchestrates the relationship between climate anomalies and commodity production and prices (Barlow *et al*., 2001; Ropelewski and Halpert, 1987). This occurs through the variability of temperature and precipitation (Ubilava, 2017a), which has an impact on agricultural production and therefore price variability (Solow *et al*., 1998). Second, the anomalies of the temperature and precipitation during growing-season generate significant changes in yields through the direct effects of pest infestations and indirect effects from pesticides (Gregory *et al*., 2009). The apparent consequence of the insects-driven yield changes is the price variability (Deutsch *et al*., 2018). Third, the size of the climate anomalies matter. For example, the large magnitude weather anomalies such as drought, tropical cyclones, hurricanes and tsunamis are more likely to happen during the ENSO extreme phases, which causes significant loss to agricultural production over a larger geographical area (Camargo and Sobel, 2005; Siegert *et al*., 2001). Such extreme cases can cause large scale crop failure, famine and food insecurity (Limsakul, 2019), leading to prices spikes (Noy, 2009; Ubilava, 2017a). Fourthly, hazardous ENSO-triggered weather extremes damage the storage conditions, transport infrastructure and international logistics, thereby lead to increased commodity prices (Ubilava, 2013). Finally, ENSO-caused weather condition affects grain prices through substitution of related commodities (Ubilava and Holt, 2013). However, this effect could be clouded based on the geographical distribution of the countries and the teleconnections strength for the different regions (Brunner, 2002).

While the earlier mentioned discussion of the numerous channels in which ENSO events could impact commodity price movements, further work is required because there is mounting evidence to suggest the impact of ENSO on agricultural prices is not adequately modelled by a linear model (Ubilava and Holt, 2013). In this study, we aim to contribute to the extant literature by investigating the possible asymmetric relationship of the two extreme phases, El Niño and La Niña, to agricultural commodity price movements. We adopt this approach as ENSO itself is characterised by asymmetric cyclical variations and turbulent periods (Hall *et al*., 2001; Ubilava and Helmers, 2013). El Niño SST anomalies tend to be larger than cold anomalies, as such the El Niño magnitude is on average larger than La Niñas, and the El Niño effects are stronger than La Niña (Hannachi *et al*., 2003; Kessler, 2002; Liang *et al*., 2017), which describes the intrinsic nonlinear features of ENSO events (An and Jin, 2004; Kohyama *et al*., 2018). Secondly, the impacts of ENSO anomalies on climatic fluctuations in various regions of the world are also asymmetric (Ubilava, 2017a; Ubilava, 2017b). Specifically, in the El Niño and La Niña episodes, different regions would suffer from variable drought or flood challenges, which depends on the location and the strength of the teleconnections. Taking the United States as the example, the El Niño events typically indicate richer rains and floods in California, impaired tornadic activities in the Midwest part, increased precipitation in the south, warmer winters in the North-eastern regions and diminished hurricanes shocks along the East coast (Laosuthi and Selover, 2007). Moreover, the consequences of El Niño and La Niña events are not always similar (Cai *et al*., 2010; Ubilava, 2017b). Furthermore, the observed ENSO-teleconnection weather conditions are likely to be more pronounced during the ENSO extreme episodes than moderate episodes. The larger shocks are more pronounced on agricultural yields so that considerable deviations in the ENSO anomalies could induce the disproportionate magnitude changes in the crop prices (Ubilava, 2017b). Finally, the nonlinear linkage is closely related to the very nature of the production and distribution cycle. Distributers are able to dispose demand shocks by quickly reducing crop stocks. However, restocking can take some time. Therefore, it may result in asymmetric price dynamics (Holt and Craig, 2006). Given that El Niño and La Niña have different effects in the United States and grains are the storable agricultural commodities, we expect that the grains prices would have different responses to ENSO anomalies. Based on the above discussion, we can therefore conclude that adopting a nonlinear modelling framework would be appropriate to study the ENSO-related agricultural commodity price fluctuations (Ubilava and Holt, 2013; Ubilava, 2017a).

While extant studies have analysed the relation between ENSO and grain prices, very little has been done to understand how the extreme changes in climatic conditions affect grain prices. (Modarres and Ouarda, 2013). Appropriate modelling of the ENSO fluctuations has important implications for global and/or local agricultural production as well as agricultural commodity prices (Chu *et al.*, 2012; Peri, 2017). Because as the possible instability of the international agricultural markets The impact of extreme climatic conditions has an impact on agricultural prices, potentially causing them to fluctuate which can have implications for global food insecurity; an important concern for policymakers (Madramootoo and Fyles, 2012; Bellemare, 2015; Watson, 2017). The asymmetric ENSO-price transmission has been broadly assessed by employing point-value prices in nonlinear models. The point-value model is point estimation, which uses a single value such as the statistic mean of the prices to conduct estimation (e.g. Ubilava, 2012; 2013; Ubilava and Holt, 2013; Ubilava, 2017a). Unfortunately, the point-value series and model fail to catch the variations in information, because the data collected at a specific time point during a period is unable to record the interval information (Sun *et al.*, 2019) which can prove to be valuable. For example, consider a case where the seasonal value of ENSO indicator is 0.5 in the second quarter in 2016. However, the ENSO index values change from 0.05 to 0.99 from April to June. This wide range needs to be utilised to deliver more information for analysing the transmission between climate events and commodity prices. Time interval modelling framework is superior to conventional point value time series approaches. The major advantage lies in that it covers both the level information and volatility information such as the range between the boundaries, which makes the information set that is being utilised to be relatively richer than the traditional point-valued methods. In addition, the interval-valued series could avoid the unnecessary noises included in the higher-frequency point-valued data series (Sun *et al.*, 2018). The inappropriate frequency for commodity prices could generate a huge amount of data, but it puts the difficulties to discriminate information from noises. Constructing the interval format time series by collecting the minimum and maximum values of the variable for a specific period is an alternative method, to pick out the undesirable noises and attain useful information (Sun *et al.*, 2018).

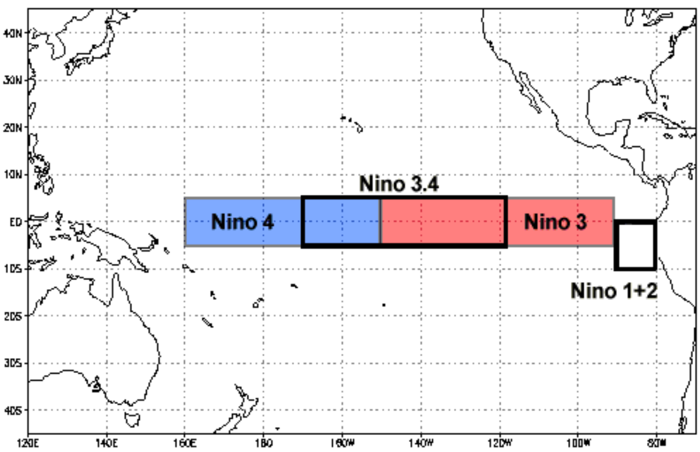
The upshot of the foregoing discussion is that the ENSO-price relations exhibit the following features: (1) ENSO-driven anomalies pass effects to commodity prices through several ways such as precipitation, temperature, pest damages, shipping and substitution effects, (2) the intrinsic nonlinear features of ENSO events lead to these effects on commodity prices to be nonlinear and asymmetric (3) though the ENSO characteristics of nonlinearity have been examined, the study considering the ENSO fluctuations and variations to prices is lacking till date, given that the volatility which generates a higher frequency of extreme events can pose more uncertainties in prices. In relation to (3), to our knowledge, past studies of ENSO events have not been examined in terms of both level and volatility effects on agricultural commodity prices. Motivated by these considerations, this paper adds to the literature in a crucial dimension by targeting to be more accurate about whether ENSO anomalies matter for agricultural commodity prices, and if so, to study such climatic effects. Previous research typically concentrates on linking ENSO anomalies to average yields and prices. However, as discussed, those methods potentially lose the 'range' information of the ENSO effects. Considering the nonlinear behaviour and higher volatility of ENSO indicators and agricultural commodity prices, this paper adopts recently developed TARI model as it allows for testing asymmetric adjustment ENSO-price relations. By employing novel TARI model to test for asymmetries in the transmission mechanism, we get more information contained in the interval data of ENSO proxies and commodity prices, and thus is expected to acquire more comprehensive inferences for understanding the asymmetries in the transmission of ENSO shocks.

This remainder of the paper is structured as follows: The next section outlines the ENSO-price transmission mechanism, and ENSO and anomalies measures. This is followed by a literature review section of the key studies for ENSO anomalies effects on commodity prices. Section 4 describes the novel econometric methods of TARI applied in the paper, followed by the description of the data used in the analysis. Data and the preliminary test results are presented in section 5. Section 6 provides the empirical results and discussions, and the final section concludes.

4.2 Transmission mechanism and ENSO measures

Wheat occupies more cropped acreage than other grains around the world and its production is sensitive to weather conditions (Ubilava, 2017b). In the United States, the ENSO mechanism impacts daily extreme precipitation during winters, as well as temperature and soil moisture over the southern high plains area, where hard red winter wheat is grown (Gershunov, 1998; Mauget *et al*., 2009; Montroy, 1997). During the peak El Niños, the excess precipitation anomalies in the Southwest and southern Great Plains lead to the positive soil moisture anomalies which remain until the next growing season. Conversely, the negative precipitation anomalies persist from boreal winter to spring, which decreases the soil moisture and drives the maximum temperatures up (Anderson *et al.*, 2017a; 2017b). ENSO significantly poses risks or benefits to the wheat yields through both water and temperature stresses (Solow *et al.*, 1998), and this supply shock could cause wheat prices fluctuations (Ubilava, 2017a). Soybean prices are expected to be influenced by ENSO through the direct weather changes as well as the effects on anchovy and tuna fishing (Keppenne, 1995). The El Niño-generated anomalous rainy weather throughout the midwestern United States forms an extreme wet condition in soybean's planting and growing periods, which hurts the harvest expectations and affect prices (Mo and Ghil, 1987). La Niña results in limited precipitation and the dry weather over the Midwest, leading to the poor harvest and a shortfall in production (Trenberth *et al.*, 1988). Aside of the ENSO-induced weather effects, the warm conditions over the equatorial Pacific during the El Niño years strongly affects the fishing conditions, pushing up the fish-protein substitutions demand of soybeans, while no negative effects of ENSO on fishing conditions are founded during La Niña years (Keppenne, 1995; Letson and McCullough, 2001). Consequently, ENSO-related weather shocks are likely to pass effects to soybean harvest and fish-protein substitute demand and, therefore, soybean prices. The United States is the global leader in corn-producing and -exporting, and the focus on corn-based ethanol production has enhanced the importance of corn (Tack and Ubilava, 2013). The U.S. corn belt agricultural production relies on favourable weather, and the climate fluctuations affect agricultural decisions and outcomes throughout the year (Motha and Baier, 2005). The far-reaching effects of the ENSO on the weather patterns pose the greatest risk on corn yields by affecting crop production conditions, including rainfall and temperature (Phillips *et al.*, 1999). La Niñas, with warmer and drier summer than neutral years in the corn belt, lead to the combination of high temperatures and low precipitations, which damages the moisture balance (Phillips *et al.*, 1999; Tack and Ubilava, 2013; Wannebo and Rosenzweig, 2003). El Niño years, on the other hand, tend to be cooler and has the excessive precipitation during the planting season across most of the corn belt states (Handler and Handler, 1983; Kellner and Niyogi, 2015). The variability in rainfall, temperature and soils result in the deviations in the farmers' decisions calendar (Haigh *et al.*, 2015), For instance, they delay the planting beyond the optimum time and therefore impair the corn yields (Handler and Handler, 1983), which, in turn, affects corn prices. Except for the rainfall and temperature, which are thought to be the primary common factors in these four crops yields, the ENSO-altered weather patterns correlate to the pest damage. It is harmful to crop production as well (Tack and Ubilava, 2013). Climate dominates the spatial and temporal distribution and proliferation of insects, weeds and pathogens because the temperature, light and water are the principal needs for their growth, development, migration and adaptation (Deutsch *et al.*, 2018; Porter *et al.*, 1991). Moreover, the pesticides that use to control and prevent pest outbreaks are characterised to be strongly influenced by the climate because the intensity and timing of rainfall affect the efficiency and persistence of the pesticides, and the temperature and light are proved to cause chemical alterations to impact the pesticides persistence (Rosenzweig *et al.*, 2001). ENSO-induced extreme weather events can increase the crop vulnerability to infection and pest infestations so that the changes in development and population rates for insects and germination rates for bacteria, fungi and nematodes are projected to extend to higher latitudes (Rosenzweig *et al.*, 2001; Tack and Ubilava, 2013). Consequently, farmers respond to climate shifts and change pest management strategies, planting dates and crop breeding. This affects crop production, which in turn influences the global grain supplies, passing on to food prices (Deutsch *et al.*, 2018). The production-side is not the sole channel through which the ENSO cycle could affect the supplies and prices of the agricultural commodities. For example, climatic variations can affect shipping (Ng *et al.*, 2018). Researchers notice climate changes pose transportation barriers (Chapman and Thornes, 2006; Jaroszweski *et al.*, 2010; McCarl and Hertel, 2018). Namely, the storage, transportation infrastructures and international logistics are damaged by the hazardous ENSO-triggered weather extremes, leading to increases in the costs of transport and storage and, subsequently, leading to the higher crop prices (Ubilava, 2013). As a sector, transportation is almost continuously subjected to the ENSO-induced climate hazards, which cause damages to the transport infrastructures and weakens the efficiency across all transportation modes (Jaroszweski *et al.*, 2010). The ENSO-related drought, high temperatures, flood and snowstorm, have been well documented, contributing to rising surface and air transportation costs through enhanced transportation facilities (Chapman and Thornes, 2006). For instance, the continuous cold days could trigger the growth of the maintenance costs for road and rail, which in turn raise the commodity price effectively paid by consumers (Jaroszweski *et al.*, 2010; Montalbano *et al.*, 2017; Renkow *et al.*, 2004; Ubilava, 2013).

The most cited ENSO indicators are the Southern Oscillation Index (SOI) and sea surface temperature (SST) indexes. Several studies have employed either or both of them (e.g. Brunner, 2002; Cashin *et al.*, 2017). SOI is the oldest indicator of the ENSO events, which describes the bimodal variation in sea-level barometric pressure between two stations at Tahiti (in the Pacific) and Darwin, Australia (on the Indian Ocean) (Allan *et al*., 1991). However, SOI only bases on the sea level pressure at two observation stations, which would cause the deviations by shorter-term fluctuations unrelated to ENSO. Besides, these two stations are located at the south of the equator, while ENSO is predominantly along the equator. Another indicator, the SST, is increasingly used since the ocean has been characterised to be an important player in ENSO (Bjerknes, 1969; Rasmusson and Carpenter, 1982; Wyrtki, 1985). Initially, certain regions measurements such as Niño 1, Niño 2, Niño 3 and Niño 4 regions are used. In April 1996, the *Niño 3.4* region which locates between and overlapping with Niño 3 and Niño 4 was identified as the most ENSO-representative and added to allow researchers gain a better understanding of the ENSO cycles (Bamston *et al*.,1997; Ubilava 2017b). The *Niño 3.4* index measures the sea surface temperature (SST) anomalies around the *Niño 3.4* region, which is a rectangular area of the Pacific Ocean between 5°North-5°South and 170-120°West (see **Figure 4.1**). The SST-based measure is a reliable indicator of ENSO occurrence (Tack and Unilava, 2015) and commonly utilised climate variables in the climate economics studies (Hsiang *et al*., 2011; Hsiang and Meng, 2015; Ubilava, 2017b).



Source: National Centres for Environmental Information, NOAA.

Figure 4.1: *Niño 3.4* region

There are three *Niño 3.4* index datasets provided by the National Oceanic and Atmospheric Administration (NOAA)[2]. **Table 4.1** shows the descriptions of these three *Niño 3.4* index datasets.

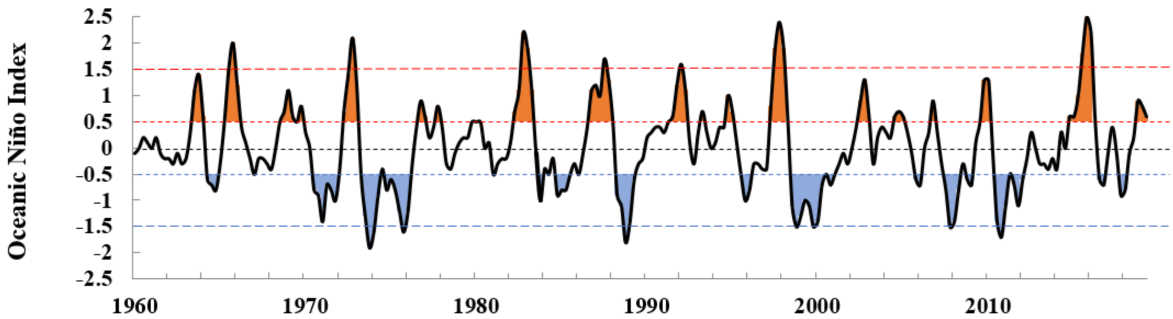
Table 4.1: Descriptions of three *Niño 3.4* index datasets

***Niño 3.4* index**	**Description**
OISST.v2 (1981-2010 base period)	Average of daily sea surface temperature values interpolated from weekly measures obtained from both satellites and buoys. And the anomaly for a given month is denoted by the deviation in this particular month from the average historic Niño *3.4* values relative to the 1981-2010 base period
ERSST.v5 (1981-2010 base period)	ERSST only bases on the in situ (ship and buoy) observations
ERSST.v5 (centred base period)	In removing the warming trend, the centred base period is updated to calculate the anomalies for successive 5-year periods in the historical value

The better known and popular applied *Niño 3.4* index, depicting ENSO events, is derived from the daily 1/4° Optimally Interpolated SST (OISST.v2) dataset, which is reported from January 1982 and updated on a weekly and monthly basis. The OISST-based measure is an average of daily sea surface temperature values interpolated from weekly measures obtained from both satellites and buoys. The anomaly for a given month is denoted by the deviation in this particular month from the average historic *Niño 3.4* values relative to the 1981-2010 base period. Another similar but different *Niño 3.4* index is derived from the monthly 2 Extended Reconstruction SST (ERSST.v5) dataset. To avoid satellite biases, the ERSST only bases on the in situ (ship and buoy) observations (Reynolds *et al*., 2007). Similar to the OISST index, the ERSST-based *Niño 3.4* uses the fixed 30-year base period (1981-2010) to calculate the anomalies as well. However, the significant global warming trends in the *Niño 3.4* region from 1950 onwards criticise the single fixed 30-year base period (1981-2010). This fixed base period used to define El Niño and La Niña episodes increasingly incorporate the long-term trends which fail to capture the interannual ENSO variability. In removing the warming trend, the centred 30-year base period is updated to calculate the anomalies for successive 5-year periods in the historical value, to ensure the El Niño and La Niña events will be defined by the contemporary climatology rather than future climatology.

[2] Source: https://www.cpc.ncep.noaa.gov/data/indices/

The Oceanic Niño Index (ONI) is defined as three-month running mean values of SST departures from average in the *Niño 3.4* region, which is an internationally accepted indicator to define the state of the ENSO cycle (Kousky and Higgins, 2007). According to the NOAA operational definitions for El Niño and La Niña episodes, the El Niño condition is characterised by the positive ONI values equal or higher than +0.5°C, and the La Niña episode is characterised by the negative ONI values equal or lower than -0.5°C. Otherwise, when the values of the ONI fall into the interval [-0.5°C, +0.5°C], a neutral phase is assumed (Royce *et al.*, 2011; Ubilava, 2017b). The results of the phases classification applied to the ONI data from NOAA are shown in **Figure 4.2**.



Note: This figure shows the warm and cold anomalies. Values exceeding thresholds of +0.5°C and -0.5°C are stippled to indicate El Niño and La Niña episodes, respectively.

Figure 4.2: Time series plots of the ONI using data from NOAA

4.3 Literature review

In this section, we review the studies that analyse the relation between ENSO anomalies and agricultural commodity prices through the supply (production, transportation) and demand channels.

Keppenne (1995) examines how soybean futures contracts traded on the Chicago Mercantile Exchange are affected by ENSO conditions by applying the multichannel singular spectrum analysis (M-SSA) approach. Applying the M-SSA method with a time window of 48-month on the ENSO indicators and soybean prices, he identifies an appreciable coherence between ENSO and soybean prices at the 48-month cycle that construed as an ENSO signal. Moreover, he finds that soybean futures prices are more responsive to the La Niña events than to El Niño events. This can be explained partly by the fact that La Niña-induced droughts in the U.S. Midwest cover large soybean producing fields, leading to the reduced supply and increased prices. In a related study, Letson and McCullough (2001) revisit the ENSO-soybean prices relations to seek to characterise the robustness of this linkage with the traditional spectral analysis to identify the periodic ENSO signals, and determine whether such climate-price connections have implications for commodity traders and government investment for climate prediction capability. In contrast to Keppenne's (1995) work, they argue the effects of ENSO events on soybean future prices should be channelled through the soybean supply and demand shocks, which are triggers for soybean cash prices; so, soybean cash price acts as a signal. Employing monthly observations spanning back to 1950, they corroborate the findings of Keppenne (1995) but notice only a 12-month cycle that corresponds to the frequency of ENSO events. Besides, they evaluate the Granger causality between soybean cash prices and ENSO phenomenon, and recognise that ENSO does not cause soybean prices, and vice versa. Curtis *et al.* (2002), investigate the impacts of ENSO phases on wheat prices fluctuations. Algieri (2014) adopts a vector error correction model (VECM) to quantify the impact of ENSO on wheat prices. This is done by using a mix of main drivers that contribute to wheat price movements. This mix is distinguished into four groups, one of which is a weather variable used to represent the climate condition effects. Monthly observations of the U.S. No. 1 hard red winter export prices, El Niño region 3.4 sea surface temperature (SST) anomalies index and Southern Oscillation Index (SOI) are tested over the sample period 1980-2012. He finds that adverse weather conditions caused by La Niña adversely impact on wheat production and thereby raise wheat prices.

Selecting the State of Ceará as the representative of the Brazilian semi-arid region, Chimeli *et al.* (2008) utilise the climate information to study the climate uncertainty on the rainfed corn market in the state. Using corn production and price data and a semi-parametric algorithm regression, they forecast quantity and prices in the Brazilian local corn market. The results provide encouraging evidence of an inverse relation between El Niño and corn yields, and a positive relation between SST anomalies and corn prices. Brunner (2002) examined the ENSO effects on a group of primary commodity prices. He employs 30 non-oil primary commodity price indices, consumer price index and real GDP to examine the impact of ENSO. By including the continuous time series indicators of ENSO intensity (instead of using a dummy variable to designate the ENSO years) in a vector autoregression (VAR) model, they find ENSO appears to account for around 20% of real commodity price fluctuations. This result indicates that the ENSO cycle has a considerable explanatory power for real commodity price volatilities, in particular real food prices. In the same vein, Laosuthi and Selover (2007) conduct the analysis for 22 individual nations, especially upon the developing countries which are most susceptible to ENSO events. This was tested by employing SOI as the indicator of the magnitude of ENSO events in the Granger causality framework. They find a weaker synchronisation between ENSO events and real GDP growth, as well as consumer price inflation; but robust evidence of ENSO effects on corn prices and coconuts, palm oil, rice and sorghum prices, while no significant influences on other commodity prices.

Ubilava (2012; 2013; 2017a; 2017b) makes a significant contribution in this field by publishing a series of studies on analysing the impact of ENSO events on commodity prices. For example, highlighting the susceptibility of coffee production to climate anomalies, Ubilava (2012) employs monthly price data from four coffee types: Columbian Mild Arabica, Other Mild Arabica, Brazilian and other natural Arabicas, and Robustas. Using a smooth transition autoregression (STAR) of four coffee variety prices, he concludes the ENSO events affect coffee prices and the ENSO-associated asymmetries have existed in coffee prices: El Niño positively affects the Robustas prices but negatively impact Arabicas prices; while the opposite is true during La Niña periods. In another pertinent work, Ubilava and Holt (2013) assesses the ENSO effects on market dynamics of major world vegetable oil prices and investigate potential asymmetry in vegetable oil prices. They first apply the STAR model to analyse the potential for nonlinearity in ENSO cycle and vegetable oil prices; then the smooth transition vector error correction (STVEC) model of Rothman *et al.* (2001), which is a multivariate version of the STAR framework, is employed to model a system of interrelated vegetable oil prices, covering the period between January 1972 to December 2010. Consistent with Ubilava's (2012) work, the results show self-exciting type nonlinearity in ENSO anomalies with the STAR model. Besides, these nonlinearities trigger the asymmetries in the world vegetable oil prices, which indicates that the vegetable oil production in different regions of the world varies considerably to the ENSO regimes. Therefore, the world vegetable oil prices respond differently to the ENSO phases. Both of these studies allowing for a continuum of switching points between the regimes, which are essential when discussing potential heterogeneous agents' behaviour. Ubilava (2013) revisits the fishmeal-soya-bean meal price ratio and analyses it in conjunction with the ENSO anomalies. The study applies a STAR modelling framework and utilises a sample of monthly observations over the period of 1982-2012 to address the regime-dependent behaviour in the monthly fishmeal-soybean meal price ratio dynamics. He finds evidence of asymmetry. Besides, he confirms findings of Keppenne (1995) that La Niña events are responsible for the fishmeal-soybean meal price ratio deviations because of the associated droughts in the soybean producing regions, which have a greater impact on soybean meal prices.

More recently, using more than three decades of monthly data, Ubilava (2017a) employs a vector smooth transition autoregression (VSTAR) approach, a particular kind of nonlinear multivariate framework, to quantify the ENSO-caused asymmetric price transmission in the world wheat markets. In so doing, this study examines the linkage between ENSO-associated wheat yields shocks and the subsequent price dynamics. Investigating the effects of El Niño and La Niña on world wheat prices separately, Ubilava (2017a) indicates the wheat prices are affected by the climate conditions and reports an ENSO-related regime dependency in the price fluctuations. This suggests the wheat prices respond differently to the two extreme ENSO phases. He finds that wheat prices tend to drop after El Niño events and rise following La Niña shocks, and with more persistent price responses during La Niña conditions than El Niño condition. To the extent wheat is a storable crop and this is consistent with the economics of storage. La Niña negatively affects wheat production, which can deplete the international grain reserves. The prices would increase dramatically in such a low-inventory regime (Algieri, 2014). These findings are in common with the conclusions of Iizumi *et al.* (2014), who report the differential prices performance within two extreme phases of ENSO through global production effect perspective. In a more comprehensive study, Ubilava (2017b) attempts to estimate the impact of ENSO climate anomalies across an extensive list of primary commodity prices over the period 1980-2016. The smooth transition models could capture the transition between regimes by allowing for a continuum of points or thresholds. The time-varying smooth transition autoregressive (TV-STAR) model is a generalised framework which considers the structural change could be gradual rather than abrupt. The ENSO-price relation is prior unknown and these relations could vary across commodities. Therefore, TV-STAR model has been wildly used in examining commodity prices (Balagtas and Holt, 2009; Holt and Craig, 2006; Hood and Dorfman, 2015). Employing the TV-STAR modelling framework of Lundbergh *et al.* (2003), he notes that the ENSO events affect selected prices depend largely on the type of commodities (some vegetable oils and protein meals respond most robustly to ENSO anomalies, while no evidence is revealing the SST effects on cereal grains prices). However, the findings of no effects on cereal grains from Ubilava (2017b) differ from Chimeli *et al.* (2008) who prove the effects of ENSO anomalies on Brazilian corn prices. The possible explanations refer to the limited exposure of the temperate area to ENSO anomalies plus the north-south diversification of the cereal grains. Because crop production is diversified in different regions, losses in one region could be more or less offset by another region (Lybbert *et al*., 2014). Besides, the resultant buffer constructed by intra-annual supply responses and global trade serves as another reason. This mixed picture is also reinforced by Iizumi *et al*. (2014), who collected the differences in averaged yield anomaly between El Niño (La Niña) years and neutral years, illustrating the overall impacts of ENSO extreme episodes on global yields are uncertain. They also highlight the various reactions of the crop yields during El Niño and La Niña years, and the grain price variations across export regions.

On balance, the extant literature tends to favour the ENSO role in uncovering asymmetric commodity price dynamics. However, there seems to be some mixed evidence about whether the ENSO anomalies would affect cereal grains prices. In previous studies, STAR type models are commonly employed. However, the STAR type models are based on the gradual transition between different regimes, which are unable to conduct regime-dependent modelling. As discussed in section 4.2, the El Niño condition is characterised by the positive ONI values equal to or higher than +0.5°C, and the La Niña episode is characterised by the negative ONI values equal to or lower than -0.5°C. Otherwise, when the values of the ONI fall into the interval [-0.5°C, +0.5°C], a neutral phase is assumed. In this way, we have the El Niño regime and the La Niña regime. The STAR type models conduct analysis by moving from the El Niño regime to the La Niña regime gradually, while there is a neutral phase between them. The neutral phase is the normal climate condition, which cannot be recognised as El Niño or La Niña. The regime-dependent modelling should be considered given the STAR type models fail to characterise the El Niño regime and La Niña regime. According to Ubilava (2013) and Ubilava (2017a), regime-dependent modelling has emerged as a tool to facilitate improved predictability of climate anomalies. They suggest that the regime-dependent models could better quantify the relationship between climate anomalies and commodity prices; and possibly, improve the predictability of commodity prices. TARI model is employed because it allows for conducting the regime-dependent analysis. In addition, as discussed earlier, the recently introduced interval-based TARI procedures are superior to the point-based STAR and TV-STAR models by allowing us to produce more efficient parameter estimates and statistical inferences for the dynamic ENSO-price relations. Moreover, we can exploit the variability range of climate anomalies on agricultural prices. This will allow us to trace the effects of extreme climate conditions on grain prices. This aspect of causality has not been analysed in the literature so far.

4.4 Threshold autoregressive interval framework

In this section, we begin by providing a brief description of the threshold autoregressive interval (TARI) models proposed by Sun *et al*. (2018). Then we move to introduce the TARIX model, which is the extension of TARI that allows for including exogenous explanatory interval variables. The TARIX model that employed to test the ENSO-price relationship will be described in the last part.

The TARI model can be described as follows:

$$Y_t = \begin{cases} \alpha_{01} + \alpha_{11} I_0 + \beta_{11} Y_{t-1} + \cdots + \beta_{p1} Y_{t-p} + \varepsilon_t, q_t \leq \gamma \\ \alpha_{02} + \alpha_{12} I_0 + \beta_{12} Y_{t-1} + \cdots + \beta_{p2} Y_{t-p} + \varepsilon_t, q_t > \gamma \end{cases} \tag{4.1}$$

where $\{Y_t = [Y_{L,t}, Y_{R,t}]\}$ indicates a stochastic interval procedure with the lower bound $Y_{L,t}$ and the higher bound $Y_{R,t}$. β_{ji} are the unknown scalar-valued coefficients with j=1,…, p and i=1, 2. $I_0 = [-\frac{1}{2}, \frac{1}{2}]$ is the unit interval so that $\alpha_{0i} + \alpha_{1i} I_0 = [\alpha_{0i} - \frac{1}{2}\alpha_{1i}, \alpha_{0i} + \frac{1}{2}\alpha_{1i}]$ is a constant interval intercept. q_t is the threshold variable which could be endogenous or exogenous and γ denotes an unknown scalar-valued threshold indicator. $\varepsilon_t = [\varepsilon_{L,t}, \varepsilon_{R,t}]$ is the interval innovation. Sun *et al*. (2018) assume the interval innovation item ε_t as an interval martingale difference sequence (IMDS) with respect to the information set I_{t-1} so that $\mathbb{E}(\varepsilon_t | I_{t-1}) = [0, 0]$ almost surely.

Noting that Y on a probability space (Ω, F, P) is a calculable mapping $Y: \Omega \to I_{\mathbb{R}}$. Here, $I_{\mathbb{R}}$ indicates the space of closed sets of sequenced numbers in $\mathbb{R}$, as $Y(\omega) = [Y_L(\omega), Y_R(\omega)]$, where $Y_L(\omega)$ and $Y_R(\omega) \in \mathbb{R}$ for $\omega \in \Omega$. Particularly, $Y(\omega)$ is a group of ordered real-valued numbers, fluctuating continuously from $Y_L(\omega)$ to $Y_R(\omega)$, for each $\omega \in \Omega$. Following Kaucher (1980), the left bound of an interval-valued time series (ITS) could be larger than the right bound, and this extended interval improves the traditional bivariate internal approach (Sun *et al*., 2018). The regular intervals ($Y_{L,t} \leq Y_{R,t}$) are included in this definition as well. Alternatively, the equivalent expression of equation (4.1) could be written as

$$Y_t = X_t'\beta_1 I(q_t \le \gamma) + X_t'\beta_2 I(q_t > \gamma) + \varepsilon_t \tag{4.2}$$

where $X_t = ([1,1], \left[-\frac{1}{2}, \frac{1}{2}\right], Y_{t-1}, \dots, Y_{t-p})'$, $\beta_i = (\alpha_{0i}, \alpha_{1i}, \beta_{1i}, \beta_{2i}, \dots, \beta_{pi})' \in \mathbb{R}^{p+2}$, i=1, 2.

To utilise interval information to estimate the parameters and whether these coefficients are significantly different, Sun *et al.* (2018) define the minimum D_K-distance estimator $\hat{\theta}$ in their model. Let $\delta = \beta_2 - \beta_1$ represent the threshold effect. The idea of their solution is letting $\delta \to 0$ as $T \to \infty$. The equivalent expression of the equation (4.1) is

$$Y_t = X_t'\beta + X_t(\gamma)'\delta + \varepsilon_t \tag{4.3}$$

Changing the equation (4.3) and deriving

$$Y_t = Z_t(\gamma)'\theta + \varepsilon_t \tag{4.4}$$

where $X_t(\gamma) = X_t I(q_t > \gamma), Z_t(\gamma) = \left(X_t', X_t'(\gamma)\right)', \theta = (\beta', \delta')$ and $\beta = \beta_1$ in equation (4.2).

The main concern is whether the nonlinear term $X_t(\gamma)$ in the regression, which is, whether $\delta = 0$. Applying a local-to-null reparameterization, the distributional theory will be facilitated as $\delta = \mathrm{c}/\sqrt{T}$. As such, the testable null hypothesis is $H_0\colon c = 0$ and the alternative hypothesis $H_A\colon c \ne 0$. Note that this test is nonstandard since γ is not identified under $H_0\colon c = 0$.

Before taking the asymmetry test, the first step is estimating parameters. Under $H_0\colon c = 0$, the model changes to $Y_t = X_t'\beta + \varepsilon_t$. The estimator of β_1 is acquired by minimising

$$Q_T(\theta) = \frac{1}{T-k}\sum_{t=1}^{T} D_p^2(Y_t - X_t'\beta) \tag{4.5}$$

where $D_p(.)$ calculates the distance between intervals. When the γ is known, θ could be estimated by applying the minimum D_K-distance approach, which aims to minimise the sum of squared residuals below

$$Q_T(\theta) = \frac{1}{T-k} \sum_{t=1}^{T} D_p^2(Y_t - Z_t'(\gamma)(\theta) \tag{4.6}$$

where $D_p(.)$ calculated the distance between the observed interval Y_t and the fitted interval $Z_t'(\gamma)\theta$. When the γ is unknown, two steps estimations are needed to get the estimators. The first step is minimizing the sum of squared residuals of TARI model in equation (4.6). The second step gets the estimator of γ by minimizing the $Q_T(\theta)$, which is

$$\hat{\gamma} = arg\ min_\theta Q_T(\theta)|_{\theta=\hat{\theta}(\gamma)}$$

Then the estimator of θ is acquired as

$$\hat{\theta} = \hat{\theta}(\hat{\gamma}) = (\hat{\beta}(\hat{\gamma})', \hat{\delta}(\hat{\gamma}))$$

Then, the sum of squared distance between the fitted interval-valued sets and interval-valued observations could be measured by following the D_K metric introduced by Körner (1997) and Körner and Näther (2002). The D_K metric for the interval Y_t and the fitted interval $Z_t'(\gamma)\theta$ is given by

$$\begin{aligned} D_K^2(Y_t, Z_t'(\gamma)\theta)) &= \int_{(u,v)\in S^0} [s_{Y_t}(u) - s_{Z_t'(\gamma)\theta}(u)][\, s_{Y_t}(v) - s_{Z_t'(\gamma)\theta}(v) dK(u,v), \\ &= \langle s_{Y_t - Z_t'(\gamma)\theta}, s_{Y_t - Z_t'(\gamma)\theta} \rangle_K \\ &= ||Y_t - \ Z_t'(\gamma)\theta||_K^2 = ||\varepsilon_t||_K^2 \end{aligned} \tag{4.7}$$

Where the unit space $S^0 = \{u \in \mathbb{R}^1, |u| = 1\} = \{1, -1\}, K(u,v)$ is a symmetric positive definite weighing function on S^0 to ensure that $D_K^2(Y_t, Z_t'(\gamma)\theta))$ is a metric for extended intervals, and $\langle \cdot, \ \cdot \rangle$ indicates the inner product in S^0 in terms of kernel $K(u,v)$. And the support function is

$$s_A(u) = \begin{cases} sup_{a\in A}\{u \cdot a | u \in S^0\}, if\ \ A_L \le A_R, \\ sup_{a\in A}\{u \cdot a | u \in S^0\}, if\ \ A_R \le A_L, \end{cases}$$

Which follows the $s_A(u) = A_R$ when $u = 1$, while $s_A(u) = -A_L$ when $u = -1$.

Under $H_0: c = 0$, the minimum D_K estimator $\tilde{\beta}$ for β is obtained, that is $\tilde{\beta} = (\sum_{t=1}^{T} \langle s_{X_t}, s'_{X_t} \rangle_K)^{-1} \sum_{t=1}^{T} \langle s_{X_t}, s_{Y_t} \rangle_K$ and $\tilde{\sigma}^2 = \sum_{t=1}^{T} ||\tilde{\varepsilon_t}||_K^2/(n-k)$, where $\tilde{\varepsilon_t} = Y_t - X_t'\tilde{\beta}$. And under $H_A: c \neq 0$, the parameter estimator is given by

$$\hat{\theta} = (\textstyle\sum_{t=1}^{T} \langle s_{Z(\gamma)}, s'_{Z_t(\gamma)} \rangle_K)^{-1} \left(\sum_{t=1}^{T} \langle s_{Z_t(\gamma)}, s_{Y_t} \rangle_K\right) \tag{4.8}$$

Last, the interval-based Wald test for testing the asymmetry with a known γ is conducted by employing a heteroscedasticity-robust Wald test expressed as

$$W_t = T\hat{\theta}' R (R \hat{V}_T^* R)^{-1} R' \hat{\theta}$$

Where $R = (\mathbf{0} \quad I_{p+2})'$ is the selector matrix and $\hat{V}_T^* = \hat{M}_T^{-1}(\hat{\theta}) \hat{V}_T(\hat{\theta}) \hat{M}_T^{-1}(\hat{\theta})$, $\hat{V}_T(\hat{\theta}) = \frac{4}{T} \sum_{t=1}^{T} \hat{u}_t \hat{u}'_t$, $\hat{M}_T(\hat{\theta}) = \sum_{t=1}^{T} \langle s_{Z(\gamma)}, s'_{Z_t(\gamma)} \rangle_K$, $\hat{u}_t = \langle s_{Z_t(\gamma)}, s_{\hat{\varepsilon}_t} \rangle_K$.

By incorporating exogenous explanatory interval variables, Sun *et al.* (2018) extend their TARI model to a TARIX model and the generalised form could be expressed as

$$Y_t = [\alpha_{01} + \beta_{01} I_0 + \sum_{j=1}^{p} \beta_{j1} Y_{t-j} + \sum_{l=0}^{s} \delta_{l1}^{s} A_{t-j}] I(q_t \leq \gamma) + [\alpha_{02} + \beta_{02} I_0 +$$

$$\textstyle\sum_{j=1}^{p} \beta_{j2} Y_{t-j} + \sum_{l=0}^{s} \delta_{l2}^{s} A_{t-j}] I(q_t > \gamma) + u_t \tag{4.9}$$

where $A_t = (A_{1t}, \dots, A_{qt})'$ is the exogenous strictly stationary interval vector procedure and $\delta_{ji} = (\delta_{l1i}, \dots, \delta_{lqi})'$, $l =$ 0,…, s and i=1, 2, which denotes an unknown point-valued parameter vector. The asymptotic theory for the TARIX model is similar to the TARI model (Sun *et al.*, 2018).

In this study, we expect to find in ENSO-commodity price relations which may be asymmetric to the warm and cold shocks from the climate conditions. Furthermore, the variability in ENSO can have important effects on agricultural commodity prices variability as emphasised by Madramootoo and Fyles (2012). The upshot is that we need to consider climatic extremes as well when conducting the tests for asymmetry (Ubilava, 2013). To completely determine the

ENSO effects, the TARIX model is an effective procedure to test for the presence of the asymmetry between weather and prices.

Focusing on testing the relationship between cereal grain prices and the two ENSO extreme phases, El Niño and La Niña, respectively. The two-regime TARIX model in this study is constructed as follows

$$\Delta R_t = \alpha_0 + \delta_0 I_0 + \delta_1 \Delta R_{t-1} + \delta_2 E_{t-1} I(O_{t-1} \leq -0.5) + \delta_3 E_{t-1} I(O_{t-1} \geq 0.5) + \nu_t \tag{4.10}$$

Where $R_t = [R_{L,t}, R_{R,t}]$ is the quarterly logarithmic interval-valued agricultural commodity prices and $E_t = [E_{L,t}, E_{R,t}]$ is the logarithmic interval-valued ENSO index (SST anomalies). O_{t-1} is the seasonal point-valued Oceanic Niño Index (ONI), which is the National Oceanic and Atmospheric Administration (NOAA)'s primary indicator to monitor the El Niño and La Niña conditions and rank the strength of the ENSO. In our model, ONI serves as the threshold parameter to recognise the climate pattern of the ENSO. If the $O_t \leq -0.5$, which is the indicative of La Niña conditions exist and the east-central tropical Pacific is cooler than usual. Whereas the $O_t \geq 0.5$ associated with El Niño conditions and the region is significantly warmer than usual (Kousky and Higgins, 2007); and if the value of ONI falls into the interval $[-0.5, 0.5]$ then it denotes a neutral episode (Royce *et al.*, 2011). $I_0 = [-\frac{1}{2}, \frac{1}{2}]$ is a unit interval and $\alpha_0 + \delta_0 I_0 = [\alpha_0 - \frac{1}{2}\delta_0, \alpha_0 + \frac{1}{2}\delta_0]$ is a constant interval intercept. Here, the α_0 and δ_0 measures for the constant mark-up in the trend and volatility, respectively. In equation (4.10), $v_t = [v_{L,t}, v_{R,t}]$ is an interval innovation. Following Sun et al. (2018) and assuming $\{v_t\}$ is an interval martingale difference sequence (IMDS) with respect to the information set I_{t-1}, that is $E(v_t | I_{t-1}) = [0,0]$ almost surely. δ_1, δ_2 and δ_3 are unknown parameters. δ_1 measures the lagged agricultural commodity prices effects. δ_2 evaluates the effects of La Niña conditions on export prices and δ_3 assesses the influences of El Niño on commodity price growth, respectively. Note that, the interval is divided into two regimes in response to the La Niña phase $O_t \leq -0.5$ and El Niño phase $O_t \geq 0.5$ to capture asymmetric features in both mean and range, respectively. Besides, as the entries of the ENSO index for La Niña events are negative and below -0.5, the negative estimated coefficients suggest that the climate changes have a positive impact on commodity prices under La Niña conditions.

Hypothesis I: La Niña and El Niño events would increase grains prices.
In light of the ENSO-price transmission mechanism explained in the above section, both El Niño and La Niña could affect prices through hurting the grains yield. Therefore, we would expect $\delta_2 < 0$ and $\delta_3 > 0$, which describes the La Niña and El Niño events would increase grains prices, respectively.

Hypothesis II: La Niña and El Niño do not asymmetrically affect grain prices.
Following Ubilava (2017a; 2017b), ENSO-price relations are characterised by asymmetric, which represents the grain prices adjustment in El Niño years would be different from the La Niña years. This type of asymmetry implies the following testable hypothesis, that is, $H_0: |\delta_2| = |\delta_3|$.

Indeed, we expect the asymmetric adjustment in grains prices described above bases on the assumption that ENSO extremes would push the prices, but the agricultural commodity prices would respond differently in the absolute magnitude.

4.5 Data and preliminary analysis

Following a series work from Ubilava (2012; 2013; 2017a; 2017b), the proxy variable for ENSO employed in this study is the *Niño 3.4* index, reported by the Climate Prediction Centre (CPC) at the National Oceanic and Atmospheric Administration (NOAA). As introduced above, three different *Niño 3.4* SST anomalies measures, which are OISST.v2 (1981-2010 base period), ERSST.v5 (1981-2010 base period) and ERSSTv5 (centred base period) are employed in the empirical analysis for the comparison. To assess the warm (El Niño) and cold (La Niña) of the ENSO cycle separately, the Oceanic Niño Index (ONI) has been selected to serve as the threshold to determine the El Niño and La Niña phases in this paper. The commodity prices of interest in this study are farm received prices of three U.S. major crops because the climatic impact on production is considered to be more direct. The farm received prices data are for the wheat, soybean and corn are obtained from the online publications of the National Agricultural Statistical Service (NASS) of the United States Department of Agriculture (USDA). These are cash prices and represent the sales from producers to first buyers, including all grades and qualities. Considering the inflation effects, the nominal spot and cash prices are deflated applying the U.S. producer price index (PPI) which reported by the U.S. Bureau of Labor

Statistics. All the prices used in this study are quoted in U.S. dollars, and hereafter the analysis of data is carried out on logarithm of real commodity prices unless otherwise stated.

All the data, including both ENSO indices and commodity prices introduced above, are monthly point-valued data. To investigate the pass-through of ENSO cycles to agricultural commodity prices, we utilize these monthly prices to construct interval-valued quarterly prices. Considering the ENSO influences on rainfall take more time, quarterly frequency data is chosen as it would be more likely to capture the ENSO effects (Hansen *et al*., 1998). Besides, climate variability reflects the climatic changes across seasons and years (Woli *et al*., 2015), making a quarterly interval-valued data series more appropriate. The quarterly interval-valued prices are formed by using the minimum and maximum monthly point-valued prices within a quarter. Thus, for each price series, the minimum and maximum monthly point-valued data form the lower and upper bounds, respectively. Due to the negative values existed in ENSO indices, the quarterly interval-valued ENSO variables are constructed in the same way but using the minimum and maximum monthly point-valued data without taking logarithms. In a given period, the interval-based observations enjoy the information gain by capturing the price trend as well as the volatility information (Sun *et al*., 2019).

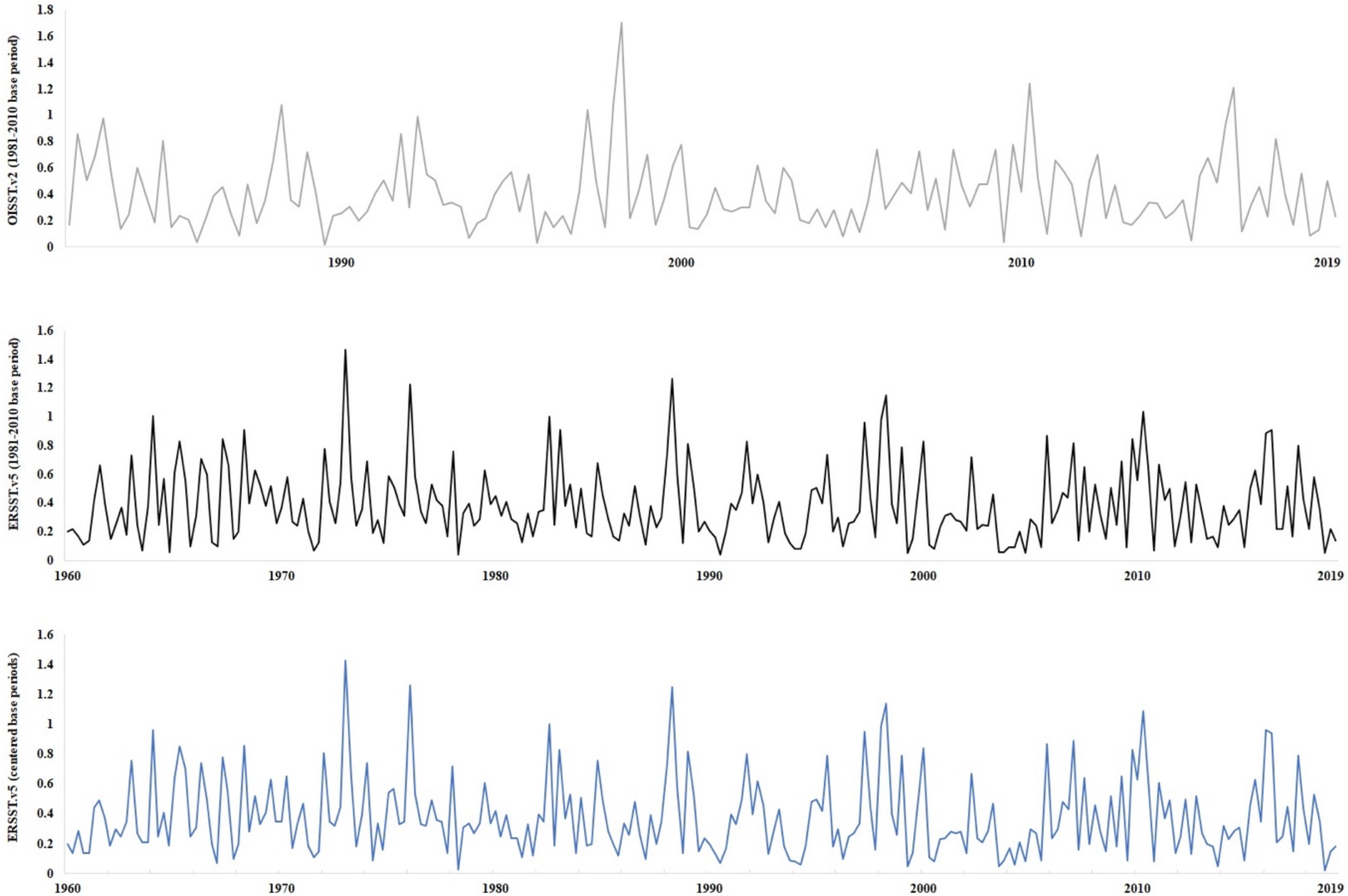
A complete list and detailed descriptions of ENSO indicators, ONI, along with the farm received commodity prices, are shown in **Table 4.2**.

Table 4.2: Description of the ENSO indicators, threshold variable and commodity prices

Variable		Description	Time range
ENSO indicators	OISST.v2	(1981-2010 base period) *Niño* 3.4 (5°North-5°South) (170-120°West)	1982:01-2019:06
	ERSST.v5	(1981-2010 base period) *Niño* 3.4 (5°North-5°South) (170-120°West)	1964:01-2019:06
	ERSST.v5	(centred base periods) *Niño* 3.4 (5ºNorth-5ºSouth) (170-120ºWest)	1964:01-2019:06
Threshold variable	Oceanic Niño Index	3-month running average in *Niño* 3.4 (5ºNorth-5ºSouth) (170-120ºWest)	1964:01-2019:06
Farm received prices	Wheat Soybean Corn	national-level season-average price received by farmers($/bu)	1964:01-2019:06

Note: This table lists the description and time range of the raw data collected from the Climate Prediction Centre (CPC) at the National Oceanic and Atmospheric Administration (NOAA) and National Agricultural Statistical Service (NASS) of the United States Department of Agriculture (USDA).

To give an intuitive sight of the interval-based data could contain more information than their representative point-valued processes, **Figure 4.3** shows the range between the lower and upper boundaries, which measures the points of extreme fluctuation occurring in the ENSO measures. The volatility is prominent, and the lower-upper interval could be extreme for selected quarters. We proceed to test whether such interval-valued time series could provide a contrasting case in comparison to point-valued observations, especially for the changing climate conditions.



Note: This figure reports the lower-upper interval ranges for three *Niño 3.4* SST anomalies measures from OISST.v2 (1981-2010 base period), ERSST.v5 (1981-2010 base period) and ERSSTv5 (centred base period) dataset.

Figure 4.3: Quarterly three ENSO indicators range

As a prelude to the TARIX estimation, we first determine the order of integration of the ENSO intensity measures and the prices series examined in the study. To this end, we employ the augmented Dickey-Fuller (ADF) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) unit root tests. According to the ADF test result, all ENSO indices reject the null hypothesis of a unit root, thus denoting that the ENSO indicators are integrated of order zero, or I (0). The test results for the farm received prices are mixed, implying the two bounds of interval-valued wheat prices are stationary I (0) while others are I (1). The KPSS test results give the same conclusion as the ADF test except for wheat prices. This study focus on the ADF test results but use the KPSS test results as the reference. Therefore, the subsequent TARI modelling is carried out on all first differenced commodity prices except for the wheat prices which are modelled in levels. **Table 4.3** summaries the unit root test rests on all variable.

4.6 Empirical results and discussion

To characterize the robustness of the estimated relations over alternative measures of the ENSO, as introduced in the previous data section, three different Niño 3.4 SST anomalies measures, which are OISST.v2 (1981-2010 base period), ERSST.v5 (1981-2010 base period) and ERSSTv5 (centred base period) are employed. Both the OISST.v2 and ERSST.v5 (1981-2010 base period) use the fixed 30-year base period (1981-2010) to calculate the SST anomalies. As discussed earlier, considering the single fixed 30-year base period (1981-2010) failed to incorporate the contemporary climatology, we repeat the TARIX regression again by replacing the SST anomalies index from ERSST.v5 (centred 30-year base period) dataset. **Table 4.4** displays the results for TARIX model of the ENSO events against the grain prices when different choices of ENSO proxies are used.

Table 4.3: Unit root test on variables

		ENSO indicator			Threshold variable	Farm received prices		
		OISST.v2 (1981-2010 base period)	ERSST.v5 (1981-2010 base period)	ERSST.v5 (centred base periods)	Oceanic Niño Index	Wheat	Soybean	Corn
ADF_L	Lower bound	-6.876***	-8.635***	-8.857***		-2.783*	-2.346	-1.446
	Upper bound	-5.740***	-6.752***	-6.935***		-3.066**	-2.269	-2.316
	Threshold				-6.951***			
ADF_Δ	Lower bound	/	/	/		-6.045***	-11.711***	-5.970***
	Upper bound	/	/	/		-13.402***	-12.173***	-7.219***
	Threshold				/			
$KPSS_L$	Lower bound	0.049	0.224	0.041		1.047***	1.173***	1.147***
	Upper bound	0.044	0.153	0.034		0.991***	1.133***	1.141***
	Threshold				0.035			
$KPSS_\Delta$	Lower bound	/	/	/		0.039	0.034	0.032
	Upper bound	/	/	/		0.033	0.044	0.029
	Threshold				/			

Note: This table presents the standard ADF and KPSS unit root tests results for three ENSO indicators and selected cereal grains farm received prices, based on the interval time series sample information. The ADF and KPSS unit root tests for the Oceanic Niño Index is based on the point time series sample information. ***, ** and * denote rejection of the null hypothesis of unit root process at the 1%, 5% and 10% significance level, respectively.

Table 4.4: Estimation results of interval-based regression for three cases

	ENSO-wheat prices			**ENSO-soybean prices**			**ENSO-corn prices**		
	OISST.v2 (1981-2010 base period)	ERSST.v5 (1981-2010 base period)	ERSST.v5 (centred base periods)	OISST.v2 (1981-2010 base period)	ERSST.v5 (1981-2010 base period)	ERSST.v5 (centred base periods)	OISST.v2 (1981-2010 base period)	ERSST.v5 (1981-2010 base period)	ERSST.v5 (centred base periods)
$\boldsymbol{\alpha_0}$	0.1895***	0.1217***	0.1181***	-0.0122	-0.0119	-0.0133	-0.0238*	-0.0200**	-0.0210**
$\boldsymbol{\delta_0}$	0.0184***	0.0115*	0.0108*	-0.0008	-0.0047	-0.0045	0.0018	-0.0004	0.0002
$\boldsymbol{\delta_1}$	0.8078***	0.8878***	0.8915***	-0.2771	-0.2165	-0.2149*	-0.1665*	-0.1485**	-0.1483**
$\boldsymbol{\delta_2}$	**-0.0308***	**-0.0262***	**-0.0247**	**-0.012**	**0.0024**	**0.0006**	**-0.0436****	**-0.0264****	**-0.0309****
$\boldsymbol{\delta_3}$	**-0.0097**	**-0.0044**	**-0.0028**	**0.0161***	**0.0333****	**0.0335****	**0.0265****	**0.0300*****	**0.0294*****
$\boldsymbol{Ho{:}\delta_2 = \delta_3}$	**0.3381**	**1.1872**	**1.0397**	**1.8129**	**1.7895**	**1.8832**	**8.2131*****	**7.9806*****	**8.1568*****

Note: This table reports the estimated results of the TARIX regression on *Niño 3.4* SST anomalies measures from OISST.v2 (1981-2010 base period), ERSST.v5 (1981-2010 base period) and ERSSTv5 (centred base period) dataset. The last row of results reports the asymmetry test statistics. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

In **Table 4.4**, we tabulate the estimated results of the relationship between three interval-valued ENSO indicators and interval-valued commodity prices. Of the agricultural commodities under consideration, in general, the farm received grain prices are affected by ENSO cycles. In terms of wheat, the estimates of the $\boldsymbol{\delta_1}$ are significant at 1% level, which denotes the autocorrelation. As the entries of the ENSO index for La Niña events is negative and below -0.5, the negative estimated coefficients suggest that the climate changes have a positive impact on commodity prices under La Niña conditions. The estimator $\boldsymbol{\delta_2}$ is negative and significant at 10% level, implying the La Niña shocks, or negative deviations of the SST, tend to affect wheat prices positively. However, no observed relations between La Niña events and wheat farm prices are obtained when we choose the updated ERSST.v5 (centred 30-year base period) SST anomalies measures. We observe that El Niño would not affect wheat prices, confirm by the insignificant $\boldsymbol{\delta_3}$. For U.S. soybean cases, only the estimator of $\boldsymbol{\delta_3}$ is significantly positive at 5% significance level (10% significant for OISST.v2 ENSO measure case), which implies the El Niño phenomenon has a positive impact on prices and the La Niña events have no influences. Possible reasons for the wheat and soybean prices only respond to either La Niña or El Niño will be discussed later.

In the case of U.S. corn price, the estimates of the $\boldsymbol{\delta_1}$, $\boldsymbol{\delta_2}$ and $\boldsymbol{\delta_3}$ are found to be significant, indicating the corn prices are autocorrelated and respond to both the El Niño and La Niña phenomenon. The estimated coefficient $\boldsymbol{\delta_1}$ is significant at 5% significance level (10% significant for OISST.v2 ENSO measure case), implying autocorrelation. Besides, the estimates of the $\boldsymbol{\delta_2}$ and $\boldsymbol{\delta_3}$ are significant at 5% and 1% significance level, respectively, denoting both La Niña and El Niño affects corn price. The negative sign of the estimator $\boldsymbol{\delta_2}$ is predicted because the La Niña-caused high temperatures and low precipitations along the U.S. corn belt could hurt the moisture balance and then production (Phillips *et al*., 1999; Wannebo and Rosenzweig, 2003; Tack and Ubilava, 2013), as such an increase in corn prices is expected during La Niña episodes. During El Niño years, the excessive rainfalls lead to the delay of the corn planting and therefore impair the corn yields (Handler and Handler, 1983), and drive the prices. The positive sign of $\boldsymbol{\delta_3}$ meets the expectations of the positive effects of El Niño on corn prices. Another noteworthy result is the null hypothesis $\boldsymbol{H_0}: \boldsymbol{\delta_2} = \boldsymbol{\delta_3}$ of the asymmetric test has been rejected for corn case, which confirms that the corn prices respond asymmetrically to La Niña and El Niño anomalies. This asymmetric response is related to the differential crop yields within two extreme phases of ENSO (Iizumi *et al*., 2014). Our result departs from Hansen *et al*. (1998) and Ubilava (2017b) who fail to find evidence of ENSO effects on cereal grain prices.

To provide an intuitive comparison**, Table 4.5** summarises the estimated results we obtained from using different ENSO proxies.

Table 4.5. Estimation results comparison

	ENSO indicator		
	OISST.v2 (1981-2010 base period)	ERSST.v5 (1981-2010 base period)	ERSST.v5 (centred base periods)
Wheat			
	L	**L**	
Soybean	**E**	**E**	**E**
Corn	**E**	**E**	**E**
	L	**L**	**L**

Note: This table compares the TARIX regressions of climate variability on selected cereal grain prices using different proxies for ENSO events. E and L denote the effects of El Niño and La Niña events, respectively.

As is clear from **Table 4.5**, when we use different ENSO indices, the results keep unchanged for soybean and corn cases. In other words, the soybean prices are only affected by El Niño condition when we use different ENSO indicators in estimation. While corn prices respond to both El Niño and La Niña events when using the ENSO indicators from different datasets. In the case of wheat, the empirical evidence regarding the impact of ENSO-induced weather shocks is mixed. Note that overall the El Niño events do not impact on farm received prices of wheat, which confirms the findings of Ubilava (2017a) that wheat prices are more pronounced during La Niña periods than El Niño periods. However, when we use the ENSO proxies from OISST.v2 and ERSST.v5 (1981-2010 base period) dataset, the La Niña-like conditions have an impact on wheat prices, causing them to increase. This result supports Ubilava (2017a) of where it has been explained by the fact that SST anomalies are based on a fixed 30-year base period (1981-2010), a period in which extreme La Niña realizations including 1988-1989 and 2007-2008 were found to trigger price spikes (Ubilava, 2017a). But the base period of the updated ERSST.v5 (centred 30-year base period) is shifted every 5 years to ensure the El Niño and La Niña events will be defined by the contemporary climatology. The extreme La Niña events exist in 1988-1989 and 2007-2008. Compared to the ERSST.v5 (1981-2010 base period) that uses the constant 1981-2010 base period, ERSST.v5 (centred 30-year base period) dataset incorporate the gentler La Niña events after 2008. The total effects of La Niña decrease. This may explain the result that La Niña does not significantly affect wheat prices when using ERSST.v5 (centred 30-year base period). The results of the ENSO-soybean price relation are unchanged regardless of the ENSO choice, which implies the positive correlation exists between the soybean prices and El Niño. El Niño impacts soybean prices either through the weather conditions or through its influences on substitution demand (Keppenne, 1995). For example, drier weather over the soybean plant area results in the poor harvest, which reduces the supply and raises the prices (Letson and McCullough, 2001). Besides, warm conditions associated with the El Niño events hurt the fishing industry by decreasing the harvests of anchovy and tuna, triggering the higher demand for the fish-protein substitutes for livestock feeding propose and then growing U.S. soybean trades (Hansen *et al*., 1998; Keppenne, 1995). During the La Niña years, we notice that the soybean prices do not respond as significantly to the climate anomalies as El Niño did. Perhaps, this lack of causality could be attributed to the fishing conditions over the equatorial Pacific are not negatively affected by the La Niña shocks (Keppenne, 1995). Results of this analysis do not support the hypothesis that both El Niño and La Niña shocks could affect the commodity prices simultaneously, for wheat and soybean. The lack of significant interaction is confirmed between El Niño and wheat prices, and the soybean prices are only responsive to El Niño events. These would seem to contradict the previous research (e.g. Hansen *et al*., 1998; Keppenne, 1995; Letson and McCullough, 2001; Peri, 2017) that presents evidence concluding that both El Niño and La Niña phases could improve the soybean prices. Hansen *et al*. (1998) and Keppenne (1995) have shown a 2-year lag price response and 48-month cycle correspond to La Niña shocks. A potential explanation for this apparent lack of interaction would be that a longer time period may be necessary for prices to respond to climate changes. What we find is that there is no short-term effect of prices to climate effects.

Table 4.5 also characterises the robustness of the ENSO-corn price relationship founded by Tack and Ubilava (2013) to alternative definitions of ENSO proxies employed in the analysis. Combing the estimation parameters results discussed above, we corroborate that corn prices respond asymmetrically to La Niña and El Niño anomalies. Specifically, price-makers adjust corn prices upwards in response to the warm and cool conditions, but in a slightly different rate. Intuitively, the considerable spatial climate effects have important implications for the supply, because the ENSO-driven extremes could simultaneously create large-scale crop losses across a wide production area. Although Phillips *et al*. (1999) point the spatial pattern of ENSO effects is not homogeneous for the U.S. corn belt, a reduction of the corn yields is established throughout the corn belt region when the El Niño hits the United States. In addition, this pattern holds during the La Niña period as well (Tack and Ubilava, 2013). A similar pattern of results is found in the study by Adams *et al*. (1999), who present evidence of the spatially aggregated effects which are negative for both El Niño and La Niña events. The contraction of corn production is a major reason for explaining the increased corn farmgate prices. Because La Niña and El Niño anomalies both will lead to the reduction in corn yields throughout the corn belt region in the United States. This study indicates that such an asymmetric pattern seems much more likely to be due to the corn yields adjustment nuances facing the La Niña and El Niño shocks. Our results are in sharp contrast with some of the studies that have been conducted into investigating the relationship between ENSO anomalies and cereal grain prices. Our results are in contrast to Ubilava (2017b), who are unable to support the hypothesis that ENSO affects cereal grain prices. In addition, the results of this study are partly in line with some studies which inquires the price response to ENSO events for individual crops. For example, we lend support to Ubilava (2017a) and Letson and McCullough (2001) by confirming the ENSO phases could affect the soybean and wheat prices. Moreover, we add to the previous study by showing the corn prices respond asymmetrically to the different phases of ENSO events.

To investigate the robustness of our results, we also run a basic TAR using point-valued data instead of interval-based. A comparison will give a good idea to see how different the results might be with the range taken into account. **Table 4.6** reports the results of the point-based regression. The OISST.v2 measure for ENSO is not applicable due to the insufficient observations. For all cases, the estimated coefficients $\boldsymbol{\delta_1}$ are significant, indicating the prices are autocorrelated. We observe that the estimators $\boldsymbol{\delta_2}$ and $\boldsymbol{\delta_3}$ are both significant at 5% level or higher in the case of wheat. This implies that both La Niña and El Niño shocks would increase wheat prices. In the case of soybean, there are no linkages found with ENSO as shown by the results in **Table 4.6**. La Niña is found to raise the corn prices given the negative estimator $\boldsymbol{\delta_2}$. The results for soybean and corn are in contradiction to the interval-based estimations. Considering the ENSO-prices transmission mechanisms discussed in section 4.2, these point-based findings do not meet a priori expectation of the soybean price should be affected by ENSO events. The potential reason would be that the average value is unable to capture the extreme and volatility information of the climate and price variables. Therefore, the point-based estimation results may not capture complete information. The novel interval-based approach assists in providing more information when modelling the ENSO-price linkage, which allows us to conclude that grains prices respond to the climate shocks, and the ENSO extremes affect corn prices in an asymmetrical manner.

Table 4.6. Estimation results of point-based regression for three cases

	ENSO-wheat prices			ENSO-soybean prices			ENSO-corn prices		
	OISST.v2 (1981-2010 base period)	ERSST.v5 (1981-2010 base period)	ERSST.v5 (centred base periods)	OISST.v2 (1981-2010 base period)	ERSST.v5 (1981-2010 base period)	ERSST.v5 (centred base periods)	OISST.v2 (1981-2010 base period)	ERSST.v5 (1981-2010 base period)	ERSST.v5 (centred base periods)
$\boldsymbol{\alpha_0}$	/	-0.0240***	-0.0252***	/	0.0939**	0.0874**	/	0.0304	0.0273
$\boldsymbol{\delta_1}$	/	0.1431**	0.1363**	/	0.9487***	0.9541***	/	0.9467***	0.9547***
$\boldsymbol{\delta_2}$	**/**	**-0.0416****	**-0.0494*****	**/**	**0.0109**	**0.0154**	**/**	**-0.0281***	**-0.0259***
$\boldsymbol{\delta_3}$	**/**	**0.0292****	**0.0281****	**/**	**-0.0144**	**-0.0147**	**/**	**0.0102**	**0.0078**

Note: This table reports the estimated results of the TAR regression on *Niño 3.4* SST anomalies measures ERSST.v5 (1981-2010 base period) and ERSSTv5 (centred base period) datasets. The results are non-applicable with OISST.v2 (1981-2010 base period) measure because it leads to the insufficient observation issue in point-based regression. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

4.7 Conclusion

Climate change has been dominating the headlines and, in this light, a great deal of attention has been paid to the issues of global climate variability on grain prices. Empirical evidence to date is mixed. While previous studies such as those by Letson and McCullough (2001) and Ubilava (2012; 2013; 2017a) have investigated the impacts of climatic changes on individual crops, systematic research linking climatic anomalies to a group of cereal grains prices has been scarce. We argue that using global climate anomalies, the extreme episodes of the ENSO strongly affect the temperature and precipitation, which motivates and the need to understand its effect on agricultural prices (Iizumi *et al.*, 2014; Ubilava, 2017b).

The newly proposed interval-based threshold method neatly fits to evaluate the ENSO-caused asymmetric price transmissions on a group of U.S. grain prices received by farmers. Accordingly, this study quantifies the connection between two ENSO phases and the subsequent grain price fluctuations. The interval-based nonlinear framework is advantageous to allow for testing the nonlinearities of changes in both trend and volatility simultaneously. Besides, the TARI model assists in obtaining more efficient estimations and robust statistical inferences because the intervals could provide sufficient information over the standard point-value data (Sun *et al.*, 2018; 2019). For instance, our results contrast the view in recent empirical studies of Ubilava (2017b) where the conclusion is that cereal grains prices are not responsive to the ENSO shocks. We provide support to Ubilava (2017a) and Letson and McCullough (2001) by identifying the different phases of ENSO could affect the soybean and wheat prices. In addition, we add to the research analysing ENSO effects on corn prices by showing the corn prices respond asymmetrically to the different phases of ENSO events. Applying more appropriate modelling methods and comparing different ENSO measures in this study, the key and robust findings of this study suggest that the ENSO anomalies lead to price fluctuations in selected U.S. grain prices.

These results add to the extant literature by providing new evidence that climate variability is an important factor when analysing the impact it has on grain prices. What are the policy implications? This study is useful for farm risk management and planning crop plantation. For instance, the rotations strategy for corn and soybean could be adjusted in light of the information we obtain on climate change (Tack and Ubilava, 2013). Our results report the ENSO-induced price changes for soybean and corn are of the same sign, but the soybean only responds to the El Niño events. In the case of competing for acreage between corn and soybeans, strategies of land allocation to the preferable crops could be planned in advance to hedge against climate risks and improve the economic returns during different phases of ENSO.

This study adds more knowledge to the existing studies on ENSO and price relations and underscores the novel tests demonstrate better properties in estimating the ENSO-price linkages for cereal grains. Unfortunately, the ability of forecasting prices is limited. Future work on the predictions based on interval-valued forecasts could be an avenue for added research an area for future research. Furthermore, it is helpful to investigate the interaction between ENSO shocks and cereal grain prices from the regional perspective because of the spatial heterogeneity of ENSO effects following Phillips *et al*. (1999) and Tack and Ubilava (2013).

Chapter 5. Time-varying Causality among the U.S. Grains Cash and Futures Price

5.1 Introduction

Agricultural commodity futures contracts have been traded for over 150 years in the United States (Working, 1953). With the Grain Futures Act enacted on September 21, 1922, the United States has established the federal law involving the regulation of trading in certain commodity futures. Since then, trading in futures contracts is under federal regulation (Carlton, 1984). Nowadays, the grains futures including corn, soybean and wheat futures contracts are the top three actively traded agricultural commodity futures contracts in the Chicago Mercantile Exchange (CME). It is well known that futures markets play an important role in price discovery mechanism and risk transfer in agricultural commodity markets (Irwin *et al.*, 2008). Price discovery mechanism refers specifically to the functions and mechanisms of the futures markets that are formed through option auctions and can indicate the future direction of price change in t spot markets (Working, 1949), and the risk transfer refers to the process of hedgers using futures to shift the risks in price changes to others (Working, 1953). Given the price discovery role of futures contracts and the possibility of risk transfer, it is important to have some understanding of the relationship between spot and futures prices (Garbade and Silber, 1983), because spot-futures relations are important to various sectors in the agricultural commodity markets including production, marketing and consumption (Xu, 2019).

An understanding of this relationship is essential for four reasons. First, grains producers fix sales prices ahead of production and adjust supply decisions basing on the futures contract prices (Nicolau and Palomba, 2015; Xu, 2019). Second, commodity processors and exporters rely on the futures contracts to cover continuous supply requirements (Hieronymus, 1977; Peck, 1985), and the physical traders price their commodities using the futures as the references (Nicolau and Palomba, 2015). Third, futures contract, as an important financial instrument for hedge, knowledge of the relationship between spot and futures prices could be valuable for speculators and hedgers to forecast the possible deviations in between spot and futures prices to generate profits and mitigate risks (Hieronymus, 1977). Finally, exchange administrators need to understand the linkage of the cash and futures prices to design and evaluate new financial derivative contracts (Xu, 2019). These reasons motivate this article as to investigate the lead-lag relations between grains cash prices and futures prices.

The continual interest in the lead-lag relationship between the agricultural commodity cash markets and futures markets has led to the extant literature on this subject. This lead-lag relation indicates the speed at which the futures market transmits new information relative to the spot market as well as how closely they interact (Chan, 1992). Economic theory suggests that, in a perfect frictionless world, cash and futures prices should be contemporaneously linked (Chan, 1992), implying they adjust instantaneously to incorporate new information under efficient markets where no profitable arbitrage opportunities exist, and as a result, the lead-lag relationship is not to be expected (Xu, 2019). However, if the futures (spot) markets respond faster to information and spot (futures) markets behave slowly, then this gives rise to a lead-lag relation (Chan, 1992). The empirical evidence based on analysing the lead-lag relations in commodity markets has generated empirical results that are at best mixed (Xu, 2019). Nonetheless, the weight of evidence is in favour of futures markets to dominate spot commodity markets (Nicolau and Palomba, 2015; Xu, 2019). This could be owing to the advantages of the futures markets being able to incorporate new information faster than spot markets because of high liquidity and transparency, low transaction costs and initial outlays and short sell opportunities (Herbst *et al.*, 1987). For instance, futures markets facilitate price information flows by offering a central but virtual place to register commodity values. Therefore, futures prices, especially commodity futures, convey new information to economic agents more quickly (Xu, 2018). However, some studies have found that cash markets play the leading roles in price discovery (e.g. Kawaller *et al*., 1987; Moosa, 1996; Rosenberg and Traub, 2009). This could result from increased transparency, which allows new information to be contained in spot markets (Moosa, 1996; Rosenberg and Traub, 2009). At any time, market participants filter their information sets that are associated with either spot or futures markets, thereby possibly causing the lead-lag relationship to change in respond to the new information (Kawaller *et al*., 1987). Since the lead-lag relationship is found to be mixed in extant studies, it is reasonable to assume that the relationship changes with time as new information received (Kawaller *et al*., 1987). At certain periods of time, the flow of information may be relatively sluggish thereby affecting the lead-lag relationship. This implies that the relationship between futures and spot prices can be sensitive to the chosen time period. A natural question that can arise is whether the lead-lag relationship changes over time between futures and spot prices and whether we can identify those time periods when the change occurs. The result can be useful as it may point to regimes where the agricultural policy or market conditions affect the causal relationship.

This paper adds to the extant literature of spot-futures lead-lag interactions, which so far have produced mixed results. The contributions and novelties of this paper are as follows. First, this study contributes to the on-going research on the lead-lag relationship between agricultural commodity futures and cash prices. We provide empirical evidence to support the lead-lag relationship can change over time and find the periods when the change occurs. Agricultural commodity futures and spot prices could be affected by the current market information. The lead-lag pattern change as new information in the commodity market arrives. At any time point, each could lead the other because agricultural commodity market participants filter and respond to the information relevant to their positions, which may be spot or futures. Besides, the lead-lag relationship is time-varying due to changes in the information flows. In certain periods of time, it can be fast or sluggish compared to other times. Since the early 2000s, financialisation among commodity markets makes the commodity futures traded as a class of assets. Increasing futures trading in commodity markets serves as a key platform for aggregating information. The centralised futures exchange accelerates the information flows and affects the lead-lag pattern. Second, this paper adopts a novel econometric method that can be used to exploit the lead-lag relationship between spot and futures prices employing the concept of time-varying Granger causality. Phillips *et al*. (2015a; 2015b) has proposed the recursive evolving window method. Later, Shi *et al*. (2020) introduce a new time-varying Granger causality test base on this recursive evolving window procedure. Given the commodity prices are characterised as highly volatile, especially since 2000, use of the long sample period data may include multiple breaks of exuberance and collapse. The recursive evolving window approach proposed in Phillips *et al*. (2015a; 2015b) is more effective to identify the causal relationships with non-stability. This novel approach adds the flexibility to allow the testing procedure to search for the optimum starting point of the regression for each observation, which able to accommodate re-initialisation in the subsample to square with any structural changes that may exist within the entire sample. Therefore, it assists in detecting any unknown change points in the causal relationship (Shi *et al*., 2018). By identifying the causal periods, we are able to link these causal periods to specific agricultural commodity market events. Of particular interest is that recursive evolving window causality test allows us to identify the exact dates of the origination and end dates of any causality period. Besides, a problem with extant studies is that when testing for Granger causality, there are several transformations that are made to the data when adopting a conventional vector autoregressive (VAR) framework. For example, whether agricultural prices contain a stochastic or deterministic trend is a contentious issue (Ghoshray 2019, Wang and Tomek, 2007) and therefore uncertainty shrouds over the question of whether or not to difference or detrend the data when incorporating the price variables in the VAR. The problem is that if we choose to difference the data, then the meaning of the variable changes as it is expressed in growth form. Other problems arise if such transformation of the data is made leading to arbitrary transformations that can cause error misspecification (Christiano and Ljungqvist 1988). However, the method by Shi *et al*. (2020) is robust in the sense that it does not require pretesting of the data leading to detrending or differencing of the data. Besides, the procedure allows for causality to change over time by endogenously determining the switching points, which contributes to the point we raise before that changes in the flow of information can affect the lead-lag relationship. The procedure also allows for potential heteroscedasticity in the testing process. This may be particularly useful because it is well-known that agricultural prices are highly volatile in nature.

According to Shi *et al*. (2020), the traditional forward expanding window causality test (Thoma, 1994) and the rolling window causality test (Swanson, 1998) are the two special cases of this recursive evolving window method. For comparison, we adopt both the traditional and newly presented time-varying Granger causality tests, to examine the time-varying lead-lag causality for grains spot and futures spanning nearly half-century. The remainder of this paper is organised as follows: Section 2 reviews the previous literature on testing the lead-lag relations; Section 3 describes the econometric methods to test for time-varying Granger causality; Section 4 describes the data applied to this study and present the empirical results, and Section 5 provides the conclusions.

5.2 Literature Review

The spot-futures lead-lag relationships have been studied both theoretically and empirically (Alzahrani *et al*., 2014). Two important theories, traditional cost of carry model (Brennan, 1958; Kaldor, 1939; Working, 1949) and market efficiency theory (Fama, 1970), have agreed on the existence of the relationship between spot and futures prices, but only the latter indicates a causality between spot and futures prices (Alzahrani *et al*., 2014). With respect to the market efficiency theory, futures prices are the unbiased predictors of future cash prices, and hence futures prices are expected to lead cash prices (Alzahrani *et al*., 2014; Garbade and Silber, 1983). However, applying different methodologies, researchers have provided inconsistent and diverse empirical evidence for lead-lag interaction relationship between cash and futures prices in different markets and time periods (Shao *et al*., 2019). Lead-lag pattern causality between cash and futures markets has been widely studied in the context of financial markets and commodity markets. Some researchers have dealt with the lead-lag pattern issues among commodity spot and futures markets with the objective of analysing the issues of price discovery and market efficiency (Silvapulle and Moosa, 1999). Although there are extensive studies that test the lead-lag relations, we only concentrate on reviewing studies that relate to commodity markets.

Identifying the direction of information flows between cash and futures markets appears to be an empirical issue, as economic theory only indicates the variables to be related (Bessler and Brandt, 1982). This study builds on three types of empirical evidence on the causality between the cash and futures markets. The first posits that the direction of the causal lead-lag relations runs from futures market to spot market (Brorsen *et al*., 1984; Carter and Mohapatra, 2008; Garbade and Silber, 1983; Khoury and Yourougou, 1991; Koontz *et al*., 1990; Oellermann and Farris, 1985; Schroeder and Goodwin, 1991; Schwarz and Szakmary, 1994). The second evidence shows that the spot market causal leads the futures markets (Moosa, 1996; Quan, 1992). The third suggests that the direction of the causal link changes over different sub-samples or described as time-varying (Alzahrani *et al*., 2014; Bekiros and Diks, 2008; Silvapulle and Moosa, 1999).

A substantial amount of studies have modelled the lead-lag relationship in commodity markets and analyse the price discovery process between cash and futures prices. Generally, past studies have found to lend more support to futures prices dominating cash prices (Judge and Reancharoen, 2014). The common rationalisation of this finding is that the futures contract prices react to new information faster than cash prices because the flexible short selling opportunities and lower transaction costs make the futures markets are better informed (Herbst *et al*., 1987; Xu, 2019). Further, the futures market are more prone to market manipulations (Newbery, 1989) and serve as reference points for speculators and arbitrageurs (Moosa and Al-Loughani, 1995). Many studies on commodity lead-lag relationships lend support for the hypothesis that causality runs from futures prices to spot prices. Garbade and Silber (1983) have analysed the characteristics of price flows between spot and futures market for storable commodities, including wheat, corn, oats, frozen orange juice concentrates, copper, gold, and silver. They present a theoretical model of the concurrent spot and futures price changes to identify the direction of information flows and then empirically test the model to study the notion of price discovery. Their findings show in general, that futures markets play a leading role over spot markets, with about 75% of new information incorporated in futures markets first and then flowing to spot markets for wheat, corn and orange juice because the cash markets for these commodities are largely satellites of the futures markets. In contrast, they find the price discovery function shows the information of silver, oats and copper is more evenly divided between spot and futures markets, and no conclusive statement can be found for gold because of the data limitations. Similar studies of Schroeder and Goodwin (1991) have also applied Garbade and Silber (1983) model to the live hog markets and draw the same conclusions of the leadership role of futures prices. Several theoretical studies by Khoury and Martel (1985;1986;1989) abandon the previous assumption of equal dissemination of new information to all market participants, and propose the issues of optimal hedging when the new information is asymmetrically distributed between hedgers and speculators. To empirically test this, Khoury and Yourougou (1991) analyse the lead-lag relations between cash and futures for agricultural commodity prices, including barley, canola and oats. Following the studies that generally employ the model of Garbade and Silber (1983), they examine price series including barley, canola and oats using daily data for the period March 1980 to July 1977. They pose that the futures prices are empirically confirmed to lead cash prices on a day-to-day basis, and also hold for varying periods before maturity. But the reverse feedback effects from cash to futures are weak for oats and do not occur in the cases of barley and canola. Brorsen *et al*. (1984) publish the study that analyses the role of the futures market in cotton price discovery by comparing the current cash and current futures prices and exploring whether the cotton prices are discovered in futures markets, spot markets or if they are decided simultaneously. They use the closing quoted daily time series prices over a period ranging from June 15, 1976, and April 30, 1982, and test causalities between spot and futures cotton prices in a bivariate autoregressive (AR) framework. The empirical results show that the spot prices have a strong positive relationship with the lagged one period of the futures prices. Therefore, the cotton prices are discovered in the futures markets and transferred to the spot markets in a short period of time, implying futures price changes are the leading sources of the spot price movements and cause the cash price changes unidirectionally. Oellermann and Farris (1985) use the Granger causality test (Granger, 1969) to determine for live beef cattle between 1966 and 1982. They take the view that live cattle futures started to gain public attention from 1964 to the early 1970s, then experienced high price volatility during the mid of 1970s, after partially returning to stability around 1980. Taking into account these changes in price stability that occurred in the sample period, they divide this sample period into three time spans: 1966 through 1972, 1973 through 1977 and 1978 through 1982. These three-time spans have been further separated into six time-of-year sub-periods to accommodate the seasonal nature of cattle production and marketing. The empirical results indicate the live cattle futures prices lead changes in spot prices for nearly each sub-period. Besides, they also notice the instantaneous feedback within some years. As a result, they provide strong evidence that in most instances, the futures prices play the centre role of price discovery for live cattle. In a similar vein, dividing the observation period of 1973-1984 into three sub-periods (1973-1976, 1977-1980 and 1981-1984), Koontz *et al.* (1990) conduct a Granger causality test to identify the live cattle dominant-satellite relationship. They find evidence to support that none of the markets is independent, implying that the information runs between all markets over a 1-week trading period. They did confirm that causality runs from end-of-week futures prices to cash prices early in the next week. However, the dependence of cash prices on future prices has generally decreased over time. Using data on hog cash and futures prices spanning 1998 to 2014, Carter and Mohapatra (2008) employ an error-correction cointegration framework and test both the short-run and long-run price discovery process. They reveal that hog futures are the unbiased predictor of spot prices especially for the closed futures contracts and prove the futures markets are the primary price discovery point. Further, the empirical results of the short-run causality test show the hog futures contracts prices lead movements in spot prices, but no reverse feedback found from hog spot prices. Similar studies have focused on the crude oil markets and found futures prices lead the spot prices. In the oil market, the new information such as the OPEC decides to restrict production would indicate that oil prices will increase. Speculators tend to purchase oil futures over physical oil, as the latter needs a relatively higher initial outlay and relatively long time to implement the physical purchase deal. Besides, speculators are not interested in physical oil but prefer to hold futures contracts. Hedgers with storage constraints would prefer to buy futures contracts. As such, both speculators and hedgers respond to new information by choosing futures contracts than spot transactions. Spot prices reactions would be lagged since executing a spot transaction takes more time (Bekiros and Diks, 2008; Silvapulle and Moosa, 1999). Schwarz and Szakmary (1994) explore the lead-lag relations among the light sweet crude oil, No.2 heating oil and unleaded gasoline cash and futures prices, from 1985 to 1991. They strongly favour the standpoint that oil futures prices lead the cash prices. Xu (2019) identifies causal linkages among seven major corn-producing states cash prices and futures prices in the United States. This study adds to the previous research by examining both the in-sample and out-sample causal directions based on the VECM and first attempting to explore contemporaneous Granger causality among U.S. corn spot and futures prices. Testing the contemporaneous causality is important to understand the contemporaneous effects of shocks or interventions. An analysis of contemporaneous causality supplements the Granger causality by offering more insight into dynamic linkages between cash and futures prices. To perform contemporaneous causality test, Xu (2019) adopts a data-determined method, directed acyclic graphs (DAGs), which identifies the structural models through data-determined orthogonalisation of the contemporaneous innovation covariance, so that facilitates to determine the directions of instantaneous causal flows and provide inference in innovation accounting (Swanson and Granger, 1997). Using VECM and DAGs, she concludes that the contemporaneous and in-sample causality tests report a causality runs from futures prices to cash prices in the corn markets. No causal relations are found from corn cash prices to futures prices, which lends support to the studies of Garbade and Silber (1983).

Although a majority of studies have proved for futures leading cash prices, there also exists some empirical evidence for cash prices' leading role in lead-lag causality relations. For example, Quan (1992) examine the price discovery process using the monthly crude oil prices data employing two-step testing procedures; the first-step reveals the long-run relations and the second-step aims to test the lead-lag causality in the crude oil market. The results conclude that new information originates from cash prices spreading over to the futures prices, contrary to the view that futures prices lead spot prices. However, Schwarz and Szakmary (1994) argue that Quan (1992)'s failure to confirm the leadership role of oil futures prices attribute to the inappropriate choice of data frequency. Given that markets change quickly, Schwarz and Szakmary (1994) point out that the lead-lag relations only appear within short intervals so that high-frequency data should be considered. In another study, Moosa (1996) introduces a model in which crude oil futures prices is triggered by cash prices, because the markets participants including arbitrageurs and speculators set the cash prices as reference point to motivate their actions in futures markets.

A group of empirical findings have revealed a time-varying lead-lag causality between futures and spot prices. Several studies find that the causal lead-lag relationship varies over different subperiods applying linear econometric methods (Foster 1996; Moosa 2002; Narayan and Sharma, 2018; Oellermann *et al.*, 1989). Focusing on analysing the price discovery process and causality among spot and futures prices for feeder cattle and live cattle, Oellermann *et al*. (1989) utilise the model constructed by Garbade and Silber (1983) and modify it by deleting the storage costs adjustments as it is not appropriate for livestock. Considering the structural changes in the daily observations, they divide the full sample into two periods of 1979-1982 and 1983-1986 and find the lead-lag causality significantly changed between two periods. They find futures prices to lead cash prices for feeder cattle, but the leading power becomes weak in the more recent period. In addition to applying the dynamic regression model of Garbade and Silber (1983), they use a Granger causality technique that follows Mishken (1983) to further examine the spot-futures price linkages for feeder cattle. The results confirm feeder cattle futures prices play the leadership role in generating new pricing information and serve as the centre of price discovery for feeder cattle in the early period, but the leading strength of futures prices tend to be less in more recent years. The possible explanations could be that futures markets are the focal point of information assimilation for both purchasers and sellers, which contributes significantly to improving the price discovery efficiency for feeder cattle. But in recent years, some feedback occurs from the feeder cash prices to futures prices, which explains the leading strength of futures prices become weak. Foster (1996) and Moosa (2002) have modified the Garbade and Silber (1983) model by employing the time-varying parameter estimation based on the Kalman filter. Foster (1996) use daily West Texas Intermediate (WTI) crude oil prices from January 1990 to September 1991 and find the evidence of a strong time-varying price discovery function, and concludes that the first Gulf conflict in 1990-1991 causes a shift. Moosa (2002) also use the WTI crude oil prices covering the period 1985-1986 and find 60 per cent of the price discovery function is performed by the future market. This result indicates a time-varying price discovery function, which is in support of the conclusions reached by Foster (1996). In a recent study, Narayan and Sharma (2018) propose a rolling-window-based error correction model to examine the time-varying price discovery (spot and futures) for 17 commodities, including metals, energy and agricultural commodities. Applying the monthly time series prices spanning 1977-2012, they find strong evidence of time-varying price discovery for 14 commodities including corn, soybean oil and soybean yellow, etc. Namely, they conclude that the price discovery process is oscillatory for these commodities, implying the spot market dominate price discovery over some time periods while futures markets lead spot markets during other periods. They indicate that for different phases, the dominance of price discovery is linked to the specific commodity market events.

Several more recent empirical studies point out that the lead-lag causal relation between spot and futures prices is nonlinear and time-varying (Alzahrani *et al*., 2014; Balcilar *et al*., 2015; Bekiros and Diks, 2008; Polanco-Martínez and Abadie, 2016; Silvapulle and Moosa, 1999). These papers use both linear and nonlinear causality tests to capture the lead-lag linkages between commodity cash and futures markets and compare the results. The nonlinearities are typically related to nonlinear transaction cost, noise traders, market microstructure impacts (Silvapulle and Moosa, 1999). To account for the nonlinearity, nonparametric form methods are appealing given it places direct focus on prediction without using a linear function form (Bekiros and Diks, 2008). The linear causality test is typically conducted in the parametric form and the nonlinear test is performed using nonparametric techniques. For example, Silvapulle and Moosa (1999) first apply the Hsio's (1981) sequential procedure for linear Granger causality test and use a bivariate VAR to analyse the lead-lag relationship between the spot and futures prices of crude oil. Then, they test for a nonlinear dynamic causal relationship by adopting a nonparametric procedure of Hiemstra and Jones (1994), which is a modified version of the Baek and Brock (1992) test. Their analysis covers the period 02 January 1985 and 11 July 1996, using one-month, three months and six-months futures contract daily prices. The results of the linear causality test confirm that there is feedback from spot to futures prices. On the contrary, the nonlinear causality testing reports a bidirectional relationship, namely implying both markets respond to new information simultaneously. In addition, they find that the lead-lag pattern should change over time. Bekiros and Diks (2008) investigate the lead-lag causal relations between oil spot and futures prices using daily data covering two separate periods, namely 21 October 1991 to 29 October 1999, and 1 November 1999 to 30 October 2007. A traditional linear Granger causality test based on a vector error correction model (VECM) is employed. The linear causality test indicates a strong bidirectional Granger causal lead-lag relation between crude oil cash and futures prices during both periods, which are in contrast to the unidirectional results from the linear test in the study by Silvapulle and Moosa (1999). Bekiros and Diks (2008) also apply a new nonlinear nonparametric causality test introduced by Diks and Panchenko (2005). When accounting for the nonlinear effects, the causality test results suggest neither market leads or lags the other consistently. The studies of Silvapulle and Moosa (1999) and Bekiros and Diks (2008) both conclude the pattern of leads and lags changes over time. These two studies both explain that given the spot-futures causal linkage can change from one direction to the other at any time point, the result of bidirectional causality over the sample periods may imply a changing pattern of leads and lags over time, which provides support to the Kawaller *et al.* (1987) hypothesis. Kawaller *et al.* (1987) hypothesis indicate that market participants filter the information relevant to their positions as new information comes in, at any time point, cash may lead futures and vice versa. Therefore, on balance, though futures prices are found to play a bigger role in price discovery, there is still some evidence to suggest spot prices can play a key role in the price discovery process. Similar to Bekiros and Diks (2008), Alzahrani *et al.* (2014) also employ both the linear Granger causality test based on a VAR and a modified nonlinear nonparametric causality test of Diks and Panchenko (2005) to test the lead-lag causality using the daily oil prices from February 20, 2003 to April 19, 2011. They apply a wavelet approach to transform the data into frequency domain without losing the time domain information, so that the time-dependent volatility and structural breaks in oil cash and futures prices series can be accommodated, and avoid the effects of data frequency on causality tests. The outcomes of both linear and nonlinear tests in this study reconcile the findings of Bekiros and Diks (2008) who find bidirectional causality and conclude neither markets necessarily lead the other. Inspired by Alzahrani *et al.* (2014), Polanco-Martínez and

Abadie (2016) estimate the lead-lag relations from different time-scales (short, medium and long-term scales), with the use of a stochastic model (Abadie and Chamorro, 2016), a wavelet correlation graphical tool (Polanco-Martínez and Fernández-Macho, 2014), as well as a nonlinear causality test (Diks and Panchenko, 2006). Their results show bidirectional causal relations for most time scales, from intra-week to biannual, over the period 24 February 2006 to 2 April 2016, which implies the concurrent response of spot and futures prices to the new information. Noticing some of the previous studies have mostly been supportive of the time-varying causal links between spot and futures markets, Balcilar *et al*. (2015) examine time-varying causal relations between the daily spot and futures prices for maturities of one, two, three and four months of the WTI crude oil benchmark spanning periods from January 2, 1986-July 31, 2013. They propose a Markov-switching vector-error correction (MS-VEC) model which is capable of capturing the nonlinear, asymmetric and time-varying causal linkages. Namely, this method is helpful in identifying the causal linkages that are likely to be operative for each point in time. Moreover, it allows the causal patterns change over time accordingly to a Markov-switching process. The results indicate a strong time-varying causality between spot and futures prices. The lead-lag relations between spot and futures crude oil prices for the maturities of one, two, three and four months are proved to experience significant changes over the sample years. They indicate that the change periods are all related to the times of volatile prices and continues flows of new information to the markets, triggered by the diversified important events.

In summary, the empirical evidence on price discovery and lead-lag relationships between spot and futures prices is mixed. A potential gap that appears in the above studies is that although they highlight the fact of the changing pattern of leads and lags over time, implying the lead-lag causality are likely to contain time-varying features, very few have attempted to study the time-varying pattern of causality. Besides, a large number of studies have acknowledged the lead-lag relationships and the associated time-varying causal relations between crude oil cash and futures prices, however, this aspect of time-varying lead-lag causality has received limited attention in the context of the agricultural commodity prices. This literature review suggests that the lead-lag causality is a dynamic one, especially for the periods with consistent uncertainty, which results in significant incongruities among studies in terms of the dominant role of the prices. We address this gap by adopting the traditional time-varying Granger causality tests of forward expanding window causality test (Thoma, 1994) and the rolling window causality test (Swanson, 1998), with recent developments that use recursive evolving window causality test that allow us to be agnostic about the order of integration of the data, a problem that is known to plague agricultural spot and futures prices. (Phillips *et al*., 2015a; 2015b; Shi *et al*., 2020). Given the data stationarity could impact price variable modelling, previous empirical studies first determine the order of integration of each price series using unit root tests (Xu, 2018). In this study, the forward recursive algorithm, rolling window algorithm, and recursive evolving algorithm, all of which use subsample tests of Granger causality within a lag-augmented VAR model. This approach is particularly designed to be robust to the integration and cointegration properties of the time series employed in the regressions and can hence be used without accurate prior knowledge of the presence or absence of unit root (Shi *et al*., 2020). The advantages of applying these novel tests are that they allow to revealing the changing pattern informational directions running between cash and futures prices over time; and we could identify the exact time periods and capture the corresponding information flows between agricultural commodity cash prices and futures prices. Therefore, instead of giving a general conclusion of changing causality, we can be more specific in explaining how causality changes over time. Besides, regarding the statistical analysis perspective, commodity prices are characterised to be highly volatile and may contain structural breaks (Ghoshray, 2019). Typically, the structural breaks are the most challenging problems when conducting time series analysis (Granger, 1996). Hansen (2001) and Perron (2006) have affirmed that issues of the structural breaks should be distinctly considered when applying the econometric tools with the time series data. The possible presence of structural breaks in the underlying data can lead to the parameters of the econometric models to be time-variant. Hence the statistical tests based on the assumption of the constant parameter can give invalid and incorrect inferences (Balcilar *et al.*, 2019). Accordingly, we consider the possibility of structural breaks in agricultural commodity prices. This study conducts the time-varying Granger causality tests against the effects of structural breaks. The econometric procedures of these three time-varying Granger causality tests are now described in the following section.

5.3 Econometric Methods

When performing an empirical test on the hypothesis, one should consider the underlying nature of the data series because the conclusion drawn will be relying on the econometric framework (Ghoshray and Johnson, 2010). It is widely known that commodity prices are characterised as being volatile, given it is the common features of commodity prices (Deaton and Laroque, 1992). The agricultural commodity price series under investigation could be nonstationary. To conduct a Granger causality test by allowing for possibly integrated variables, we adopt a lag-augmented vector autoregression (LA-VAR) model (Toda and Yamamoto, 1995; Dolado and Lütkepohl, 1996) and the bivariate case with a maximum order of integration d, which could be expressed as

$$y_{1t} = \alpha_{10} + \alpha_{11}t + \sum_{i=1}^{k+d} \beta_{1i} y_{1t-i} + \sum_{i=1}^{k+d} \theta_{1i} y_{2t-i} + \varepsilon_{1t},$$
$$y_{2t} = \alpha_{20} + \alpha_{21}t + \sum_{i=1}^{k+d} \beta_{2i} y_{1t-i} + \sum_{i=1}^{k+d} \theta_{2i} y_{2t-i} + \varepsilon_{2t},$$

where k indicates the lag order of the original VAR model and additional d lags represents the possible maximum order of integration of the variables. t is the time trend and ε_{it} are the error terms. $y_{2t} \nrightarrow^{GC} y_{1t}$ denotes that y_{2t} does not Granger cause y_{1t}, implying the situation that the predictions of y_{1t} conditional on its own previous cannot be improved by incorporating the k lags of y_{2t} in the model. The null hypothesis for testing the causality from y_{2t} to y_{1t} is

$$H_0: \theta_{11} = \cdots = \theta_{1k} = 0$$

Extend to the general version for n-dimensional vector y_t, the LA-VAR model is expressed as

$$y_t = \delta_0 + \delta_1 t + \sum_{i=1}^{k} J_i y_{t-i} + \sum_{j=k+1}^{k+d} J_j y_{t-j} + \varepsilon_t, \tag{5.1}$$

where $J_{k+1} = \cdots = J_{k+d} = 0$ and d is the maximum order of integrated variable y_t. Thus rewrite the above regression equation as

$$y_t = \Gamma\tau_t + \Phi x_t + \Psi z_t + \varepsilon_t, \tag{5.2}$$

where $\Gamma = (\delta_0, \delta_1)_{n\times(q+1)}$, $\tau_t = (1, t)'_{2\times1}$, $x_t = (y'_{t-1}, \ldots, y'_{t-k})'_{nk\times1}$, $z_t = (y'_{t-k-1}, \ldots, y'_{t-k-d})'_{nd\times1}$, $\Phi = (J_1, \ldots, J_k)_{n\times nk}$ and $\Psi = (J_{k+1}, \ldots, J_{k+d})_{n\times nd}$. The null hypothesis of testing the Granger non-causality is given as

$$H_0: \boldsymbol{R}\emptyset = 0 \tag{5.3}$$

on the coefficient $\emptyset = vec(\Phi)$ applying row vectorisation and $\boldsymbol{R}$ is the $m \times n^2 k$ matrix. The final d lagged vectors parameter matrix Ψ is ignored because its elements are set to be zero.

Rewriting the equation (5.1) in a more compact representation as

$$\mathrm{Y} = \tau\Gamma' + X\Phi' + Z\Psi' + \varepsilon,$$

where $Y = (y_1, y_2, \dots, y_T)'_{T\times n}$, $\tau = (\tau_1, \dots, \tau_T)'_{T\times 2}$, $X = (x_1, \dots, x_T)'_{T\times nk}$, $Z = (z_1, \dots, z_T)'_{T\times nd}$ and $\varepsilon = (\tau_1, \dots, \tau_T)'_{T\times 2}$. Then set out

$$Q = Q_\tau - Q_\tau Z(Z'Q_\tau Z)^{-1}Z'Q_\tau$$

and the OLS estimator could be given as

$$\hat{\Phi} = Y'QX(X'QX)^{-1}$$

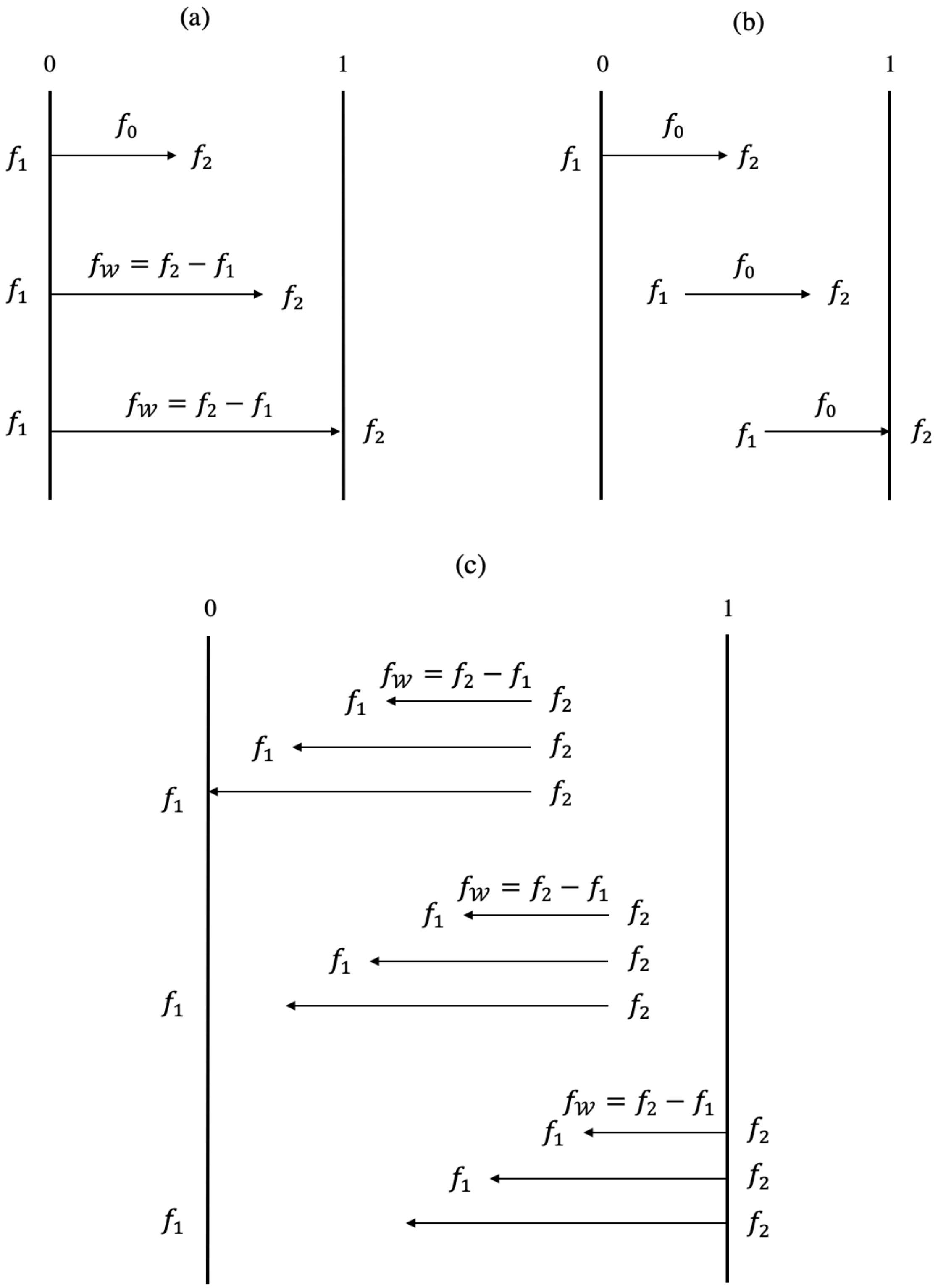
The standard Wald statistic $\mathcal{W}$ for testing the null hypothesis H_0 is

$$\mathcal{W} = \left(\boldsymbol{R}\hat{\emptyset}\right)'[\boldsymbol{R}\{\widehat{\Sigma_\varepsilon} \otimes (X'QX)^{-1}\}\boldsymbol{R}']^{-\mathbf{1}}\boldsymbol{R}\hat{\emptyset} \tag{5.4}$$

where $\hat{\emptyset} = vec(\hat{\Phi})$, $\widehat{\Sigma_\varepsilon} = \frac{1}{T}\hat{\varepsilon}'\hat{\varepsilon}$, and $\otimes$ denotes the Kronecker product. This Wald statistic has the χ^2_m asymptotic null distribution with m being the number of restrictions (Toda and Yamamoto, 1995; Dolado and Lütkepohl, 1996).

As indicated in the literature review, there are some studies expect the lead-lag causality should change over time because the market participants will filter the information relevant to cash and futures positions over time (Silvapulle and Moosa, 1999; Bekiros and Diks, 2008). In such circumstances, testing the time-varying causality using the entire sample will average the sample information and inevitably fail to capture the changes in information receiving (Shi *et al*., 2018). Although estimating the Granger causality with exogenously determined subsamples of the data could give useful information, it does not allow the data to reveal the potential change points. Accordingly, the ultimate objective for this study is conducting tests that allow for the change points endogenously defined and identified in the sample data (Shi *et al*., 2018). The recursive Granger causality procedures calculate the Wald statistics by using the subsamples of the data. To clearly illustrate the testing algorithms, we follow Shi *et al.* (2018; 2020) and explain with sample fractions in the following exposition. Let f represents the fractional observation of interest and f_0 is the minimum fractional window size needed to conduct the estimations. Besides, assuming the f_1 and f_2 denote the fractional start and end points of the regression sample, respectively, and $f_W = f_2 - f_1$. And $\mathcal{W}_{f_1}^{f_2}$ indicates the Wald statistic based on the LA-VAR model and calculated from the subsample.

In **Figure 5.1** we illustrate the subsampling process subsampling processes and the window widths of forward expanding, rolling window and recursive evolving procedures, respectively. For the forward expanding procedure, $f_0 = 0$ is fixed and sets $f = f_2$, and the rolling window assumes a fixed window width $f_W = f_2 - f_1 = f_0$ and window initialisation $f_1 = f_2 - f_0$. Forward expanding and rolling window procedures are the special cases of the recursive evolving approach. The recursive evolving method allows variation in the window widths $f_W = f_2 - f_1 \geq f_0$ applied in the regression, which adds the flexibility by relaxing f_1 to allow the procedure to search for the optimum starting point of the regression for each observation. This flexibility is able to accommodate re-initialisation in the subsample to square with any structural changes that may exist within the entire sample, and thereby assists in detect any changes in the structural and causal direction. Although the subsampling processes are different, these three methods all rely only on the past information and hence can be employed for real-time monitoring at the present observation f (Shi *et al.*, 2018).



Note: Sample sequences for forward expanding, rolling window and recursive evolving procedures are displayed in (a), (b) and (c), respectively.

Figure 5.1: Sample sequences for forward expanding, rolling window, and recursive evolving procedures

Set $\tau_1 = \lfloor f_1 T \rfloor$, $\tau_2 = \lfloor f_2 T \rfloor$ and $\tau_W = \lfloor f_W T \rfloor$, where T denotes the total observation number and $\tau_0 = \lfloor f_0 T \rfloor$ is the minimum observation number required for the VAR estimation. To achieve the goal of testing the dynamic lead-lag causality, this study employs three time-varying Granger causality tests, which are the forward expanding window causality test (Thoma, 1994), the rolling window causality test (Swanson, 1998) and the recursive evolving window causality test (Phillips *et al.*, 2015a; 2015b; Shi *et al.*, 2020). They all focus on testing the changing pattern causality but calculate the Wald statistics in different ways. The forward expanding window approach sets starting point τ_1 fixed at the first observation, for example: $\tau_1 = 1$, and the regression window starts to expand from τ_0 to T. This procedure could be view as to having τ_2 runs from τ_0 to T and hence the test basing from this method is mentioned to as a forward expanding window test. For the rolling window procedure, by contrast, the regression window size keeps fixed and set the window size equals to τ_0 in the sequence of regressions. The starting point is not fixed and the regression window moves from the first available observations to $T - \tau_0 + 1$ and the ending point $\tau_2 = \tau_1 + \tau_0 - 1$. We can rewrite in an alternative form to τ_1 and τ_2 of the procedure as $\tau_2 = \{\tau_0, \dots, T\}$ and $\tau_1 = \tau_2 - \tau_0 + 1$. Then the ending point of the process moves from τ_0 to the last observation in the sample T, and the starting point follows to move to keep the window size fixed at τ_0. For the recent proposed recursive evolving window procedure, the end point $\tau_2 = \{\tau_0, \dots, T\}$, which is the same as the rolling window method. But the start point τ_1, rather than keeping a constant distance with τ_2 as in the rolling window process, varies from 1 to $\tau_2 - \tau_0 + 1$ to cover all possible values.

We could obtain a sequence of Wald statistics $\{\mathcal{W}_{f_1,f_2}\}_{f_2=f}^{f_1 \in [0, f_2 - f_0]}$ for each fractional observation of interest $f \epsilon [f_0, 1]$. Defining the test statistic based on the supremum norm of the Wald statistic sequence

$$SW_f(f_0) = \sup_{f_2 = f, f_1 \in [0, f_2 - f_0]} \{\mathcal{W}_{f_1,f_2}\}. \quad (5.5)$$

And we make inferences on Granger non-causality for available observation $\lfloor fT \rfloor$ based on this sup Wald statistic $\mathcal{SW}_f(f_0)$.

The above Wald statistic and sup Wald statistic are under the assumption of the residual error term is homoskedasticity. When the errors are heteroskedastic, the Granger causality test based on the assumption of homoskedasticity could be accompanied by power loss. To account for the potential effects of heteroskedasticity in the residuals, Shi *et al*. (2020) propose heteroskedastic consistent versions of the Wald and sup Wald statistics. Shi *et al*. (2020) define the heteroskedastic-consistent subsample Wald test statistic as

$$\mathcal{W}^*_{f_1,f_2} = T_W\left(\boldsymbol{R}\widehat{\emptyset}_{f_1,f_2}\right)' [\boldsymbol{R}\{\hat{V}^{-\mathbf{1}}_{f_1,f_2}\hat{\Sigma}_{f_1,f_2}\hat{V}^{-\mathbf{1}}_{f_1,f_2}\}\boldsymbol{R}']^{-\mathbf{1}}\boldsymbol{R}\widehat{\emptyset}_{f_1,f_2}, \tag{5.6}$$

Where $\widehat{\emptyset}_{f_1,f_2} = vec(\widehat{\Phi}_{f_1,f_2})$ with $\widehat{\Phi}_{f_1,f_2}$ denotes the OLS estimate of Φ from the sample running from f_1 to f_2,

$$\hat{V}_{f_1,f_2} = I_n \otimes \hat{Q}_{f_1,f_2} \text{ with } \hat{Q}_{f_1,f_2} = \frac{1}{T_W}\sum_{t=\lfloor Tf_1 \rfloor}^{\lfloor Tf_2 \rfloor} x_t x_t'$$

$$\hat{\Sigma}_{f_1,f_2} = \frac{1}{T_W}\sum_{t=\lfloor Tf_1 \rfloor}^{\lfloor Tf_2 \rfloor} \hat{\xi}_t \hat{\xi}_t' \text{ with } \hat{\xi}_t = \hat{\varepsilon}_t \otimes x_t.$$

The heteroskedastic-consistent sup Wald statistic is defined as

$$\mathcal{SW}^*_f(f_0) = \sup_{f_2=f, f_1\in[0,f_2-f_0]} \{\mathcal{W}^*_{f_1,f_2}\}. \tag{5.7}$$

According to Shi *et al*. (2020), the heteroskedastic consistent version includes the homoscedastic one as a special case. Therefore, this study employs the heteroskedastic consistent version test to consider the potential heteroskedasticity effect, which normally been ignored in past studies.

The issue of multiplicity is the common-known phenomenon that the probability of making a Type I error increases with the number of hypotheses being tested in a test sequence. In the current application context, the test statistics in these three testing algorithms are needed to be compared with the corresponding critical values for every observation moving from $\lfloor f_0 T \rfloor$ to T. Namely, for a sample size T data series, the test statistics calculated starting from $\lfloor f_0 T \rfloor$ to T, which requires to test the hypotheses of non-causality for $T - \lfloor f_0 T \rfloor + 1$ times. To avoid the size distortion occurring from the recursive procedures, we follow Shi *et al*. (2020) and adopt their bootstrap approach to address the multiplicity problem for the simulations and empirical analysis part.

To make the bootstrap process more simply and easier to understand, Shi *et al*. (2020) describes it in the context of a bivariate VAR(1) model. Following the study of Shi *et al*. (2020), five steps are introduced to perform the bootstrap procedures.

Step 1: Using the data from the full sample period, we estimate the bivariate VAR(1) model which imposes the null hypothesis of non-causality runs from y_2 to y_1.

$$\begin{bmatrix} y_{1t} \\ y_{2t} \end{bmatrix} = \begin{bmatrix} \widehat{\emptyset}_{11} & 0 \\ \widehat{\emptyset}_{12} & \widehat{\emptyset}_{22} \end{bmatrix} \begin{bmatrix} y_{1t-1} \\ y_{2t-1} \end{bmatrix} + \begin{bmatrix} e_{1t} \\ e_{2t} \end{bmatrix}$$

where $\widehat{\emptyset}_{11}$, $\widehat{\emptyset}_{12}$ and $\widehat{\emptyset}_{22}$ are the estimated parameters, and e_{1t} and e_{2t} denotes the estimated residuals.

Step 2: As mentioned above, τ_b denotes the number of observations in the window over which size is to be restricted. Let the sample size of the bootstrapped data series and denote by $\tau_0 + \tau_b - 1$, the bootstrap sample could be generated as

$$\begin{bmatrix} y_{1t}^b \\ y_{2t}^b \end{bmatrix} = \begin{bmatrix} \widehat{\emptyset}_{11} & 0 \\ \widehat{\emptyset}_{12} & \widehat{\emptyset}_{22} \end{bmatrix} \begin{bmatrix} y_{1t-1}^b \\ y_{2t-1}^b \end{bmatrix} + \begin{bmatrix} e_{1t}^b \\ e_{2t}^b \end{bmatrix} \tag{5.8}$$

in which e_{1t}^b is randomly drawn with replacement from the estimated residuals e_{1t}. Following the same logic, e_{2t}^b is drawn from the estimated residuals e_{2t}. The initial values of y_{1t}^b and y_{2t}^b equal to the y_{1t} and y_{2t}, respectively.

Step 3: The test statistic sequences for the forward expanding window, rolling window and recursive evolving window are

$$\text{Forward expanding window: } \{\mathcal{W}_{1,t}^b\}_{t=\tau_0}^{\tau_0+\tau_b-1}$$

$$\text{Rolling window: } \{\mathcal{W}_{t-\tau_0+1,t}^b\}_{t=\tau_0}^{\tau_0+\tau_b-1}$$

$$\text{Recursive evolving window: } \{S\mathcal{W}_t^b(\tau_0)\}_{t=\tau_0}^{\tau_0+\tau_b-1}$$

respectively, based on their algorithms we have introduced above. In this step, we calculate each test statistic sequence by applying the bootstrapped series. The maximum values for these bootstrapped test statistic sequences are computed such that

$$\text{Forward expanding window: } \mathcal{M}_{1,t}^b = max_{t\in[\tau_0,\tau_0+\tau_b-1]}(\mathcal{W}_{1,t}^b)$$

$$\text{Rolling window: } \mathcal{M}_{t-\tau_0+1,t}^b = max_{t\in[\tau_0,\tau_0+\tau_b-1]}(\mathcal{W}_{t-\tau_0+1,t}^b)$$

$$\text{Recursive evolving window: } S\mathcal{W}_t^b(\tau_0) = max_{t\in[\tau_0,\tau_0+\tau_b-1]}(S\mathcal{W}_t^b(\tau_0)) \tag{5.9}$$

Step 4: Repeating step 2 and step 3 for $B = 1000$ times.

Step 5: The critical values for the forward expanding window, rolling window and recursive evolving window methods are expressed as 90% percentiles of

$$\text{Forward expanding window: } \{\mathcal{M}_{1,t}^b\}_{b=1}^B$$

$$\text{Rolling window: } \{\mathcal{W}_{t-\tau_0+1,t}^b\}_{b=1}^B$$

$$\text{Recursive evolving window: } \{S\mathcal{W}_t^b(\tau_0)\}_{b=1}^B$$

respectively.

For practical implementation and empirical analysis, in step 1, we need to determine the optimal lag order by applying information criteria and estimate the restrictive model. Likewise, the lag order should be selected for step 3 before computing the test statistics. Shi *et al.* (2020) have conducted the simulation experiments to examine the performance of forward expanding window, rolling window and recursive evolving window causality tests with the bootstrapped critical values under the DGP (12) for different parameter settings for several cases. By performing 1000 times replications for each parameter constellation, they calculate the sizes and powers of these three tests, where the sizes denote the probability of rejecting at least one true null hypothesis and powers mean the probability of rejecting at least one false null hypothesis for the same period. According to their calculations, the sizes for all these three test processes are very close to the nominal size of 5%, implying the validations of the bootstrap method in controlling the family-wise size and resolving the multiplicity issue in recursive procedures. As for the empirical powers, the recursive evolving window test characterises the highest power and the rolling window procedure follows closely. The performances the evolving window and rolling window procedures could be identical under most circumstances, but the recursive evolving test gain more powers in moderate causal strength and large sample sizes (such as $T = 200$). The forward expanding window method has the least power than that of the rolling window and recursive evolving window. The detective power of these three procedures varies. For rolling window and recursive evolving window, the detective power gains with the f_0 increase from 0.18 to 0.24 and remains roughly the same or slightly decreases for further extension to 0.36. In the case of using forward expanding procedure, the detective power rises with the increasing of the initialisation f_0. These three procedures all enjoy the power gains with the increasing sample size T, at a decreasing rate though. Besides, all causality tests powers increase with the strength of causality (Shi *et al.*, 2020).

5.4 Data description and preliminary analysis

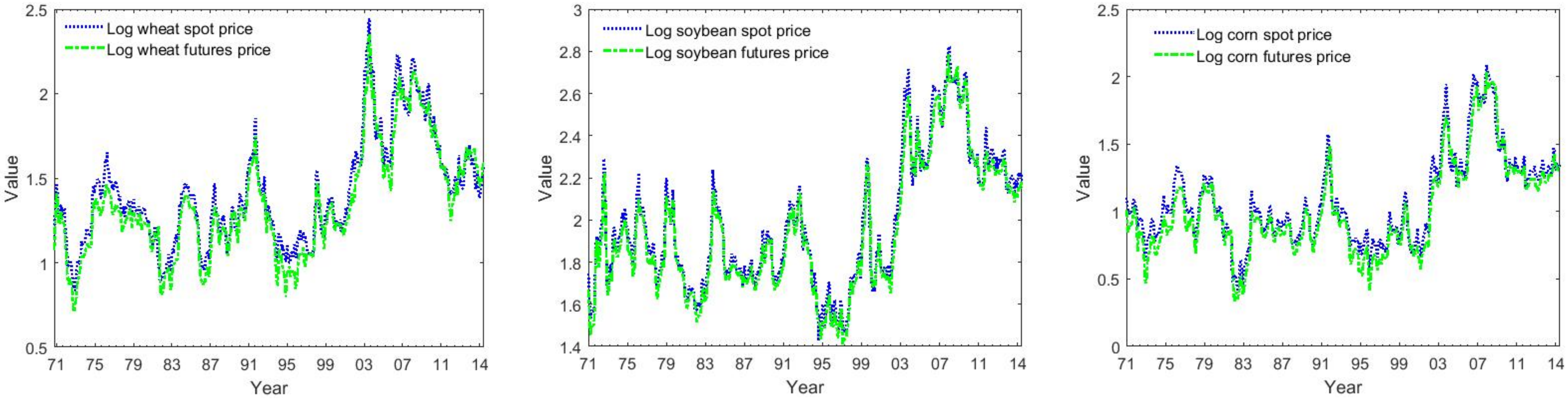
Our analysis is based on the monthly price time series for the important cereal grains, including wheat, soybean and corn spot and futures prices, which are freely available at the website of the National Agricultural Statistics Service (NASS) of the United States Department of Agriculture (USDA). The spot prices of the wheat, soybean and corn are the monthly farm received prices published by the NASS of the USDA. These are cash prices and represent the sales from producers to first buyers, including all grades and qualities. The futures prices are the prices settled by the Chicago Mercantile Exchange (CME) group's contract for wheat, soybeans and corn. The prices for the nearby contract are applied but except the marketing year month coincides with the month in which the contract expires. For instance, the November contract prices are applied for September and October, while the January contract prices are used for November and December, etc. For this reason, we choose monthly prices. We focus on the time period which is extended to the most recent period available, covering the period from June 1975 to February 2020 for the case of wheat, and spanning September 1975 to February 2020 for soybean and corn cases, in monthly frequency. The time-series properties for the different transformed commodity prices can differ (Ghoshray, 2019). Namely, though the data transformation is not unusual, the results of estimation can vary with different types of transformation (Tomek, 2000). For this reason, we choose to use logged price transformations in subsequent analysis, to reduce heteroscedasticity, stabilise the variance and straighten trend. **Table 5.1** below exhibits the descriptive information of the cash and futures price series for wheat, soybean and corn. From **Table 5.1**, wheat and soybean price series are slightly platykurtic, but the corn series are more leptokurtic than wheat and soybean. All these series are slightly right-skewed.

Table 5.1: Descriptive statistics for cash and futures price series

	Wheat		Soybean		Corn	
	Cash	**Futures**	**Cash**	**Futures**	**Cash**	**Futures**
Mean	1.3484	1.4089	1.9473	1.9825	1.0149	1.0830
Median	1.2947	1.3584	1.8710	1.9095	0.9431	1.0043
Minimum	0.7080	0.8329	1.4085	1.4255	0.3365	0.4055
Maximum	2.3514	2.4449	2.7850	2.8219	2.0321	2.0844
Standard deviation	0.3256	0.3178	0.3129	0.3135	0.3439	0.3317
Skewness	0.6525	0.8126	0.6374	0.6454	0.7928	0.8793
Kurtosis	2.9653	3.2363	2.6283	2.6256	3.3749	3.5229

The data are plotted in **Figure 5.2**, which provides visual evidence of that at all series seem much more likely to be non-stationary. Besides, visual inspection points the possibility of the structural breaks incorporated in the price series.

(a) (b) (c)



Note: Time-series plots of the logarithms of spot prices and futures prices in the United States for wheat, soybean and corn are displayed in (a), (b) and (c), respectively.

Figure 5.2: Time-series plots of the agricultural commodity spot prices and futures prices

The LA-VAR model, introduced in the last part, does not need to pre-filter the data through de-trending and/or differencing, but require the information of maximum possible integration order. Therefore, prior to applying the LA-VAR model, we should determine the maximum integration order of the system. This study determines the integrated order of the price variables by using the Augmented Dickey-Fuller (ADF) test (Dickey and Fuller, 1981), Phillips-Perron (PP) test (Phillips and Perron, 1988) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test (Kwiatkowski *et al*., 1992), which have been employed in the similar studies from Xu (2018; 2019). Given that the ADF and PP tests have low power, the KPSS test with the null of stationary, against a non-stationary alternative, is also employed. In addition, given the agricultural prices are characterised to be volatile and the possibility of a structural break in price series identified by visual inspection, this study also conducts the unit root test of Perron and Vogelsang (1992), which allows for testing one break under both the null of a unit root and alternative of stationary. This test searches for the unknown structural break either through innovational outliers (IOs) and additive outliers (AOs). The results of ADF, PP and KPSS testing procedures, as well as the test of Perron and Vogelssang (PV) (1992) are reported in **Table 5.2** The top half of **Table 5.2** conducts the standard unit root tests without breakpoint, including ADF, PP and KPSS tests. The lower half of **Table 5.2** tests for unit root allowing for a structural break. Roughly in all cases, the evidence is mixed where the ADF test results do not match with the PP test and KPSS test. For these three cases, though some tests point that the null hypothesis cannot be rejected, they all become stationary after taking first-differences, implying I(1) is the maximum integration order. When assuming one unknown structural break with IOs and AOs, all data series are found to be I(1), implying the maximum order of integration should be I(1) as well. Though the results are mixed, the LA-VAR modelling framework does not require all the variables to be integrated of the same order. Therefore, we can set the maximum order of integration as I(1) in the LA-VAR model. Considering all the data series exhibit a driftless random walk, this study therefore does not include a time trend term and sets the additional lag parameter d to one.

Table 5.2: Unit root tests on levels and first differences of cash and futures price series

		Wheat		Soybean		Corn	
		Cash	**Futures**	**Cash**	**Futures**	**Cash**	**Futures**
Without break	$\mathbf{ADF_L}$	-2.3033	-2.6772*	-2.9686**	-3.0738**	-2.7687*	-2.8532*
	$\mathbf{ADF_\Delta}$	-14.6975***	-18.4634***	-14.9836***	-13.9610***	-14.2319***	-17.4305***
	$\mathbf{PP_L}$	-2.3508	-2.6003*	-2.2223	-2.5529	-1.9954	-2.5919*
	$\mathbf{PP_\Delta}$	-14.2065***	-18.4074***	-14.1240***	-13.9610***	-13.4168***	-16.9369***
	$\mathbf{KPSS_L}$	1.4749***	1.3286***	1.3901***	1.3706***	1.2518***	1.1874***
	$\mathbf{KPSS_\Delta}$	0.0303	0.0307	0.0319	0.0302	0.0816	0.0363
With break	$\mathbf{PV_{AO,\,L}}$	-2.8124	-2.7031	-2.9295	-3.0439	-2.7863	-2.8675
	$\mathbf{PV_{AO,\,\Delta}}$	-14.5653***	-18.6379***	-15.0036***	-17.1603***	-14.1863***	-17.4279***
	$\mathbf{PV_{LO,\,L}}$	-2.2289	-2.5981	-2.8409	-2.9206	-2.5547	-2.8052
	$\mathbf{PV_{LO,\,\Delta}}$	-15.3119***	-18.3717***	-14.9696****	-13.9741***	-14.2223***	-17.2053***

Note: ***, ** and * denote rejection of the null hypothesis of unit root process at the 1%, 5% and 10% significance level, respectively

5.5 Empirical analysis

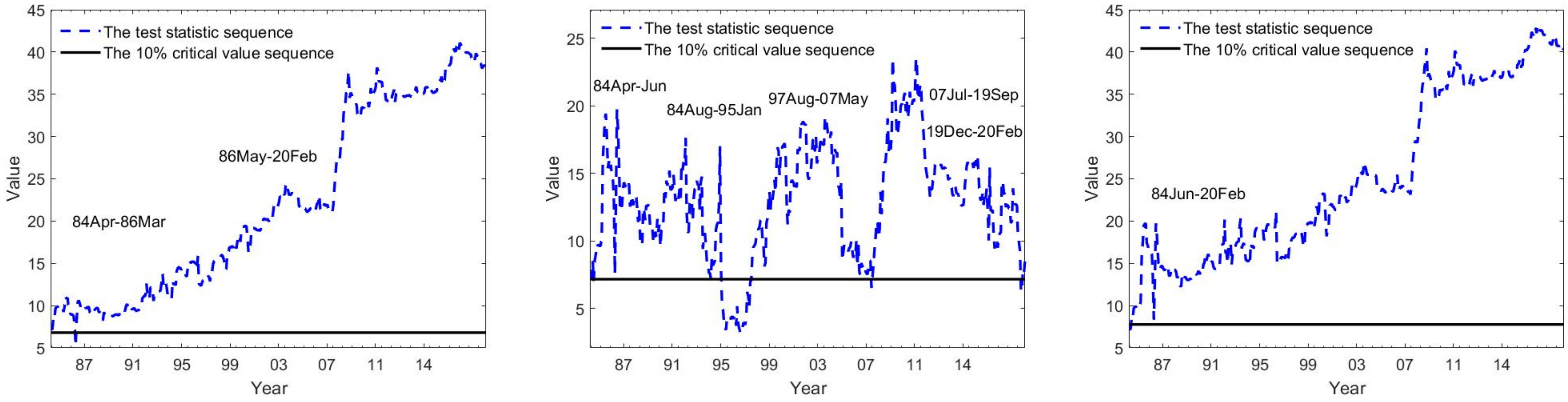
A wide range of unit root tests has been carried out on all price series. We now examine the causal relationship between cash and futures prices for each grain, applying the forward expanding window, rolling window and recursive evolving window procedures. This study follows Shi *et al*. (2018; 2020), in estimating the LA-VAR model and conducting Granger causality tests. The Bayesian Information Criteria (BIC) is used to select the lag length for the whole sample periods for all cases, and the lag order assumed the same over the subsamples. In implementing the testing procedures, the minimum window size usually set as $f_0 = 0.20$ because the powers of rolling and recursive evolving procedures increase when f_0 runs from 0.18 to 0.24 (Shi *et al*., 2018; 2020). Practically, the optimal value of f_0 depends on the strength and duration of the causal relationship. Shi *et al*. (2018; 2020)'s model fixes the duration of the causality episode as 0.2, and therefore if the minimum window size exceeds the causality duration, the regression would contain the mix of causal and non-causal observations. Given that we have 537 observations for wheat and 534 observations for the cases of both soybean and corn, we set the minimum window size as 107 for all cases based on the 20% duration of the whole sample. The 10% critical values are acquired from the bootstrapping method introduced above, and the model coefficients under the null are computed applying the whole sample period.

This study tests the causality between spot prices and futures prices of the wheat, soybean and corn in the United States. The estimation results are reported in **Figure 5.3** to **Figure 5.8**. The time-varying test statistic sequence (blue dashed line) along with the bootstrapped 10% critical value sequence (black solid line) are illustrated under the figures. We test the null hypothesis of no causal relationship between spot and futures prices and reject the null when the test statistic sequence above the 10% critical value sequence.

The time-varying test statistic sequences for causal relations between wheat cash and futures prices, along with their corresponding bootstrapped 10% critical values for the forward expanding window, rolling window and recursive evolving window methods are displayed in **Figure 5.3**. Panel (a), (b) and (c) of **Figure 5.3** report the test statistic sequences and their corresponding bootstrapped 10% critical values for testing the causal relationship from wheat futures to cash prices. According to the panel (a) and (c) in **Figure 5.3**, the test statistics are always above the 10% critical values sequence for the whole sample using the forward and recursive evolving methods. These results suggest the rejection of the null hypothesis of no causality between variables at the 10% significance level and indicate the causal relations running from wheat futures prices to cash prices. However, there is a slight discrepancy in the rolling window test as shown in panel (b), with the test statistics are higher than the critical values for most of the time except some short episodes: mid to late 1990s and at the end of the sample. This result shows that the rolling window method detects no causality from wheat futures prices to spot prices in some short periods.

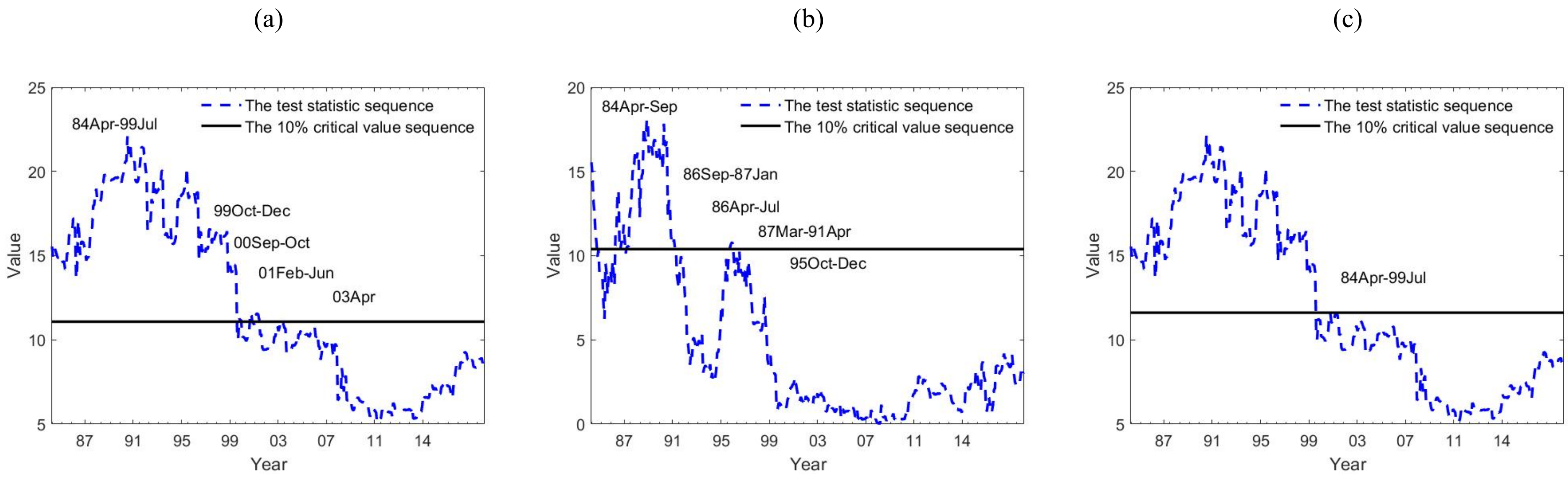
Panel (a), (b) and (c) in **Figure 5.4** display time-varying test statistics for causal effects running from wheat cash prices to futures prices. From panel (a), (b) and (c) of **Figure 5.4**, the test statistics are found to be higher than the 10% critical values during the early stage, suggesting the null hypothesis of no causality from wheat cash prices to futures prices can be rejected during the early periods. In detail, the forward expanding procedure indicates the main episode of Granger causality from wheat cash prices to futures prices but with some breaks: April 1984 – April 2003. The relatively short causality period is obtained from the rolling window process shown in panel (b) of **Figure 5.4**, suggesting a causal relation from wheat cash prices to futures prices between April 1984 and December 1995, but also with some breaks. The recursive evolving procedure detects a continues causality subperiod: April 1984 - July 1999.

(a) (b) (c)



Note: Results from the forward recursive, rolling window and recursive evolving procedures are displayed in (a), (b) and (c), respectively. Causal periods are noted on the plots. The 10% bootstrapped critical values are obtained with 1000 repetitions and controlled over a 1-year period, with a minimum window size $f_0 = 0.20$. The sequence of tests for the forward recursive, rolling window and recursive evolving procedures run from June 1975 to February 2020. Lag orders are assumed to be constant and selected using BIC with a maximum length of 20 for the whole sample period.

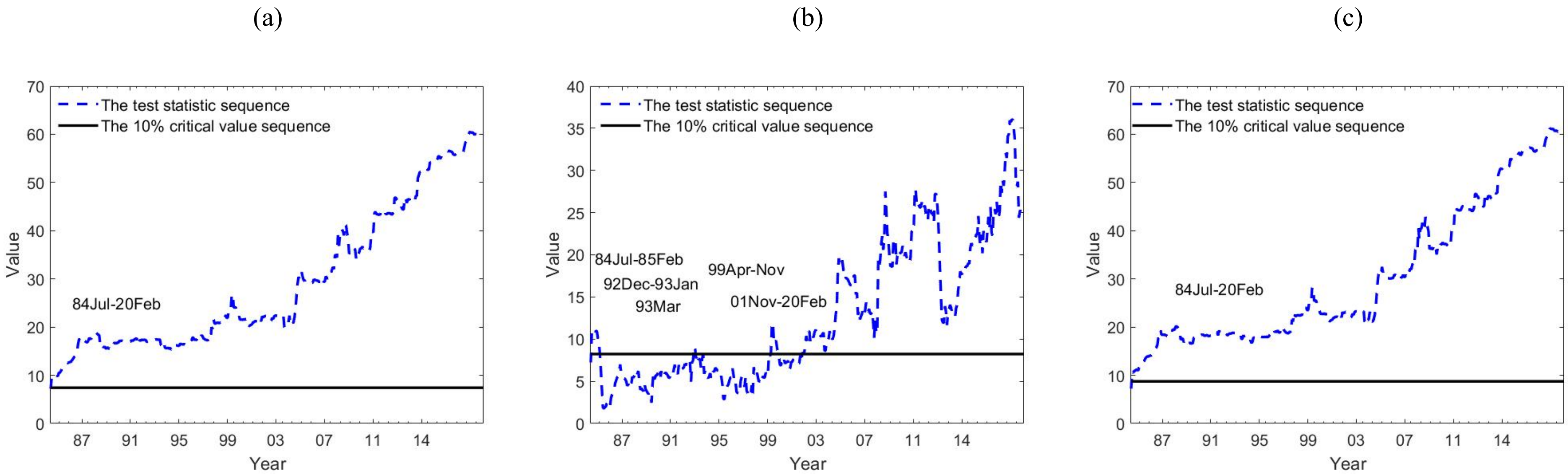
Figure 5.3: Tests for Granger causality running from wheat futures prices to cash prices



Note: Results from the forward recursive, rolling window and recursive evolving procedures are displayed in (a), (b) and (c), respectively. Causal periods are noted on the plots. The 10% bootstrapped critical values are obtained with 1000 repetitions and controlled over a 1-year period, with a minimum window size $f_0 = 0.20$. The sequence of tests for the forward recursive, rolling window and recursive evolving procedures run from June 1975 to February 2020. Lag orders are assumed to be constant and selected using BIC with a maximum length of 20 for the whole sample period.

Figure 5.4: Tests for Granger causality running from wheat cash prices to futures prices

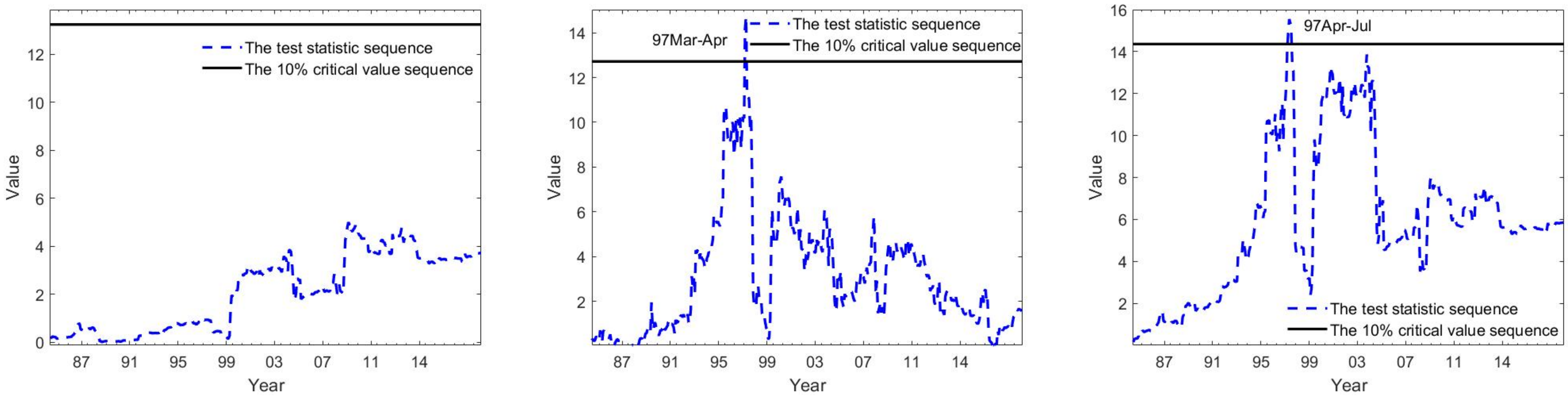
Panel (a) to (c) of **Figure 5.5** and **Figure 5.6** display the test statistics and 10% critical values applying the forward expanding, rolling window and recursive evolving approaches for the cases of soybean, respectively. Panel (a) and (c) of **Figure 5.5** report that the test statistic sequence obtained from forward expanding and recursive evolving methods are over the 10% critical value sequence persisting over the entire sample, implying the soybean futures prices are found to Granger cause the cash prices. However, a far more dynamic causal relation between cash and futures prices are revealed through a rolling window method. In panel (b) of **Figure 5.5**, the estimation results of the rolling window procedure paint a different picture. Before November 2001, the test statistics only above the 10% critical value at some episodes, suggesting the causality from soybean futures prices to cash prices occurs within some subperiods. But the rolling window procedure detects the soybean futures prices Granger cause cash prices after November 2001. The estimated test statistics in panel (a) of **Figure 5.6** are always below their 10% critical value sequence, indicating not rejecting the null hypothesis of that soybean cash prices do not Granger cause futures prices. However, in panel (b) and (c) of **Figure 5.6**, the test statistics of the rolling window and recursive evolving causality procedures are higher than the critical values at a very short period in 1997. These results indicate that the soybean cash prices were shown to Grange cause futures prices in some months in 1997.



Note: Results from the forward recursive, rolling window and recursive evolving procedures are displayed in (a), (b) and (c), respectively. Causal periods are noted on the plots. The 10% bootstrapped critical values are obtained with 1000 repetitions and controlled over a 1-year period, with a minimum window size $f_0 = 0.20$. The sequence of tests for the forward recursive, rolling window and recursive evolving procedures run from September 1975 to February 2020. Lag orders are assumed to be constant and selected using BIC with a maximum length of 20 for the whole sample period.

Figure 5.5: Tests for Granger causality running from soybean futures prices to cash prices

(a) (b) (c)

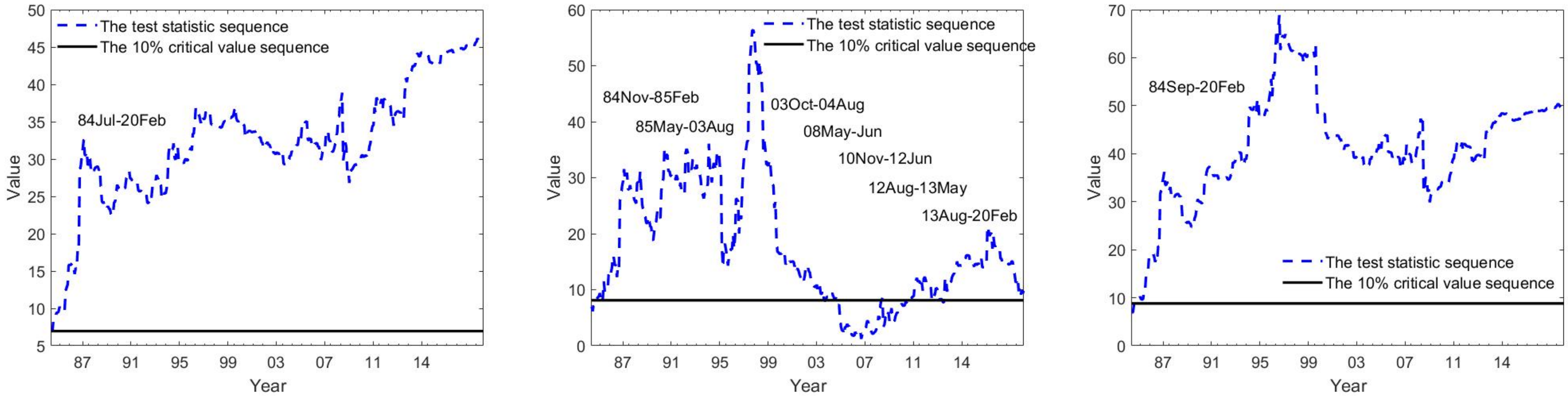


Note: Results from the forward recursive, rolling window and recursive evolving procedures are displayed in (a), (b) and (c), respectively. Causal periods are noted on the plots. The 10% bootstrapped critical values are obtained with 1000 repetitions and controlled over a 1-year period, with a minimum window size $f_0 = 0.20$. The sequence of tests for the forward recursive, rolling window and recursive evolving procedures run from September 1975 to February 2020. Lag orders are assumed to be constant and selected using BIC with a maximum length of 20 for the whole sample period.

Figure 5.6: Tests for Granger causality running from soybean cash prices to futures prices

In the case of corn prices, the results based on the forward expanding and recursive evolving methods, reported in panel (a) and (c) of **Figure 5.7**, are consistently above the 10% critical values. We can reject the null hypothesis of no causality from corn futures prices to spot prices. According to the panel (b) of **Figure 5.7**, similar to wheat and soybean cases, the rolling window causality test statistic sequence is above the 10% critical value sequence for most periods with some breaks. In a relatively long break episode, August 2004 – May 2008, the rolling window test statistics are below the critical values, indicating we cannot reject the null hypothesis of no causality from corn futures prices to cash prices. Panel (a) of **Figure 5.8** reports that the forward expanding causality test statistic sequence is below the critical value sequence at 10% level, which fails to reject the null hypothesis of non-causality runs from corn cash prices to futures prices. Similar to soybean case, panel (b) and (c) of **Figure 5.8** show that the rolling window and recursive evolving causality test statistics are below the 10% critical values except for January-February 1997.

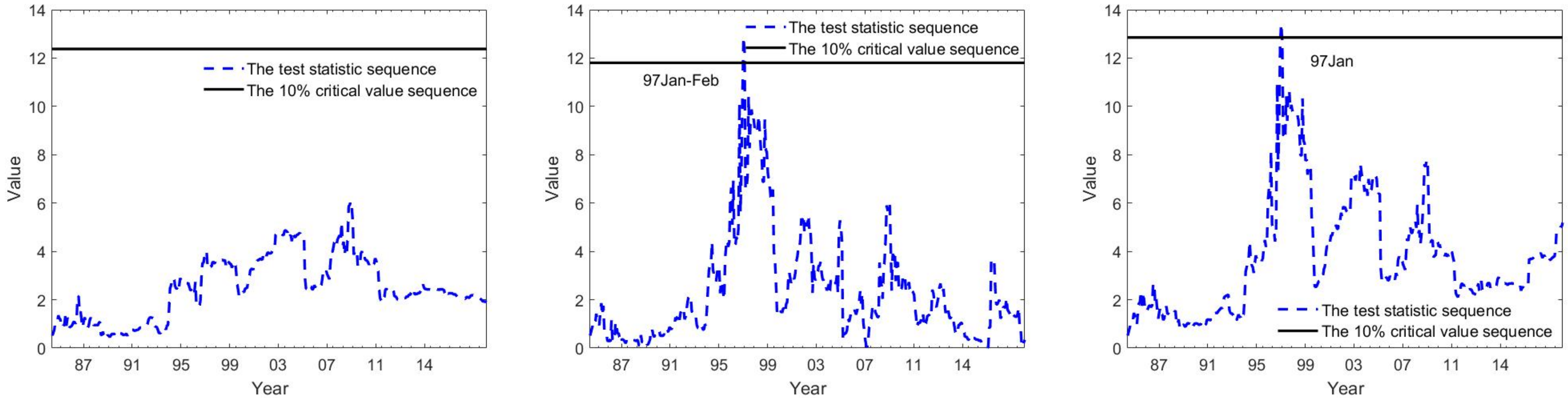
(a) (b) (c)



Note: Results from the forward recursive, rolling window and recursive evolving procedures are displayed in (a), (b) and (c), respectively. Causal periods are noted on the plots. The 10% bootstrapped critical values are obtained with 1000 repetitions and controlled over a 1-year period, with a minimum window size $f_0 = 0.20$. The sequence of tests for the forward recursive, rolling window and recursive evolving procedures run from September 1975 to February 2020. Lag orders are assumed to be constant and selected using BIC with a maximum length of 20 for the whole sample period.

Figure 5.7: Tests for Granger causality running from corn futures prices to cash prices

(a) (b) (c)



Note: Results from the forward recursive, rolling window and recursive evolving procedures are displayed in (a), (b) and (c), respectively. Causal periods are noted on the plots. The 10% bootstrapped critical values are obtained with 1000 repetitions and controlled over a 1-year period, with a minimum window size $f_0 = 0.20$. The sequence of tests for the forward recursive, rolling window and recursive evolving procedures run from September 1975 to February 2020. Lag orders are assumed to be constant and selected using BIC with a maximum length of 20 for the whole sample period.

Figure 5.8: Tests for Granger causality running from corn cash prices to futures prices

According to the explanations of subsampling processes for these three methods using **Figure 5.1** in the methodology section, the advanced recursive evolving is capable of searching for the optimum starting point of the regression for each observation, and thereby able to accommodate re-initialisation in the subsample to square with any changes in the structural as well as the causal direction that may exist within the full sample. Besides, both the forward expanding and rolling window methods are the special cases of the recursive evolving approach. The results of recursive evolving testing procedure are considered to be more comprehensive (Shi *et al*., 2018). Based on the obtained results from these causality tests, we find: (1) Before the early 2000s, a bidirectional Granger causality between wheat futures and spot prices, which suggests the information is approximate evenly divided between wheat spot and futures markets. But wheat futures prices lead the price discovery since the early 2000s. (2) For soybean and corn, there is unidirectional causality from futures prices to cash prices but with a very short break in 1997, providing strong evidence in favour of the futures prices lead the price discovery.

We attempt to explore whether the different phases of price discovery lead by either the spot or futures prices are associated with the specific events. In general, we are able to link the time-varying lead-lag causal relationship to specific agricultural commodity market events. In the case of wheat, we find a bidirectional linkage between spot and futures prices before the early 2000s. But a unidirectional causality from wheat futures prices to cash prices after the early 2000s. This paper suggests that the change point of the early 2000s is related to the financialisation among commodity markets. Prior to the early 2000s, the bidirectional causality indicates wheat futures prices and cash prices are both important in price discovery. Typically, futures prices lead the price discovery because futures markets have the advantages of lower transaction costs, higher transparency and higher liquidity. However, the bidirectional causality results suggest that wheat cash prices also play a key role in price discovery. Futures markets have a higher liquidity because it is the financial markets. However, constant reassessments of commodity future prices make the evaluation difficult and potentially affect the well-functioning price discovery of the futures markets (O'Hara, 2003). Commodities are different from financial assets, the spot market on the other hand might be less liquid but could promote the price discovery. Specifically, in the spot market, the buyers get access to the sellers easier while the sellers face difficulties in touching buyers immediately. Traders (who might even coincide with producers) could evaluate the market fundamentals better and quickly agreed on the fundamental value, the best-traded spot price, of the commodity through matching supply and demand (Dimpfl *et al.*, 2017). The demand and supply pressures over the physical commodities are equally important to the trading on the futures markets, in increasing the price discovery role of wheat cash markets (Irwin *et al.*, 2009). Besides, the increased trade liberalisation during 1970s to 1990s adds more flexibility to the agricultural commodity markets. The market-liberalising policies accelerate the information dissemination and affect the price discovery process in the agricultural markets (Olipra, 2020). The physical market becomes more responsive to changes in global supply and demand conditions (Peters *et al.*, 2009).

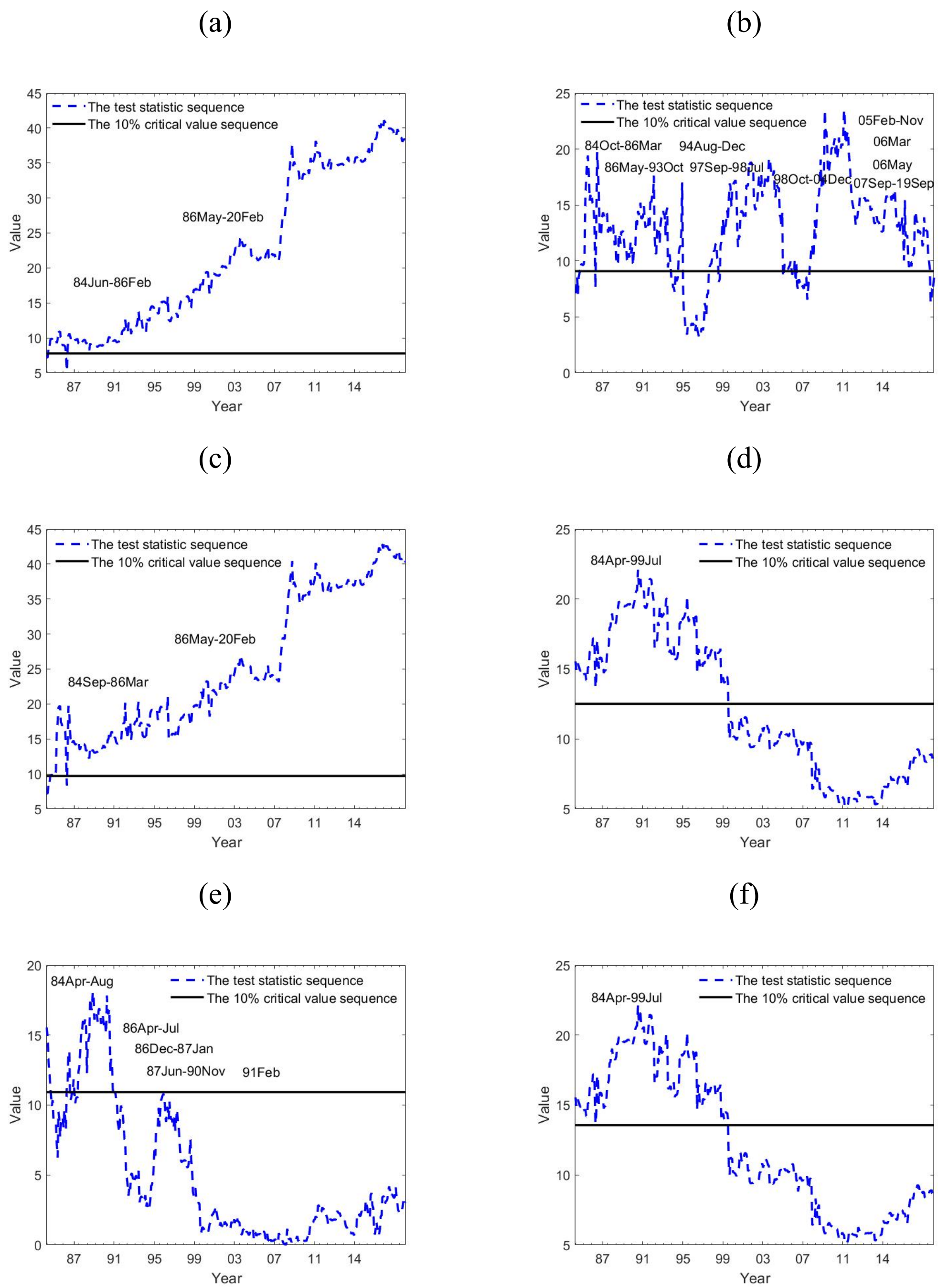
Since the early 2000s, the financialisation of commodity markets leads to rapid growth in financial investment and speculation in agricultural futures in the United States markets. For example, Irwin and Sanders (2012) report that the level of combined futures and option open interest in wheat in the late 2000s reached around five times their 1995-1999 levels. Besides, they report a more than three-fold increase in monthly wheat futures trading volume from 2000-2011. The institutional managers have considered commodity as a profitable alternative asset because commodity futures has a low or negative correlation with traditional assets such as stock and bond, and commodity prices positively correlated with inflation (Cheng and Xiong, 2014). These features encourage investors to use commodity futures as a refuge when conventional asset markets are under stress (Silvapulle and Moosa, 1999). Agricultural commodity futures emerge as an asset class and offers a diversification benefit (Cheng and Xiong, 2014). Accordingly, investment flows on the order of hundreds of billions of dollars come into the commodity markets, which attracts large liquidity. The higher liquidity results in higher price discovery (Grammig and Peter, 2013; Yan and Zivot, 2010), which interprets our result of unidirectional causality from wheat futures prices to cash prices from the early 2000s. In addition, take a close look at the financial crisis period 2007-2009 and food crisis period (2007-2008), our results suggest that the greater liquidity of wheat futures over physical wheat. Wheat futures react more quickly to unexpected information in the crisis period. In the time of crisis, wheat futures prices still play an important role in the price discovery process.

For soybean and corn, we find futures prices play the leadership role in price discovery, but the reverse is not true. Different from the wheat market, both the soybean and corn cash prices unanimously do not Granger cause futures prices. As explained above, the current best price of the commodity could be quickly agreed through matching supply and demand in the wheat cash market, and therefore the wheat cash price is also important in price discovery. However, this may not hold in soybean and corn markets because soybean and corn markets are interrelated markets. Soybean and corn are substitutable in terms of their end-use and these two commodities typically compete for acreage in the United States. The planting decisions for soybean and corn usually made jointly. Consequently, the supply responses of soybean and corn are a trade-off regarding acreage allocation decisions (Holt, 1992). In the sense that a rise in soybean acreage occurs at the expense of a decrease in corn acreage, and vice versa (Chavas and Holt, 1990). Compared to the wheat market, revising the supply and demand may relatively complex and take some time in the soybean and corn markets. Soybean and corn futures have greater liquidity over physical soybean and corn. In addition, agricultural commodity market participants face severe informational frictions regarding the supply, demand and inventory of the agricultural commodities (Cheng and Xiong, 2014). Financialisation of soybean and corn causes influences on the information discovery in soybean and corn markets. The lower costs of trading soybean and corn futures compared with the physical soybean and corn encourage greater participation and facilitates information aggregation. However, Stockin and Xiong (2015) emphasise that the noise brought about by the trading of futures investors could feed back to final-goods producers' demand for the commodity. Soybean and corn futures contracts are the most popular traded contracts in the United States. Informational frictions could exist because the soybean and corn producers cannot determine whether the futures price changes are trigged by financial investors' trading or the global economic fundamentals. Therefore, in comparison with financial traders, the participants in the physical markets may misinterpret the information of shocks. In other words, soybean and corn futures markets react more quickly to new information compared to their underlying spot markets.

These results are interesting for two reasons. First, some of the previous studies (e.g. Crain and Lee, 1996; Garbade and Silber, 1983 and Yang and Leatham, 1999) analyse the lead-lag relationship in the wheat market and conclude that wheat cash markets are largely satellites of the futures markets. Corresponding to these studies, Dimpfl *et al.* (2017) find evidence that the prices of these agricultural commodities are independently formed in the spot markets and that the spot prices contribute more in price discovery. The previous studies either support wheat futures prices lead cash prices or wheat cash prices dominate the price discovery. Our findings are different from them by indicating neither wheat futures prices nor spot prices constantly lead the other, or in other words, the lead-lag pattern changes over time. By applying their causality tests, this study identifies the exact switching time point of the changing lead-lag relationship. We are able to link these different causality periods to specific commodity market events such as the financialisation of commodity markets. Second, different from the wheat market, almost full-sample evidence does support that soybean and corn futures prices are Granger-causal of their cash prices, but the reverse does not true. This finding emphasises the price discovery drivers more related to the financial trading on soybean and corn futures markets.

5.6 Robustness checks

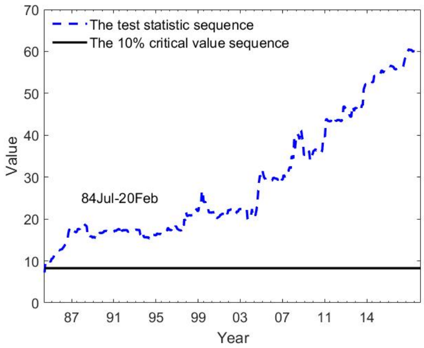
In identifying the robustness of the findings on causal relations running between spot and futures prices, a sensitivity and robust analysis is conducted. This study makes the following variants of the basic setup in the LA-VAR modelling framework: controlling the window size over a 3-year period to compute the 10% bootstrapped critical values and setting the minimum window size as $f_0 = 0.24$ to explore the finer local variability in the test statistics. We first retest the causality by controlling the size of the test sequence over a 3-year window instead of a 1-year window and the probability of making at least one false positive conclusion is taken to be 10% level. The 10% bootstrapped critical values are acquired from the 1000 repetitions and the bootstrap sample size is $T_b = \tau_0 + 35$. The low change of drawing a false positive conclusion is expected with the stricter rejection criteria, but the detection power would decrease. Remaining the basic estimation setup unchanged and the estimated results for wheat, soybean and corn are presented in **Figure 5.9**, **Figure 5.10** and **Figure 5.11**, respectively. From **Figure 5.9**, generally, the identification of the causal subperiods appears to be robust to the changes in window size. But we could also find some variations in the dates and the number of the causal episodes decreases, which attributed to the lower detection power induced by changing the window size. In the case of soybean and corn, **Figure 5.10** and **Figure 5.11** suggest that the causality pattern identified by three different algorithms keeps solid, despite some causal episode nuances.



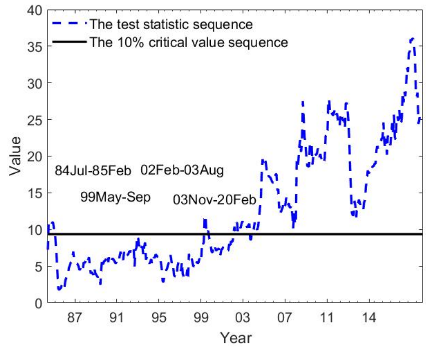
Note: The forward recursive, rolling window and recursive evolving test results for Granger causality from wheat futures to spot prices are displayed in (a), (b) and (c), and spot to futures prices are reported in (d), (e) and (f). Causal periods are noted on the plots. The 10% bootstrapped critical values are obtained with 1000 repetitions and controlled over a 3-year period, with a minimum window size $f_0 = 0.20$. Lag orders are assumed to be constant and selected using BIC with a maximum length of 20 for the whole sample period.

Figure 5.9: Tests for Granger causality between wheat futures and cash prices

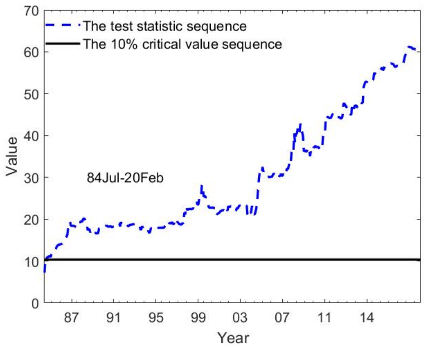
(a)



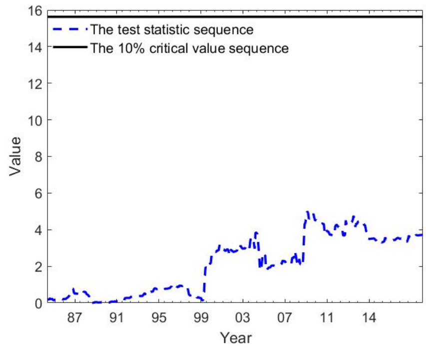
(b)



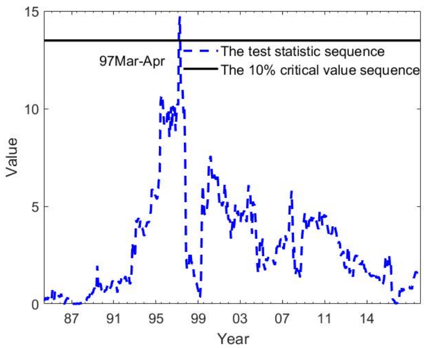
(c)



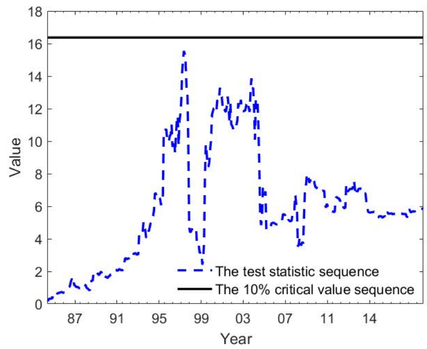
(d)



(e)

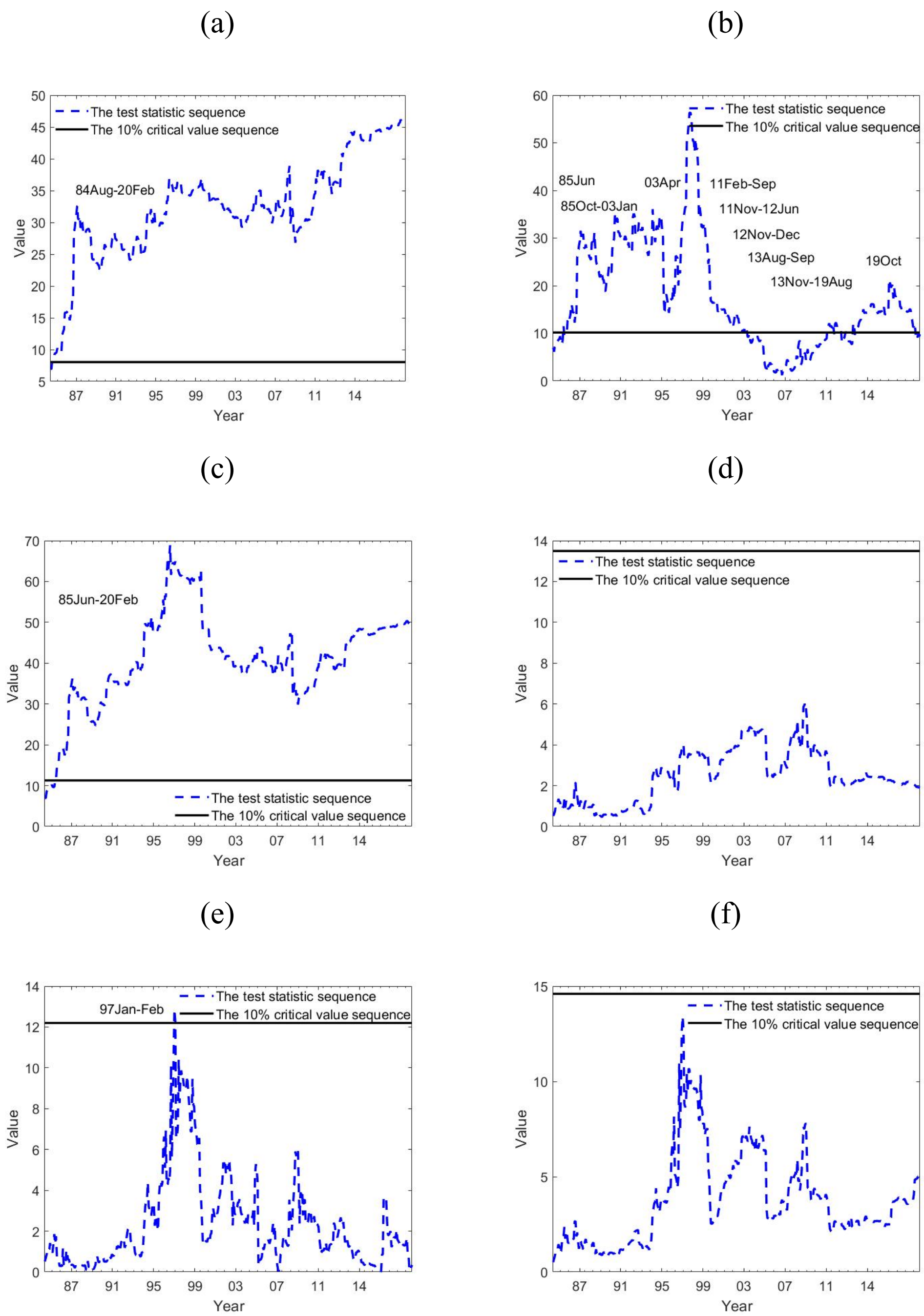


(f)



Note: The forward recursive, rolling window and recursive evolving test results for Granger causality from soybean futures to spot prices are displayed in (a), (b) and (c), and spot to futures prices are reported in (d), (e) and (f). Causal periods are noted on the plots. The 10% bootstrapped critical values are obtained with 1000 repetitions and controlled over a 3-year period, with a minimum window size $f_0 = 0.20$. Lag orders are assumed to be constant and selected using BIC with a maximum length of 20 for the whole sample period.

Figure 5.10: Tests for Granger causality between soybean futures and cash prices

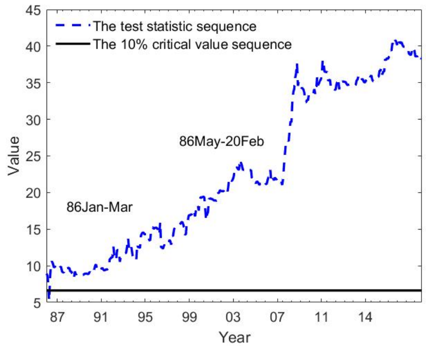


Note: The forward recursive, rolling window and recursive evolving test results for Granger causality from corn futures to spot prices are displayed in (a), (b) and (c), and spot to futures prices are reported in (d), (e) and (f). Causal periods are noted on the plots. The 10% bootstrapped critical values are obtained with 1000 repetitions and controlled over a 3-year period, with a minimum window size $f_0 = 0.20$. Lag orders are assumed to be constant and selected using BIC with a maximum length of 20 for the whole sample period.

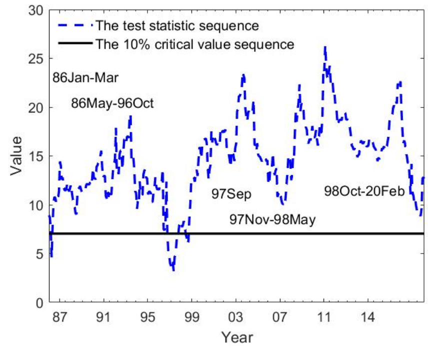
Figure 5.11: Tests for Granger causality between corn futures and cash prices

This paper subsequently changes the basic setting of the minimum window size by increasing the value of f_0 from 0.20 to 0.24 and maintain all other settings of the LA-VAR model unaltered, to test for the robustness of the Granger causality for three agricultural commodities. We re-conduct the Granger causality test with three different procedures and the results are reported in **Figure 5.12**, **Figure 5.13** and **Figure 5.14**, for wheat, soybean and corn, respectively. Once more, the entire Granger causality pattern identified appears to be robust to the changed model settings with small differences in the dates. Overall, from the robustness checks, the conclusion reached here implies that the pattern of Granger causality tested by employing sequences of Wald statistics is significantly robust to the changes of the estimation setup for the three agricultural commodities discussed in this study.

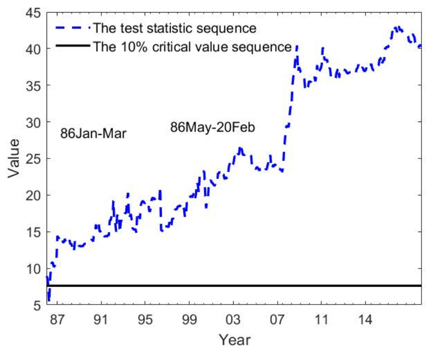
(a)



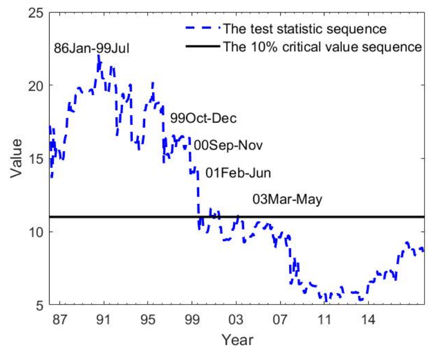
(b)



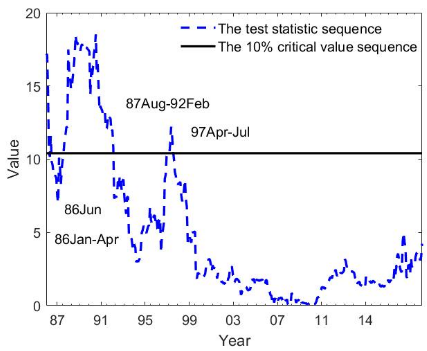
(c)



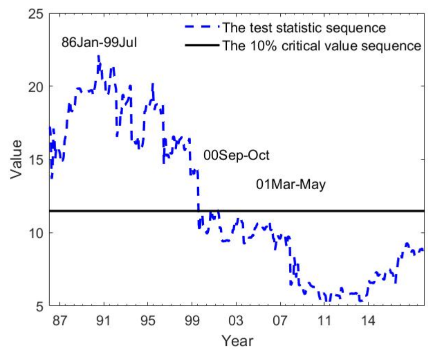
(d)



(e)



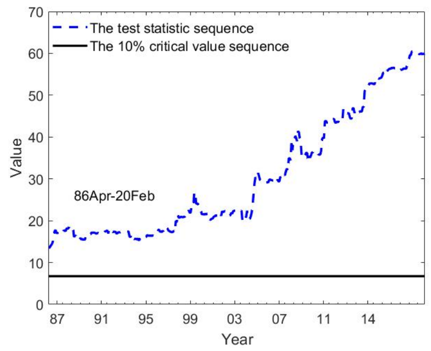
(f)



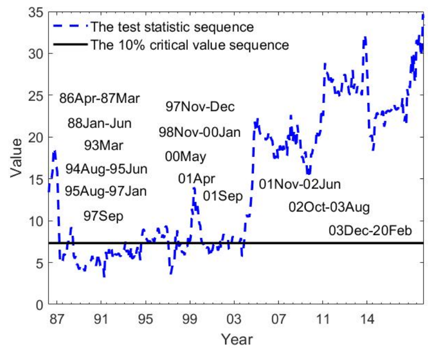
Note: The forward recursive, rolling window and recursive evolving test results for Granger causality from wheat futures to spot prices are displayed in (a), (b) and (c), and spot to futures prices are reported in (d), (e) and (f). Causal periods are noted on the plots. The 10% bootstrapped critical values are obtained with 1000 repetitions and controlled over a 1-year period, with a minimum window size $f_0 = 0.24$. Lag orders are assumed to be constant and selected using BIC with a maximum length of 20 for the whole sample period.

Figure 5.12: Tests for Granger causality between wheat futures and cash prices

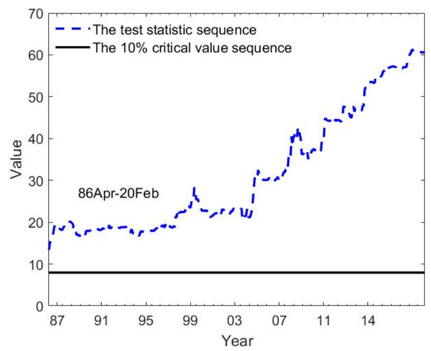
(a)



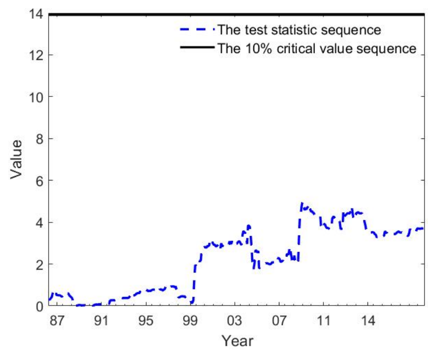
(b)



(c)



(d)



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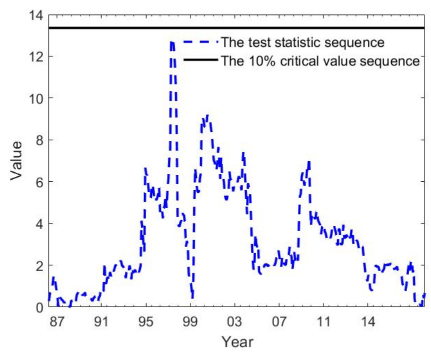
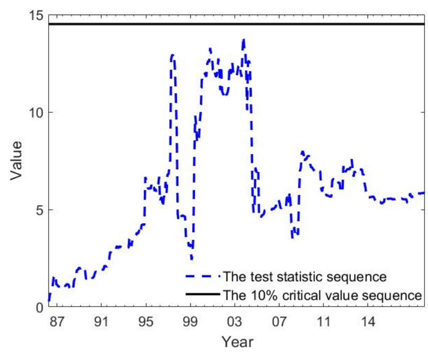
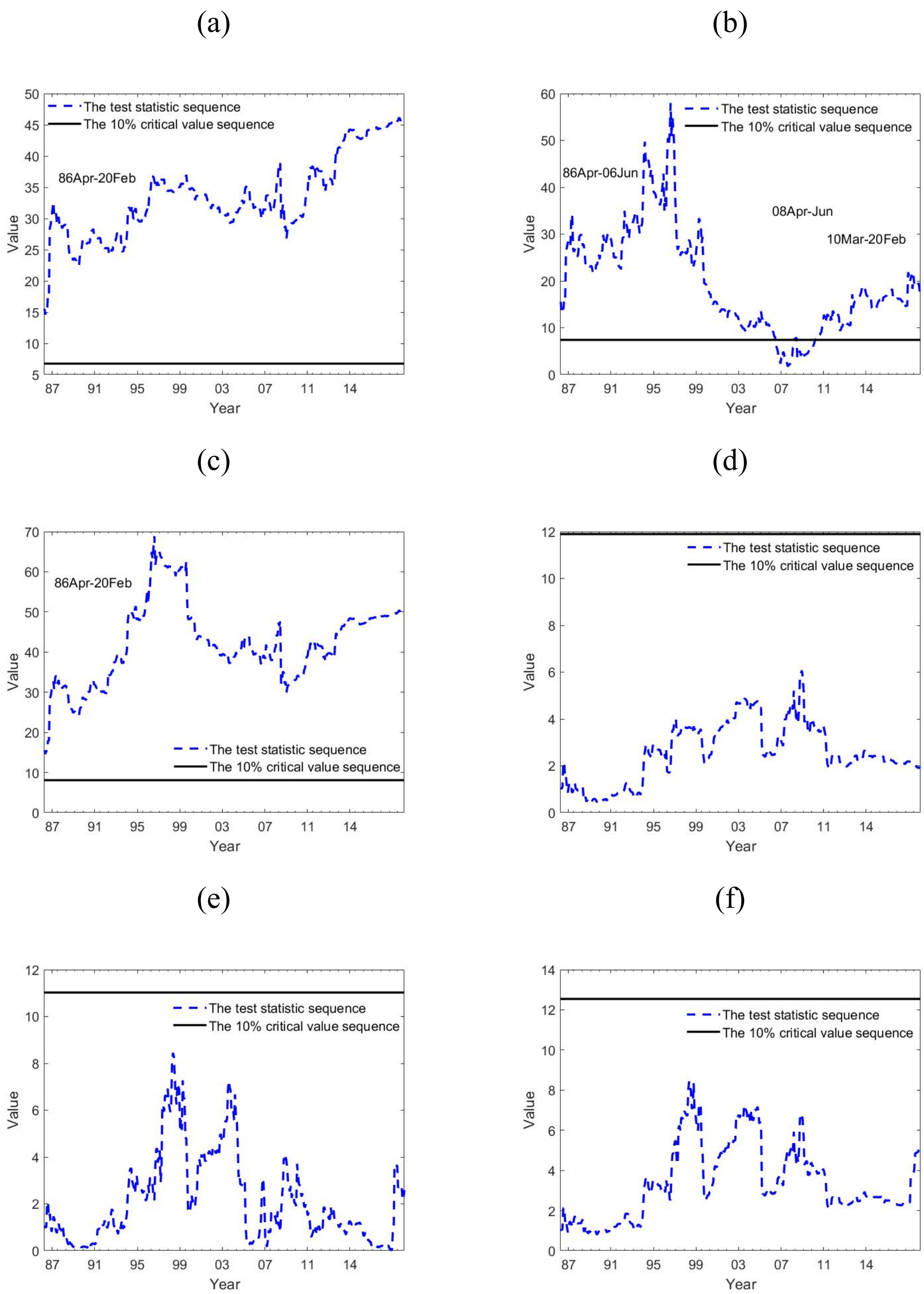


(f)



Note: The forward recursive, rolling window and recursive evolving test results for Granger causality from soybean futures to spot prices are displayed in (a), (b) and (c), and spot to futures prices are reported in (d), (e) and (f). Causal periods are noted on the plots. The 10% bootstrapped critical values are obtained with 1000 repetitions and controlled over a 1-year period, with a minimum window size $f_0 = 0.24$. Lag orders are assumed to be constant and selected using BIC with a maximum length of 20 for the whole sample period.

Figure 5.13: Tests for Granger causality between soybean futures and cash prices



Note: The forward recursive, rolling window and recursive evolving test results for Granger causality from corn futures to spot prices are displayed in (a), (b) and (c), and spot to futures prices are reported in (d), (e) and (f). Causal periods are noted on the plots. The 10% bootstrapped critical values are obtained with 1000 repetitions and controlled over a 1-year period, with a minimum window size $f_0 = 0.24$. Lag orders are assumed to be constant and selected using BIC with a maximum length of 20 for the whole sample period.

Figure 5.14: Tests for Granger causality between corn futures and cash prices

5.7 Conclusion

This study investigates the time-varying lead-lag causal relations between cash and futures markets for three important stable agricultural commodities, wheat, soybean and corn, spanning nearly half-century. We add to the literature on the lead-lag causality between agricultural commodity spot and futures markets on three counts. First, this study adopts three different time-varying causality test procedures based on LA-VAR modelling framework. Different from the previous studies, this model can be used without detailed or accurate prior knowledge of the presence or absence of unit roots. Besides, we could make Granger causality inferences in a time-varying manner and identify the exact origination and termination dates of causality periods. Second, the previous studies find a unidirectional causality between wheat futures and cash prices in the full sample, either futures prices Granger cause cash prices (e.g. Crain and Lee, 1996; Garbade and Silber, 1983; and Yang and Leatham, 1999) or cash prices Granger cause futures prices (Dimpfl *et al*., 2017). On the contrary, we find neither market leads nor lags the other consistently. We shed new light on the causal relations running from wheat spot prices to futures prices should change over time because the information flows could change with time. In our study, the lead-lag causality between wheat futures and cash prices are found to have experienced significant change around the early 2000s. A bidirectional Granger causality is observed prior to the early 2000s, but then wheat futures prices are found to lead the price discovery. This change corresponds to the financialisation among commodity markets, which attracts large liquidity and promotes the information flows in the wheat futures market. Third, we show that the spot and futures prices interactions behave differently in wheat compared to soybean and corn markets; in particular, a time-varying causality in the wheat markets but the unidirectional causality in the soybean and corn markets. The strong one-way causality is proved from futures prices to cash prices in both soybean and corn markets. The cases of soybean and corn are distinct from wheat. This finding emphasises futures markets are more liquid and react quickly to new or unexpected information. Besides, our findings are helpful for identifying the predictive power of futures and cash markets over different subperiods. Prior to the early 2000s, both only wheat futures and cash prices have predictive power for each other. But futures prices have the predictive power on the future actions of wheat cash prices since the early 2000s. Soybean and corn futures markets have strong predictive content for their cash markets.

Our findings have implications for producers, consumers and hedgers. We know that grains producers fix sales prices ahead of production and adjust supply decisions basing on the futures contract prices (Nicolau and Palomba, 2015; Xu, 2019). Our results indicate that the predictive power of wheat futures and cash prices change over different subperiods. While soybean and corn futures prices have insight information to predict the future action of their cash prices. Wheat producers may not always price wheat using futures prices as the reference ahead of production and revise wheat supply. They should pay more attention to the market events in different periods. Because these events may affect the direction or speed of the information flows, and therefore, the lead-lag relationship is sensitive to the time. However, soybean and corn producers could use the futures prices to fix sale prices and adjust supply decisions given futures prices consistently lead their cash prices. For consumers who consume the U.S. soybean and corn, they could use the futures prices to predict the future trend of the cash prices. They could store more soybean and corn in advance when the soybean and corn futures prices show an increase signal. For hedgers, this result supports the intuitive idea that hedgers in soybean and corn markets could take opposite positions in futures and spot markets to mitigate their portfolio risks. But for the hedgers in wheat markets, the information of specific events may be important for them to adjust the futures and cash positions. In addition, this chapter also gives several messages of the effects on world food price in developing economies. Developing countries are particularly affected by the volatile world food prices because of their dependence on agricultural commodity exports and their specialisation in one or a few agricultural commodities. The volatile world agricultural commodity price have serious consequences especially for the poor who spend a large part of their income on food (Banerjee and Duflo, 2007). The food price volatility leads to increased poverty in developing countries (Page and Hewitt, 2001). The U.S. wheat, soybean and corn markets play an important role in deciding the world food prices. Our results find that wheat, soybean and corn futures markets lead the price discovery in the United States since the 2000s. This means that wheat, soybean and corn futures markets are able to quickly reflect the new information related to the world agricultural commodity price changes and volatilities. The government in developing economies could plan for the appropriate preparation based on the information obtained from the grains futures markets of the United States. For example, the policymakers in the developing countries could plan for the strategic grain reserves and public stock scheme for the grains basing on the U.S. grains futures prices movements.

An interesting issue remains unresolved in this study relates to the effects of bounded rationality and rational herding on the informational content between the cash and futures markets. Further work on this topic would need an in-depth examination of the bounded rationality and rational herding. Besides, this study restricts the lead-lag time-varying causality to the linear form. However, the causal effects between markets could be nonlinear. The nonlinear lead-lag interactions might draw different pictures from their linear counterparts. To be robust to possible nonlinear causality, there are avenues for further studies on this arguable issue. The findings of these studies would no doubt improve the understanding of the causal effects and price discovery process for agricultural commodity markets.

Chapter 6. Final Remarks

Three chapters consist of this thesis and provide evidence for three core topics for the agricultural commodity price dynamics. It does so by applying recently developed novel econometric tools for the identification of effects of energy markets, climate changes and financial markets.

Chapter 3 analyses the role of the energy market in the movements of agricultural commodity prices, with particular attention on the relations between diesel prices and corn export prices, considering diesel power dominates the wide transportations, and corn has the highest energy-related expenses among eight selected major agricultural commodities (Sands et al., 2011). The results of this work show a positive co-movement between corn export prices and diesel prices. An implication from this result is that the diesel prices are currently facilitating the input costs and result in changes in export prices. The chapter also identifies the positive long-run relation patterns between diesel and corn export prices rely on the market conditions. More specifically, the long-run equilibrium relationship becomes stronger when corn export prices at the higher level. But when the corn export prices at the extreme level, the dependence between corn and diesel decreases. Because under the extreme circumstances, the excess supply or excess demand market conditions, exporters will not export corn and hence reduce the demand for diesel. In comparison, the steeper responses occur when corn export prices are at extreme levels at the median and high ranges. At this stage, exporters find the prices are within their expectations and will continue to export corn for higher profits. Thus they need more diesel to transport corn to the ports.

Chapter 3 makes a contribution to the literature in the following ways: First, this study aims to model long-run relations between corn export prices and diesel prices, given that diesel powers over two-thirds of the farm equipment and transport approximately

90% of the agricultural products in the United States. To this end, this chapter shows that there is a positive co-movement between corn export prices and diesel prices. Therefore, the importers of the U.S. corn can use diesel prices as a reference to anchor their decisions on corn export prices prediction. Secondly, this work is different from the previous studies by arguing that the magnitude of the long-run relationship between energy prices and corn export prices varies when corn export prices at a different level. Besides, this paper proves the relationship between diesel and corn is characterised as nonlinear. Since it is difficult to capture the upward and downward movements, especially if the diesel prices can be extremely volatile, this study chooses to consider the extreme effects with the help of a quantile-based cointegration method. Chapter 3 gives several interesting results from such a novel econometric tool.

Chapter 4 identifies the effects of changes in the climate conditions on the movements in agricultural commodity prices, with focus on an important global climate phenomenon, El Niño Southern Oscillation (ENSO), and examine its effects on agricultural commodity prices, particularly grain prices that are most likely to be affected by variable climate conditions. The empirical results of this chapter point that both the two phases of the ENSO event, El Niño and La Niña, lead to the increases in the grain prices. Wheat prices only respond to the La Niña events and soybean prices only affected by El Niño conditions. However, corn prices respond to both El Niño and La Niña phases but display the asymmetric price adjustment processes. The findings of this chapter imply that we can use current El Niño and La Niña conditions to predict different grain prices basing on their responses to the ENSO conditions. In addition, although it is not the primary objective of this work, the results may contribute to informing the issue associated with the agricultural commodity prices forecasting in the forthcoming decades. Particularly, how the information of ENSO events may assist in making predictions of grains prices in the United States.

This chapter makes a core contribution to the literature by providing new evidence of the effects of climate changes on agricultural commodity prices, and more concretely the asymmetric relationship of the two extreme phases, El Niño and La Niña, to the major grains price dynamics in the United States. This study differs from previous research on finding the ENSO anomalies lead to price fluctuations in selected U.S. grain prices. Further, conversely to most works in the literature that rely on using the point-based models, this chapter employs a novel interval-based tool which allows for capturing range information of climate variables.

Finally, chapter 5 identifies the time-varying price discovery issues for the three most frequent traded agricultural futures contracts, wheat, soybean and corn, in the United States. The findings of chapter 5 indicate that the lead-lag causal relations between futures and cash prices change over time and depend on agricultural commodity markets. In wheat markets, the relationship between wheat futures and cash prices are found to have experienced significant change around the early 2000s. A bidirectional Granger causality is observed prior to the early 2000s, but then wheat futures prices are found to play a bigger role in the price discovery. However, in soybean and corn markets, the results are consistent to indicate more evidence for causality from futures prices to spot prices than otherwise.

Although the subject of this chapter is the familiar price discovery process, the contribution is different from the existing literature. The core contribution chapter 5 is to reveal the time-varying features of the price discovery process in agricultural commodity markets. To progress the idea of understanding the time-varying characteristic of price discovery in agricultural commodity markets, this chapter employs both conventional forward expand and rolling window causality tests as well as recently developed recursive evolving causality method. Our findings have strong implications for producers, consumers and hedges. Given that a bidirectional causality found in wheat markets, market participants should pay more attention to the wheat market events in different periods. While for the participants in soybean and corn markets, the information in the futures markets is more important to help predictions.

This thesis provides several messages in policy terms. The insights from chapter 3 entail two important implications. First, policymakers should pay attention to the nonlinear behaviour of the diesel-corn price nexus when building the estimation and prediction modes for agricultural or energy markets. Second, corn could also be used as biofuel production. The findings in chapter 3 may help with setting land allocation plans. Corn used as biofuel production would compete with food grain in allocating land. Knowing the relationship between diesel and corn is helpful for corn supply and demand predictions. Therefore, strategies of land allocation for food grains and feedstock should consider this nonlinear relationship. Several important policy implications are derived from the findings of chapter 4. First, the design of crop plantation should consider the responses of different crops to the changing climate conditions. The findings in chapter 4 suggest that policymakers may be encouraged to adjust the rotation strategy and land allocation strategy for corn and soybean, given the two ENSO phases will increase the soybean and corn prices. However, soybean only responds to El Niño conditions while corn will respond to both El Niño and La Niña events. To this extent, considering the competing for land between corn and soybean, local planning should adjust the land-using to the preferable crops to hedge against the climate adverse effects. Second, chapter 4 is useful for farm risk management and improve the economic returns facing different phases of ENSO event.

There are several potential avenues for future research that may be different from the perceptions of this thesis. First, chapter 3 of this thesis discusses the responsive behaviour of corn export prices to diesel price changes for different market conditions.

This chapter has confirmed the corn export prices have a different response to the changing diesel prices. The findings in this chapter may be nicely complemented by analysing the adjustment behaviour of corn export prices in more detail, such as the correction behaviours when corn export prices at different levels. Due to current econometric method is unable to capture the correction process, this thesis has not addressed the detailed adjustment behaviour of corn export prices. Yet, this issue seems to be important when making accurate predictions. Second, chapter 4 concentrate sharply on the effects of climate change on agricultural commodity prices from the whole country perspective. However, agricultural commodity production is heterogeneous in different regions in the United States. In addition, the effects of climate events are also not homogeneous for different areas in the United States. Further to this, the regional level analysis could be conducted in future research. Third, chapter 5 inspects the time-varying causality between futures and spot prices. One potential reason is that the information flows could be sluggish in some time periods. Along this line, the issues of the impacts of bounded rationality and rational herding on the informational content between the cash and futures markets keep unanswered. More research is needed to elucidate the bounded rationality and rational herding.

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