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

Yichen Zhu[†*], Atanu Ghoshray[†]
[†]Newcastle University Business School, Newcastle University, Newcastle-upon-Tyne, UK.
[*]Corresponding author.

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.

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.

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

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

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

$$y_t = \Gamma\tau_t + \Phi x_t + \Psi z_t + \varepsilon_t, \tag{2}$$

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

$$H_0\colon \boldsymbol{R}\emptyset = 0 \tag{3}$$

on the coefficient $\emptyset = vec(\Phi)$ applying row vectorisation and $\boldsymbol{R}$ is the $m \times n^2k$ 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 $\mathrm{Y} = (y_1, y_2, \dots, y_T)'_{T\times n}$, $\tau = (\tau_1, \dots, \tau_T)'_{T\times2}$, $X = (x_1, \dots, x_T)'_{T\times nk}$, $Z = (z_1, \dots, z_T)'_{T\times nd}$ and $\varepsilon = (\tau_1, \dots, \tau_T)'_{T\times2}$. Then set out

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

and the OLS estimator could be given as

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

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

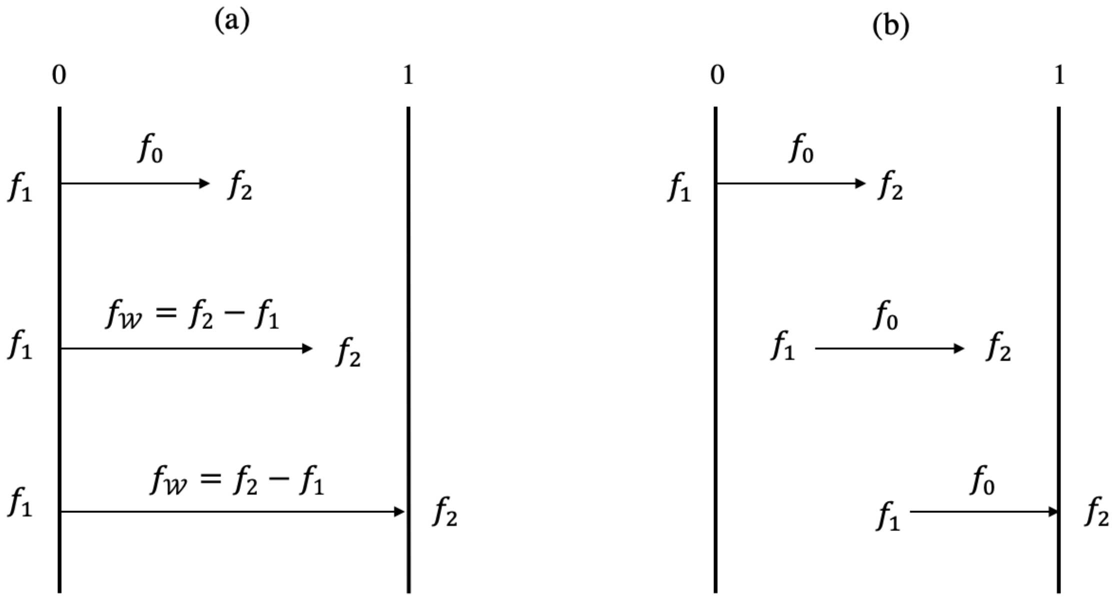
$$\mathcal{W} = \left(\boldsymbol{R}\widehat{\emptyset}\right)'[\boldsymbol{R}\{\widehat{\Sigma_{\varepsilon}} \otimes (X'QX)^{-1}\}\boldsymbol{R}']^{-\mathbf{1}}\boldsymbol{R}\widehat{\emptyset} \tag{4}$$

where $\widehat{\emptyset} = vec(\widehat{\Phi})$, $\widehat{\Sigma_{\varepsilon}} = \frac{1}{T}\hat{\varepsilon}'\hat{\varepsilon}$, 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).

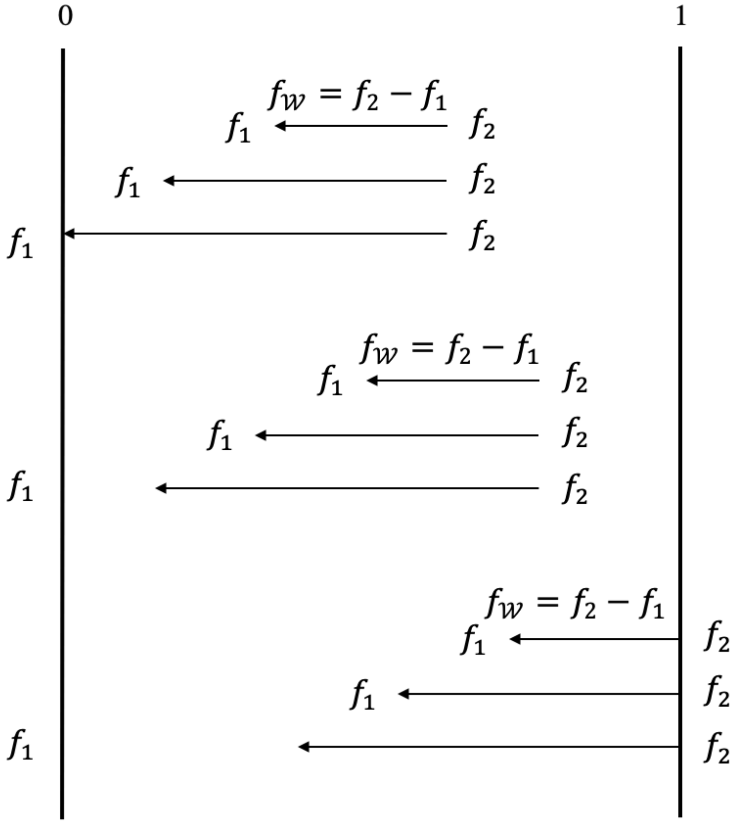
As indicated in the literature review, there are some studies expect the lead-lag causality should change over time because the market participants will filter the information relevant to cash and futures positions over time (Silvapulle and Moosa, 1999; Bekiros and Diks, 2008). In such circumstances, 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 $f_{\mathcal{W}} = f_2 - f_1$. And $\mathcal{W}_{f_1}^{f_2}$ indicates the Wald statistic based on the LA-VAR model and calculated from the subsample.

In **Figure 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).



(c)



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

Figure 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

$$SW_f(f_0) = \sup_{f_2=f, f_1\in[0,f_2-f_0]} \{\mathcal{W}_{f_1,f_2}\}. \tag{5}$$

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

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

$$\mathcal{W}^*_{f_1,f_2} = T_{\mathcal{W}}\left(\boldsymbol{R}\hat{\emptyset}_{f_1,f_2}\right)'\left[\boldsymbol{R}\left\{\hat{V}^{-1}_{f_1,f_2}\hat{\Sigma}_{f_1,f_2}\hat{V}^{-1}_{f_1,f_2}\right\}\boldsymbol{R}'\right]^{-1}\boldsymbol{R}\hat{\emptyset}_{f_1,f_2}, \tag{6}$$

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

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

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

The heteroskedastic-consistent sup Wald statistic is defined as

$$S\mathcal{W}^*_f(f_0) = \sup_{f_2=f, f_1\in[0,f_2-f_0]} \{\mathcal{W}^*_{f_1,f_2}\}. \tag{7}$$

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

$$\begin{bmatrix} y_{1t}^b \\ y_{2t}^b \end{bmatrix} = \begin{bmatrix} \widehat{\emptyset}_{11} & 0 \\ \widehat{\emptyset}_{12} & \widehat{\emptyset}_{22} \end{bmatrix} \begin{bmatrix} y_{1t-1}^b \\ y_{2t-1}^b \end{bmatrix} + \begin{bmatrix} e_{1t}^b \\ e_{2t}^b \end{bmatrix} \tag{8}$$

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

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

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

$$\text{Recursive evolving window: } S\mathcal{W}_{t}^{b}(\tau_0) = max_{t\in[\tau_0,\tau_0+\tau_b-1]}(S\mathcal{W}_{t}^{b}(\tau_0)) \tag{9}$$

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).

Data description and preliminary analysis

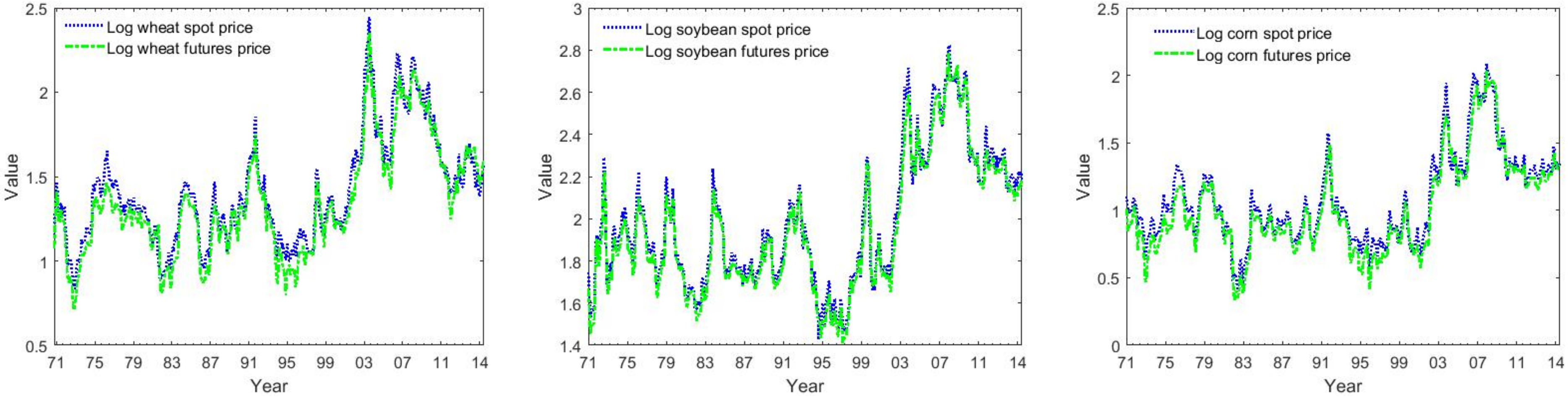
Our analysis is based on the monthly price time series for the important cereal grains, including wheat, soybean and corn spot and futures prices, which are freely available at the website of the National Agricultural Statistics Service (NASS) of the United States Department of Agriculture (USDA). The 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 1** below exhibits the descriptive information of the cash and futures price series for wheat, soybean and corn. From **Table 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 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 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 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 2** The top half of **Table 2** conducts the standard unit root tests without breakpoint, including ADF, PP and KPSS tests. The lower half of **Table 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 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	**ADF_L**	-2.3033	-2.6772*	-2.9686**	-3.0738**	-2.7687*	-2.8532*
	ADF_Δ	-14.6975***	-18.4634***	-14.9836***	-13.9610***	-14.2319***	-17.4305***
	PP_L	-2.3508	-2.6003*	-2.2223	-2.5529	-1.9954	-2.5919*
	PP_Δ	-14.2065***	-18.4074***	-14.1240***	-13.9610***	-13.4168***	-16.9369***
	$KPSS_L$	1.4749***	1.3286***	1.3901***	1.3706***	1.2518***	1.1874***
	$KPSS_\Delta$	0.0303	0.0307	0.0319	0.0302	0.0816	0.0363
With break	**$PV_{AO, L}$**	-2.8124	-2.7031	-2.9295	-3.0439	-2.7863	-2.8675
	$PV_{AO, \Delta}$	-14.5653***	-18.6379***	-15.0036***	-17.1603***	-14.1863***	-17.4279***
	$PV_{LO, L}$	-2.2289	-2.5981	-2.8409	-2.9206	-2.5547	-2.8052
	$PV_{LO, \Delta}$	-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

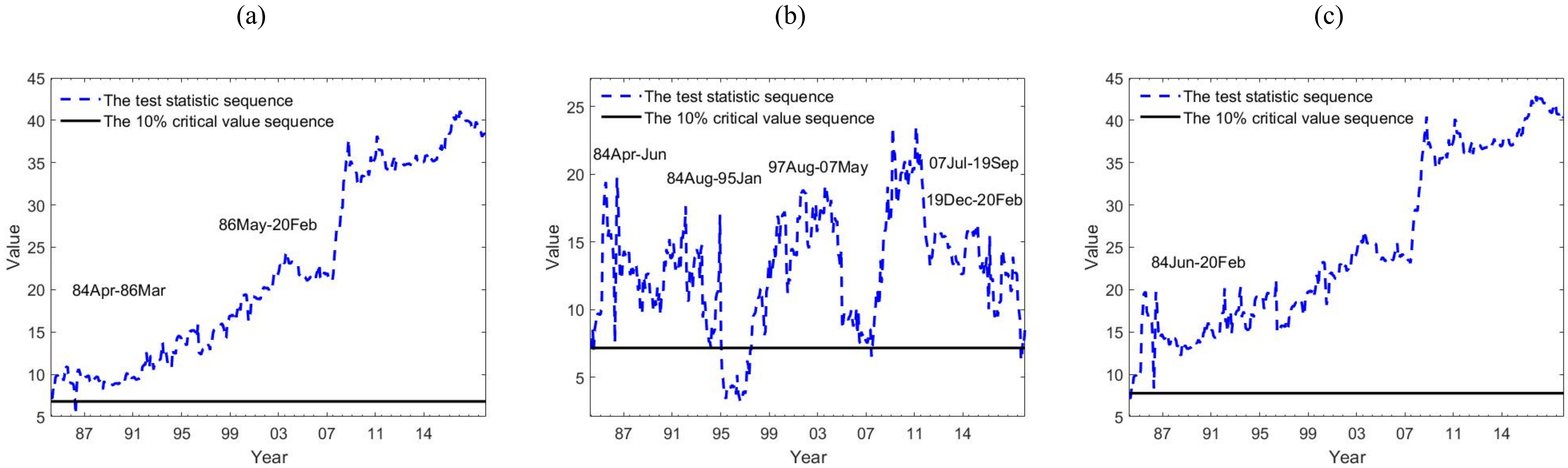
Empirical analysis

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 3** to **Figure 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.

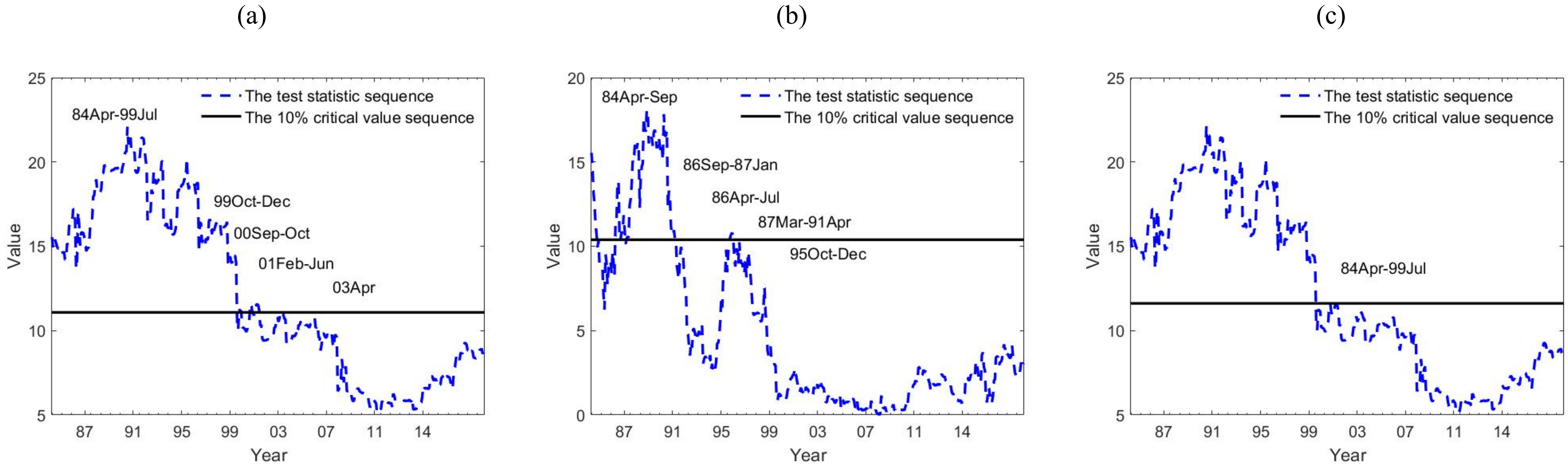
The time-varying test statistic sequences for causal relations between wheat cash and futures prices, along with their corresponding bootstrapped 10% critical values for the forward expanding window, rolling window and recursive evolving window methods are displayed in **Figure 3**. Panel (a), (b) and (c) of **Figure 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 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 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 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 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.



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.

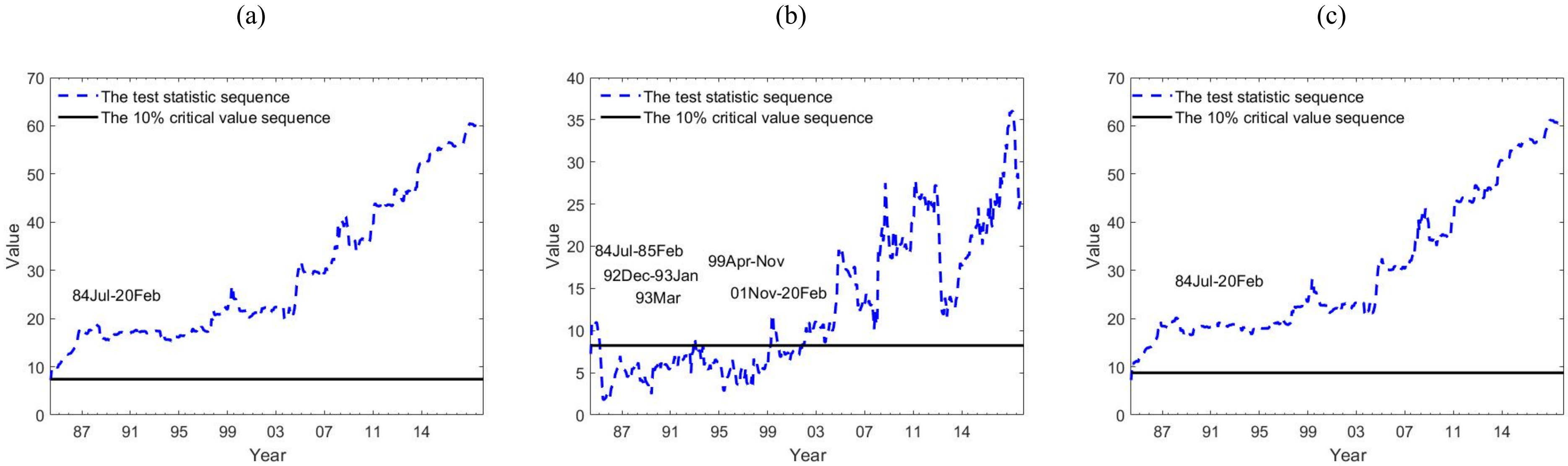
Figure 3: Tests for Granger causality running from wheat futures prices to cash prices



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

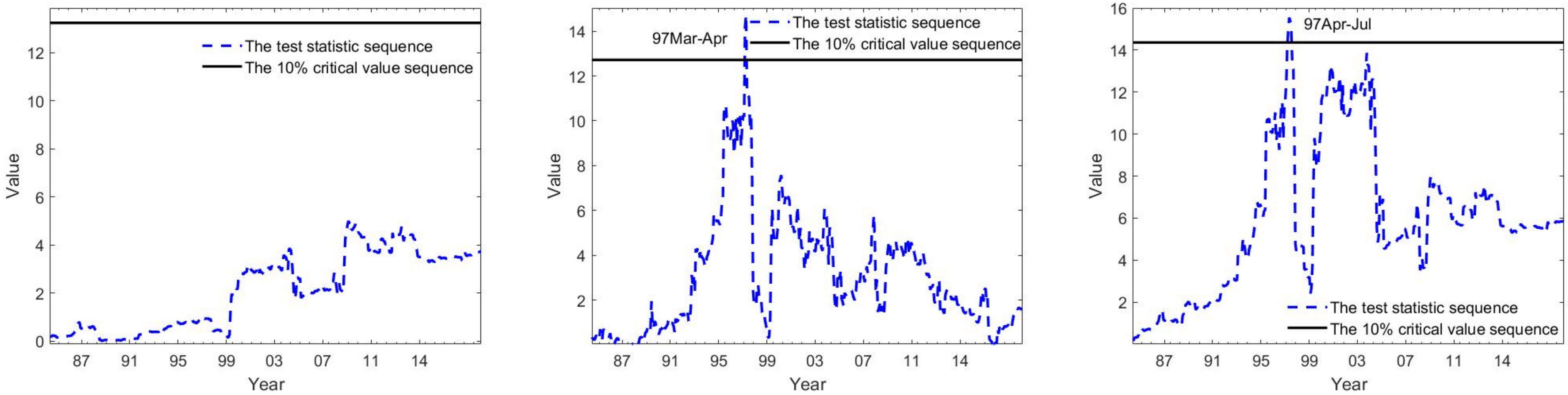
Panel (a) to (c) of **Figure 5** and **Figure 6** display the test statistics and 10% critical values applying the forward expanding, rolling window and recursive evolving approaches for the cases of soybean, respectively. Panel (a) and (c) of **Figure 5** report that the test statistic sequence obtained 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**, 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 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 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: Tests for Granger causality running from soybean futures prices to cash prices

(a) (b) (c)

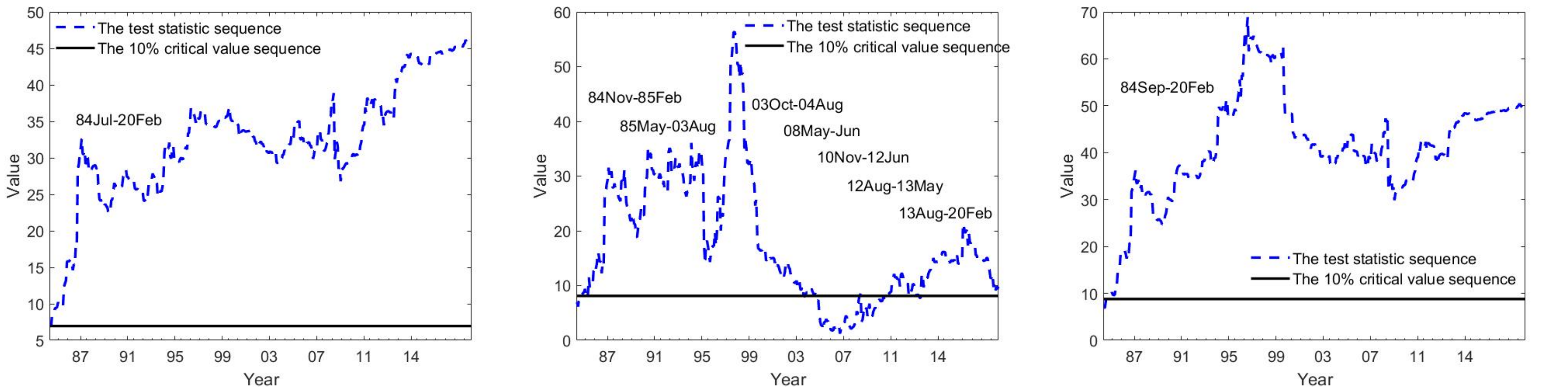


Note: Results from the forward recursive, rolling window and recursive evolving procedures are displayed in (a), (b) and (c), respectively. Causal periods are noted on the plots. The 10% bootstrapped critical values are obtained with 1000 repetitions and controlled over a 1-year period, with a minimum 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 6: Tests for Granger causality running from soybean cash prices to futures prices

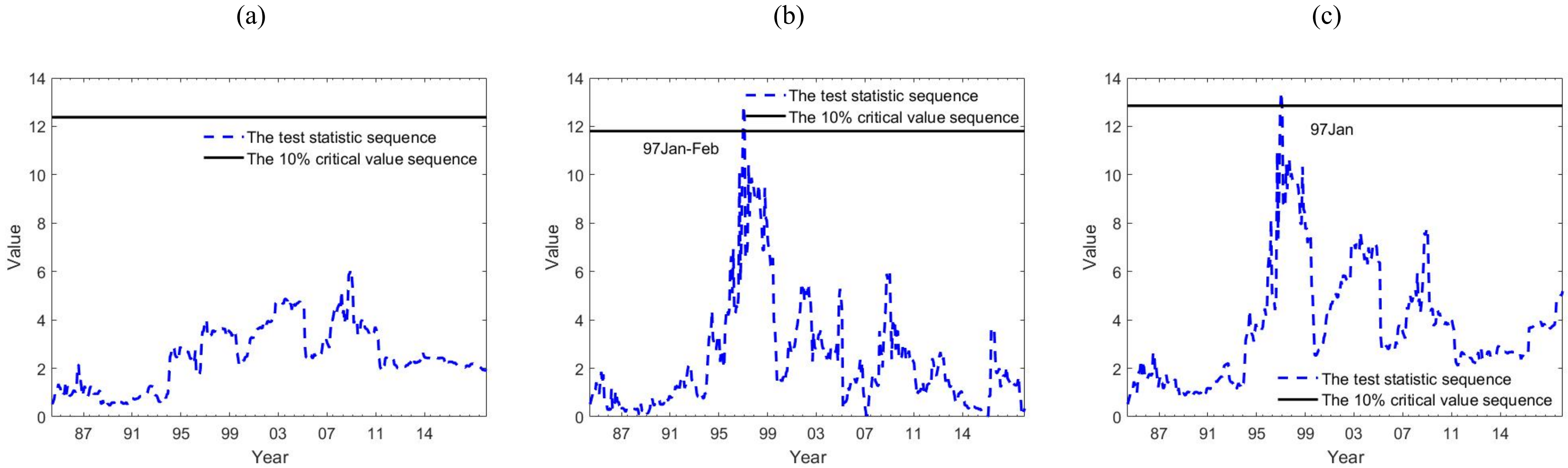
In the case of corn prices, the results based on the forward expanding and recursive evolving methods, reported in panel (a) and (c) of **Figure 7**, are consistently above the 10% critical values. We can reject the null hypothesis of no causality from corn futures prices to spot prices. According to the panel (b) of **Figure 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 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 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 7: Tests for Granger causality running from corn 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 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 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 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).

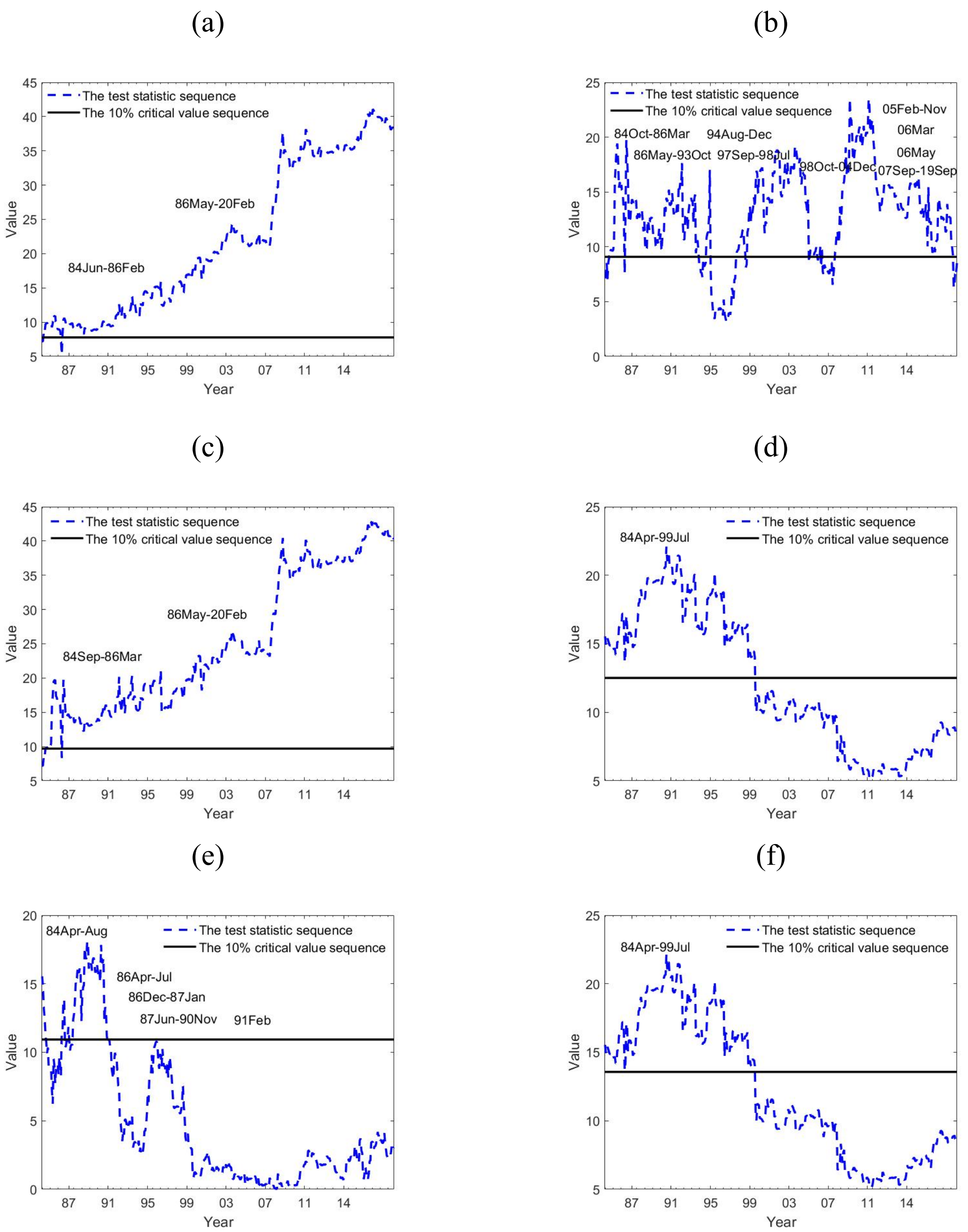
Since the early 2000s, the financialisation of commodity markets leads to rapid growth in financial investment and speculation in agricultural futures in the United States markets. For example, Irwin and Sanders (2012) report that the level of combined futures and option open interest in wheat in the 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.

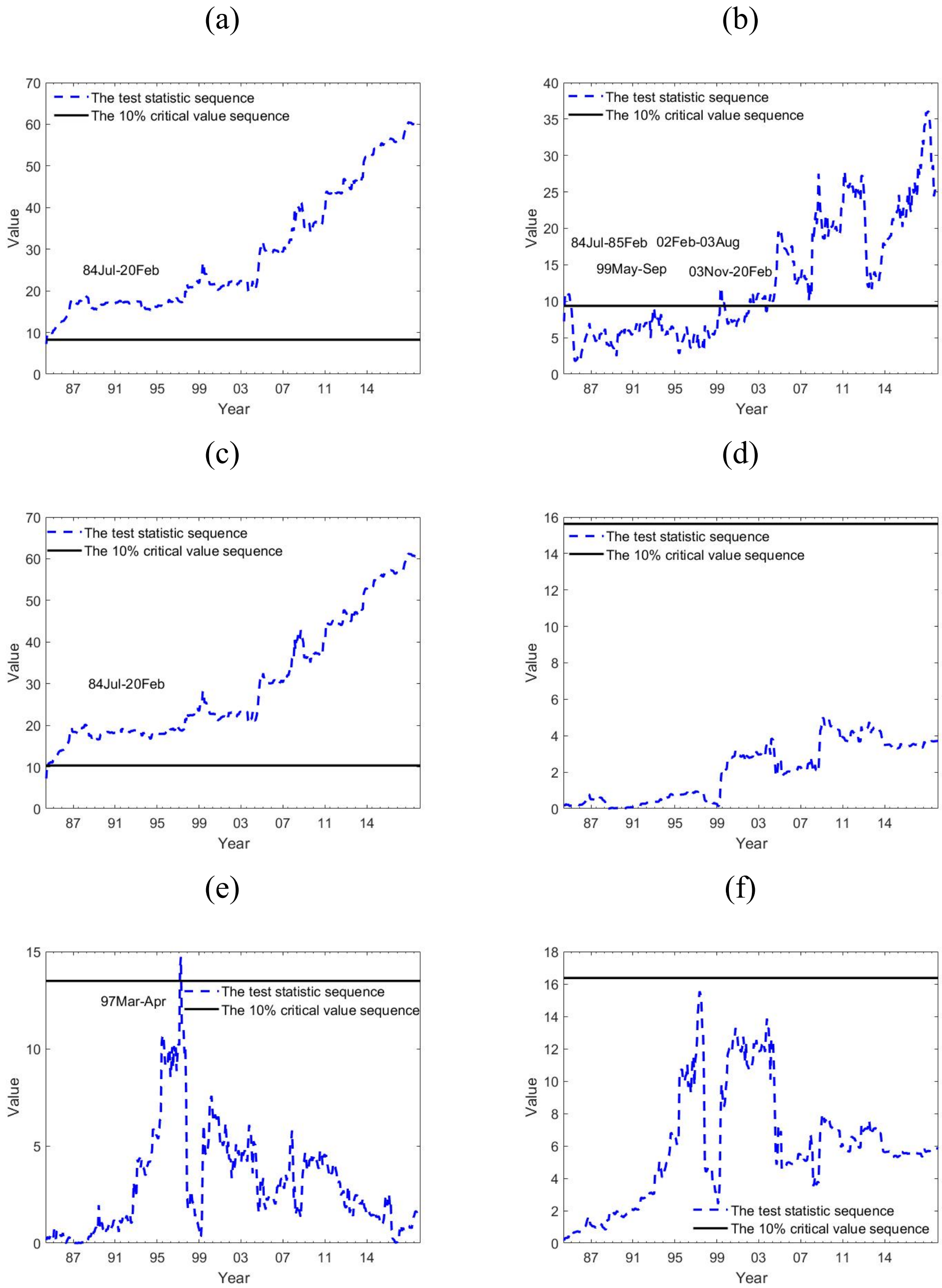
Robustness checks

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 9**, **Figure 10** and **Figure 11**, respectively. From **Figure 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 10** and **Figure 11** suggest that the causality pattern identified by three different algorithms keeps solid, despite some causal episode nuances.



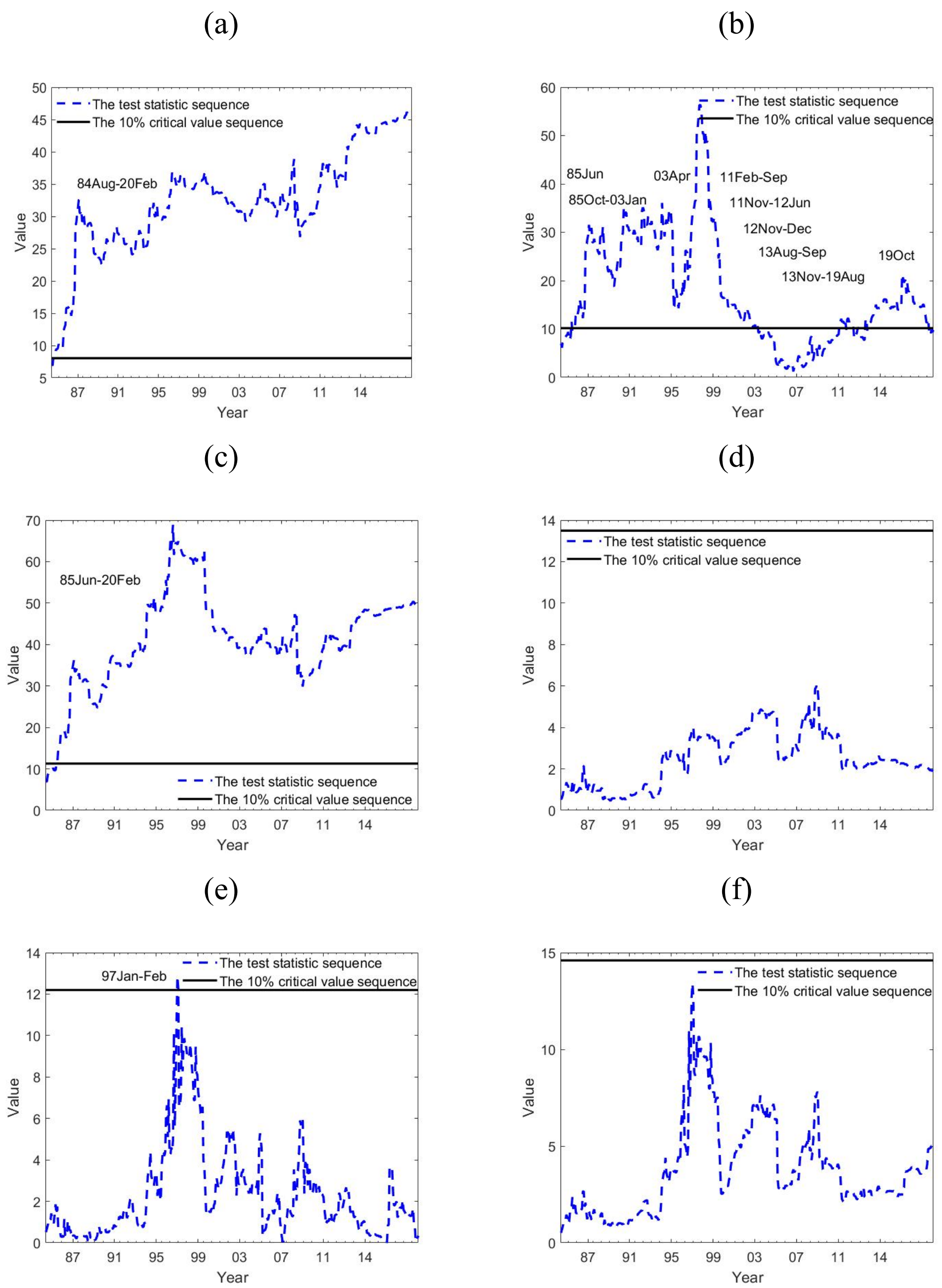
Note: The forward recursive, rolling window and recursive evolving test results for Granger causality from wheat futures to spot prices are displayed in (a), (b) and (c), and spot to futures prices are reported in (d), (e) and (f). Causal periods are noted on the plots. The 10% bootstrapped critical 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 9: Tests for Granger causality between wheat futures and cash prices



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 10: Tests for Granger causality between soybean futures and cash prices



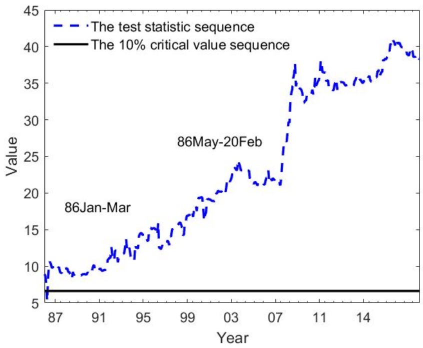
Note: The forward recursive, rolling window and recursive evolving test results for Granger causality from corn futures to spot prices are displayed in (a), (b) and (c), and spot to futures prices are reported in (d), (e) and (f). Causal periods are noted on the plots. The 10% bootstrapped critical values 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 11: Tests for Granger causality between corn futures and cash prices

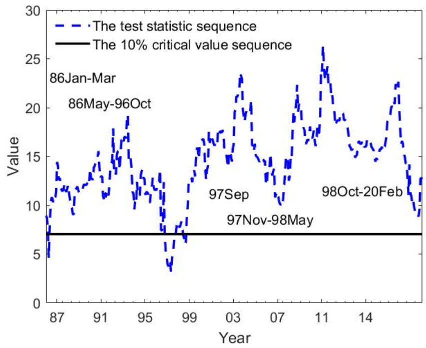
This paper subsequently changes the basic setting of the minimum window size by increasing the value of f_0 from 0.20 to 0.24 and maintain all other settings of the LA-VAR model unaltered, to test for the robustness of the Granger causality for three agricultural commodities.

We re-conduct the Granger causality test with three different procedures and the results are reported in **Figure 12**, **Figure 13** and **Figure 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.

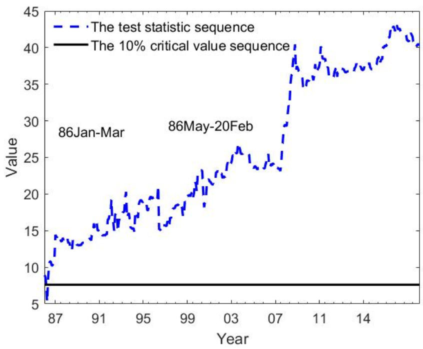
(a)



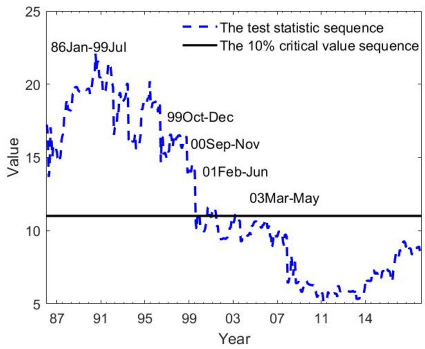
(b)



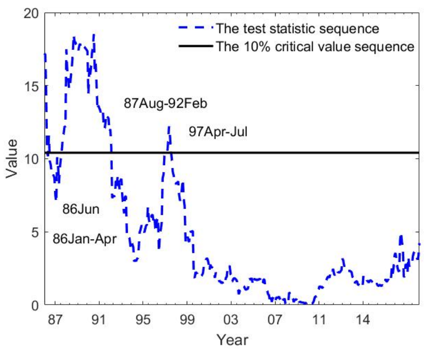
(c)



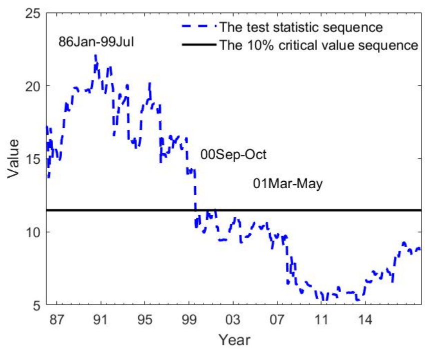
(d)



(e)



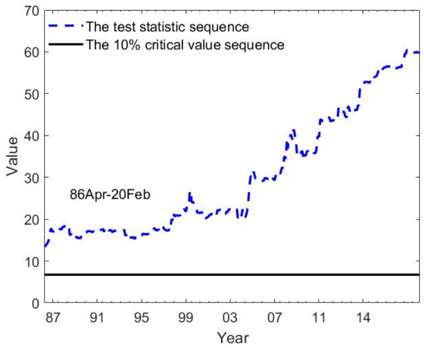
(f)



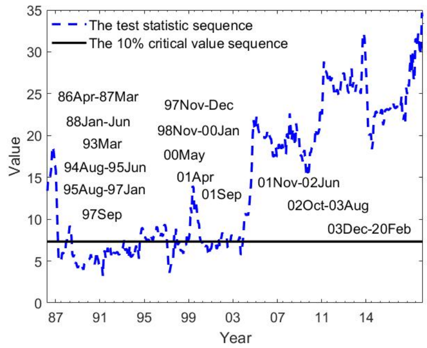
Note: The forward recursive, rolling window and recursive evolving test results for Granger causality from wheat futures to spot prices are displayed in (a), (b) and (c), and spot to futures prices are reported in (d), (e) and (f). Causal periods are noted on the plots. The 10% bootstrapped critical 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 12: Tests for Granger causality between wheat futures and cash prices

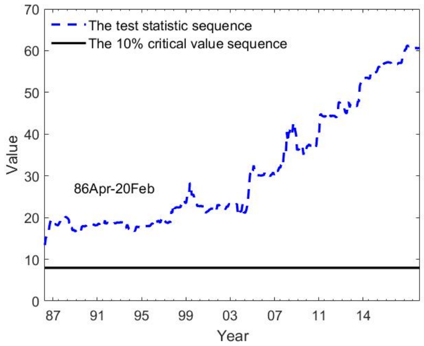
(a)



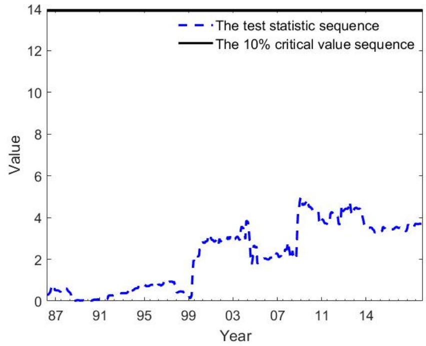
(b)



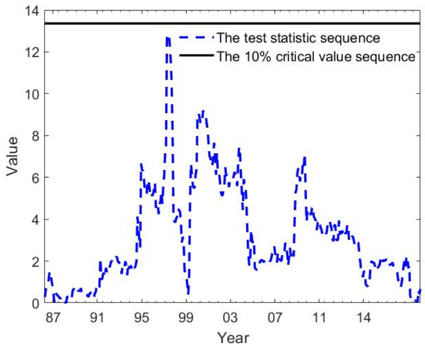
(c)



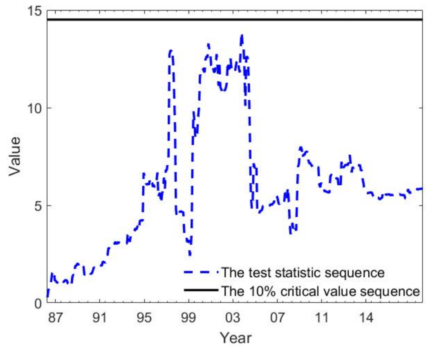
(d)



(e)



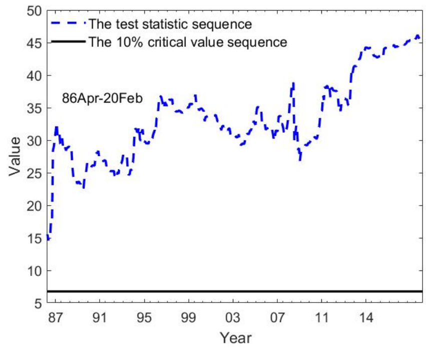
(f)



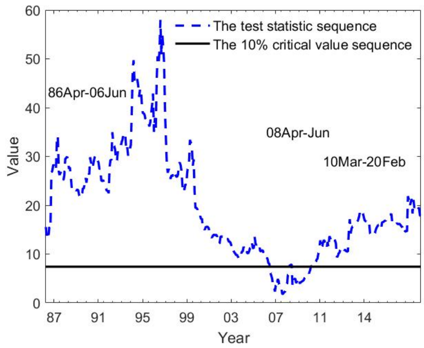
Note: The forward recursive, rolling window and recursive evolving test results for Granger causality from soybean futures to spot prices are displayed in (a), (b) and (c), and spot to futures prices are reported in (d), (e) and (f). Causal periods are noted on the plots. The 10% bootstrapped critical values are obtained with 1000 repetitions and controlled over a 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 13: Tests for Granger causality between soybean futures and cash prices

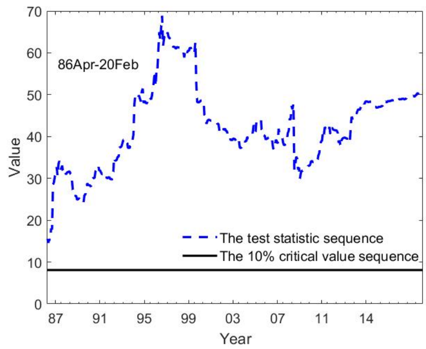
(a)



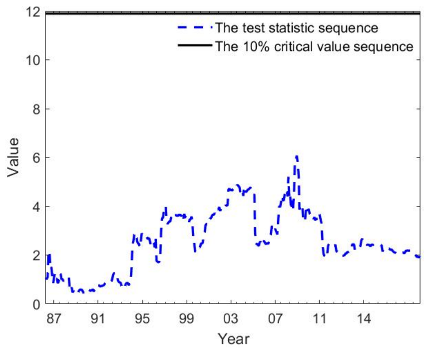
(b)



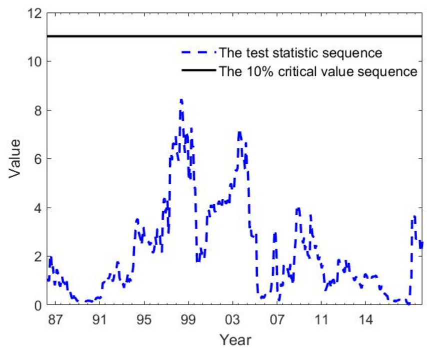
(c)



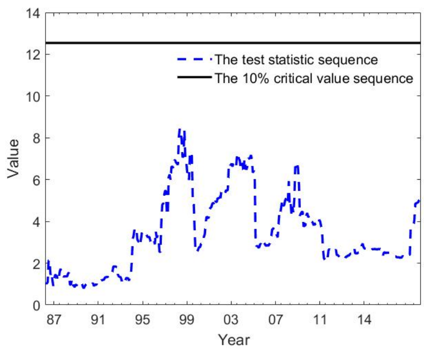
(d)



(e)



(f)



Note: The forward recursive, rolling window and recursive evolving test results for Granger causality from 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 14: Tests for Granger causality between corn futures and cash prices

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.