An Analysis of Temporal and Spectral Connectedness and Spillover in Commodity Markets

By

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Preface

This thesis is submitted in fulfillment of the requirements for the degree of Philosophiae Doctor (PhD) at the University of Stavanger (UiS), Faculty of Science and Technology, Norway. The research presented has been carried out at the University of Stavanger from November 2016 to April 2020. I acknowledge the University of Stavanger and the Norwegian Research Council for their financial support which made this project possible.

The primary contributors to this thesis have been my supervisors Atle Oglend and Roy Endré Dahl. Writing this PhD thesis has been challenging and rewarding in several areas – personally and professionally. I wish to extend a special thanks to all of my resourceful colleagues and friends at the University of Stavanger for providing memorable and enjoyable three years. For my supervisors, Atle Oglend and Roy Endré Dahl, I am deeply thankful for their patience, allowing me to focus on the fields of economics closes to my interest, and always providing insightful, critical, and friendly advice for guiding me throughout this project.

Summary

This thesis is concerned with evaluating the temporal and spectral connectedness and spillover dynamics of commodity prices. The industries of interest are crude oil, agricultural commodities, aquaculture, and Norwegian salmon as the primary datasets. World agricultural and energy commodity indexes as well as the aquaculture sector and salmon price index have experienced exceptionally volatile periods throughout the last decade. Therefore, the objective of this thesis is to detect and quantify the temporal and spectral connectedness and spillover dynamics in the prices of these assets.

This thesis falls in line with a large collection of research papers evaluating the dynamics of commodity markets. More specifically, the first two papers examine the connectedness structure between crude oil and agricultural commodities and between various aquaculture species by utilizing wavelet-based copula approach. By combining the methodologies from physics and econometrics, we evaluate how the dependence structures among the underlying assets varies across different frequencies and in the tails of the distributions. The third paper evaluates the static and temporal return and volatility spillover dynamics between crude oil and agricultural commodities. The last paper examines the firm-level cointegration relation and return spillover dynamics between Fish Pool Index (FPI) and major salmon producers. Incorporating methodologies from physics, economics, and finance is relevant when examining spectral relationship and providing an alternative angle to examine the commodity markets.

The findings of this thesis indicate that the connectedness between oil and agricultural commodities increased during post-2006 across all considered frequencies of return movements. Specifically, the wavelet decomposition reveal that the interconnectedness structure is negative during the pre-2006, but it turns positive over the post-2006 subsample. Furthermore, the findings indicate persistence in dependence variation is higher over the long-run return movements. In terms of spillover analysis, the findings indicate minuscule information transmission between crude oil and agricultural commodities over the pre-2006 subsample, but crude oil tends to be a net receiver of volatility over the post-2006 subsample. Furthermore, we report asymmetric and bidirectional information transmission between crude oil and agriculture during periods of financial and economic turmoil. In terms of connectedness in different aquaculture species, the findings indicate limited dependence in the short-run horizon, however, the price linkage among various species significantly increased over the medium- and long-run horizon, suggesting market integration over the long-run. In regard to cointegration and spillover among FPI and major salmon producers, we report that the prices of exchange traded salmon stocks reflect the flow of salmon market information earlier than the price index. Furthermore, our findings indicate that the FPI and small producers are net receiver of spillover from major salmon producers.

Contents

1 Introduction

The increased financialization and globalization of commodity markets are the primary components for the strengthened connectedness and transmission shocks among and between financial and commodity markets. Financialization of commodity futures markets and the flow of speculative investments significantly adds to the connection of different commodity markets, which are predominantly impelled due to the participation of institutional investors through the periods of high liquidity and turmoil (Gorton and Rouwenhorst, 2006; Bhardwaj et al., 2015). Due to lack of substantial potential to achieve diversification and risk management benefits, market participants has been constantly pursuing alternative investment prospects to diversify their portfolios and hedge their investments. Commodity markets, in this regard, has been a prime target for the market participants due to its heterogeneous business cycle relative to the financial markets. Over the years, the commodity markets have acted as safe-havens to hedge against investments in financial markets. Also, lower trade barriers and greater international flow of financial capital and physical products has connected otherwise localized commodity markets. This has made different markets dependent on common global supply and demand conditions, and by extension connecting the prices in different commodity markets. This provide further thrust to the interconnectedness among the commodity markets. Therefore, it is essential to quantify connectedness and spillover between and within the commodities and their changes over time.

The four papers in this thesis can be divided into two main parts. The first part comprises of papers [I] and [II] and deals with evaluating the temporal and spectral connectedness and volatility spillover dynamics, respectively, in the crude oil and agricultural markets. The second part consists of papers [III] and [IV] and focuses on examination of temporal and spectral connectedness among various aquaculture species and firm-level cointegration and spillover dynamics between Fish Pool Index (FPI) and major salmon producers in Norway. In the following subsections, the introduction of each part is presented, which is followed by the abstracts of the four papers.

1.1 The relationship between energy and agricultural commodities

World agricultural and energy commodity prices have undergone remarkably volatile phases during the course of the last decade. The increased interdependence of global financial and commodity markets are the principal components of increased connectedness and transmission shocks between assets. Understanding the temporal and spectral interconnectedness have numerous essential implications for investment allocation, asset valuation, risk management, and monetary policy making (Karyotis and Alijani, 2016; Andreasson et al., 2016; Belousova and Dorfleitner, 2012). Although, there is a large strand of literature contributed to assessing the variances and covariance of different assets, examination of connectedness dynamics and volatility transmission mechanisms among commodity markets have received relatively less attention. Historically, the large changes in crude oil prices were often resulted in an increase in other commodity prices (Nazlioglu et al., 2013), raising question of whether the variations in the price of crude oil changes the temporal and frequential dynamics of other commodities.

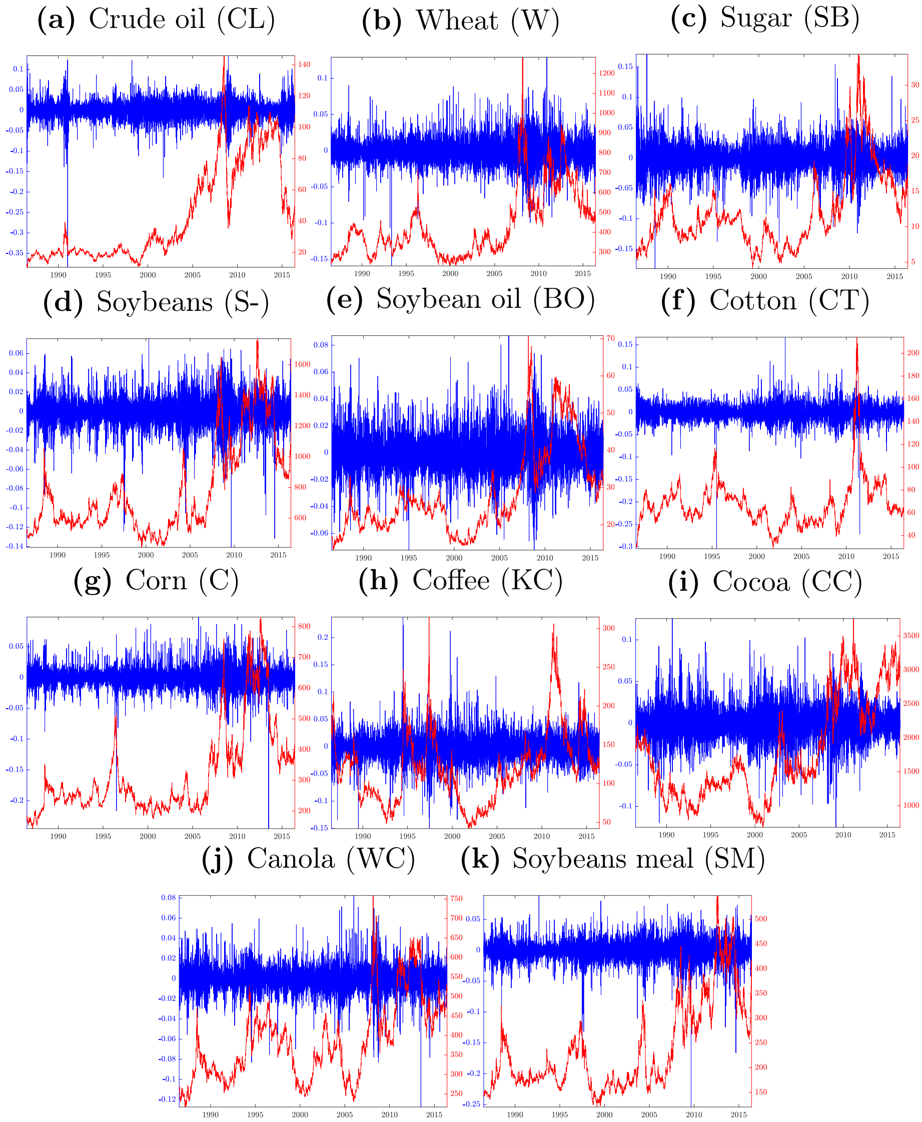
Due to the widely acknowledged importance of crude oil, studies within commodities context is predominantly restrained to assessing dependence between crude oil and a narrow set of agricultural commodities and precious metals. In addition, crude oil is the most traded commodity in the world, providing further thrust to the dominance of crude oil. Several studies demonstrate that crude oil often act exogenously and transfer shocks to other energy and non-energy commodities (see e.g. Baffes, 2007; Harri and Hudson, 2009; Alghalith, 2010; Serra, 2011, among others). In contrast, several studies discard this notion of connectedness and reports either negative or no linkage among crude oil to other commodities (see e.g. Kaltalioglu et al., 2011; Lombardi et al., 2012; Zhang et al., 2010; Nazlioglu, 2011; Sari et al., 2010, among others). In a more recent study, Kang et al. (2017) demonstrates that crude oil is a net receiver of return and volatility spillover, which add questions to the importance of crude oil as an influential commodity. As this literature indicates, the dependence dynamics between crude oil and other commodities is ambiguous, and therefore necessitates further elucidation by utilizing different methodologies and by broadening the total number of commodities.

Due to the upsurge in agricultural prices during 2005, several studies have contributed to the prevailing knowledge of connectedness and spillover dynamics by estimating the association between crude oil and agricultural commodities. The prices of various agricultural commodities – wheat, soybeans, soybean oil, corn, sugar, and canola – substantially increased from early-2005 to mid-2008. Several researchers attributed the spillover from crude oil as a primary reason of the global food crisis of 2007/2008 (Reboredo, 2012; Cabrera and Schulz, 2016). Furthermore, the increased codependence between the agricultural commodities and crude oil was also noted with the swift decline in crude oil to a low of around $32 barrel in December 2008. The dependence structure among the assets persisted with the steady increase in crude oil prices during post-2008 and persisted until mid-2013. Figure 1.1 presents an overview of the advancement of futures prices and return series' of crude oil and some major agricultural commodities. In general, it can be seen that the increase (decrease) in crude oil price is followed by an increase (decrease) in prices of the agricultural commodities. The prices of nearly all the agricultural commodities rose between 1995 and 1996, which is followed by a drop between 1998 and 1999. In addition, a gradually rising trend is evident for almost all the agricultural commodities during 2005. The price of crude oil and for almost all the agricultural commodities hit the highest point during 2008, which is followed by a sudden drop during the global financial crisis of 2008. This may be due to higher uncertainty perceived by the market participants in these assets and a preference to hold assets with less uncertainty. The periods of financial and economic turmoil further strengthen this relationship, which is commonly referred to as contagion (Kang et al., 2017; Ewing and Malik, 2016; Sensoy et al., 2015; Silvennoinen and

Thorp, 2013). This substantially increases concerns and uncertainty for nations strongly reliant on the import of agricultural commodities and among numerous stakeholders with wide exposure to the changes in commodity markets.

Figure 1.1: Development in futures prices and returns

The figure shows the development of daily futures prices and returns of crude oil and agricultural commodities. All the price series displays an upward trend post-2005 and after 2009. In addition, visual inspection for all series indicate that all the commodities are non-stationary in levels and stationary at first difference.



(a) Crude oil (CL) **(b)** Wheat (W) **(c)** Sugar (SB) **(d)** Soybeans (S-) **(e)** Soybean oil (BO) **(f)** Cotton (CT) **(g)** Corn (C) **(h)** Coffee (KC) **(i)** Cocoa (CC) **(j)** Canola (WC) **(k)** Soybeans meal (SM)

There are several reasons for the association between crude oil with food prices. First is through the biofuel channel. The surge in crude oil prices increase the demand for soybean- and corn-based biofuels, resulting in higher prices of feedstock (Pal and Mitra, 2017). Consequently, farmers tends to assign more resources and land for the production of fuel crops thereby escalating the prices other food commodities. In addition, an upward shift in crude oil price results in an increased cost of agricultural commodities due to channels such as increased prices of fertilizers, chemicals, outbound and inbound transportation, and processing cost (Hanson et al., 1993). Furthermore, the rapid growth and prosperity in the population of the world requires additional feedstock, and the rapid economic development in emerging and developing nations leads to increased consumption, resulting in demand and supply gap among the prices of agricultural commodities. Finally, the outflow and inflow of speculative investment may further impact price linkage structure between crude oil and agricultural commodities (Bekiros et al., 2017; Gorton and Rouwenhorst, 2006; Bhardwaj et al., 2015).

Unlike financial markets, the commodity markets are heterogeneous and complex systems of numerous interacting agents with distinctive term objectives. The actors in commodity markets, for instance financial and institutional investors, industrial organizations, and general population, have idiosyncratic term objectives and operates at distinct frequencies. Therefore, it is of significant importance to evaluate how the connectedness and spillover dynamics varies within the commodity markets. I focus on using wavelet transform analysis to decompose the return series into a set of subsequent wavelets corresponding to evaluate the connectedness dynamics between crude oil and agricultural commodities over short-, medium-, and long-run. In addition, I utilize the spillover framework to examine the transmission mechanism among crude oil and agricultural commodities.

1.2 Fisheries and aquaculture

Aquaculture is a subset of agriculture concerning the production of farmed fish and other seafood. Fisheries and aquaculture are the two primary production technologies for seafood, which is an important source of protein and livelihood for waterway and coastal communities (Smith et al., 2010). The significance of aquaculture production to global seafood supply is well established, and the Food and Agricultural Organization (FAO, 2018) demonstrates the growing magnitude of aquaculture production. Harvesting or production of aquaculture is inherently risky due to unavoidable effect of biological production process (Asche et al., 2015; Dahl, 2017). Based on the scale of demand and supply elasticities, production shocks instantaneously translate in the price volatility facing producing companies and consumers in the market. Price volatility of seafood markets has a substantial impact on the prices and valuations in aquaculture industry Dahl and Oglend (2014). For seafood producers and investors, understanding the price variations and connectedness dynamics are crucial as it causes significant variability in revenues and free cash flows of the firm.

The rapid growth in salmon production has attracted significant attention from the financial community to utilize salmon shares together with other asset classes in order to diversify the uncertainty of their portfolios. The salmon price volatility follows an upward trend since the mid-2000s (Oglend, 2013; Bloznelis, 2016). In addition, the price volatility of salmon has more than doubled since 2010 and is now considerably higher than the comparable commodities, thus making it an above-average volatile commodity (Asche et al., 2019; Dahl and Oglend, 2014). On average, the annualized growth in production between 2001 and 2016 was 5.8% with the highest growth recorded in Asia and Africa. Aquaculture gains from more control of production and quality, and horizontal and vertical integration has enhanced efficiency in terms of logistics. Consequently, aquaculture production is deemed to decrease risk in total seafood supply (Dahl and Oglend, 2014). In value, global seafood trade produces above 9% of total agricultural trade globally, and is presently undergoing the highest growth of food production, due to the increase in intensity seen in aquaculture production (FAO, 2018).

The evidence of market connectedness, in both price levels and volatility, is of significant importance for traders and producers using future and forward contracts to control price risk. These contracts allow seller and buyer the prospect to settle the price for future delivery, indicating quality and quantity on the fish delivered. Although current future markets are imperfect for seafood compared to other agricultural markets, the growth and innovation seen in aquaculture offers better opportunity to meet the demands set by Brorsen and Fofana (2001) for agricultural commodities futures markets with respect to commodity homogeneity and logistics. Today, futures of salmon are traded at Fish Pool, a Norwegian futures market formed in 2005, trading between 60 000 and 100 000 tonnes salmon per year. Several recent papers (Solibakke, 2012; Asche et al., 2015, 2016b,a) examined the attributes of salmon futures market.

To sum up, the price volatility of aquaculture species has significantly increased over time and remains considerably high compared to financial assets and commodities Asche et al. (2019). Despite numerous papers evaluating aquaculture and fisheries price volatility, knowledge about connectedness and spillover dynamics between different fish species and between fish prices and salmon producers is still missing. Therefore, studies related these topics are essential in order to identify and evaluate the connectedness and spillover dynamics faced by these industries.

1.3 Methodology

In this subsection, I briefly discuss the methodologies utilized in this paper to evaluate connectedness and spillovers. First, the temporal and frequential domain connectedness among the commodities are estimated by decomposition of return series into a set of subsequent wavelets corresponding to short-, medium-, and long-run trends and utilizing a time-varying DCC-Student-t copula framework. The novel characteristic of wavelet analysis is that it allows to decompose a unidimensional time series data into bivariate time-frequencies scales. Specifically, we employ maximal overlap discrete wavelet transform (MODWT) to decompose the series. Using the decomposed series, we estimate the connectedness structure among the assets by employing the GARCH-based DCC-copula frameworks. The wavelet decomposition is advantageous as it allow us to reveal information that are not apparent on "scale aggregated" data. This allows us to separately examine the short-, medium-, and long-run connectedness among the assets.

Secondly, the spillover effects among the markets are determined by utilizing Diebold and Yilmaz (2009, 2012) (DY) spillover frameworks on returns and EGARCH filtered volatilities. The studies in the spillover strand primarily utilize different specifications of multivariate generalized autoregressive conditional heteroscedasticity (MGARCH) models to analyze cross-dynamics of spillover transmission between assets. However, the primary issue with the MGARCH lies in its inability to provide direction of spillover. The DY frameworks relies on the vector autoregressive (VAR) framework and decomposition of variance from VAR framework. We extend the Diebold and Yilmaz (2009, 2012) frameworks by integrating an EGARCH specification to extract the conditional volatility. The conditional volatility from the EGARCH framework is then utilized in the DY frameworks to estimate the static and temporal volatility spillover. The structural variation is taken into account by dividing the sample into two subsamples, i.e. the calm period (pre-2006 subsample) and turmoil period (post-2006 subsample).

Finally, the cointegration approach together with the DY framework is utilized to evaluate market integration and spillover dynamics among the FPI and major salmon producers. The cointegration approach enables us to examine whether the underlying series are cointegrated and provide an estimate of short- and long-run relationship among the assets. Specifically, the Johansen's multivariate approach (Johansen, 1988; Johansen and Juselius, 1990; Johansen, 1991) is employed to examine the cointegration relationship among prices. The Johansen procedure relies on the vector autoregressive error correction model (VECM) to provide an estimate of short- and long-run relations among the assets.

1.4 Essays of the thesis

The aim of this PhD thesis is to investigate temporal and spectral connectedness and spillover dynamics of the commodity markets. This PhD dissertation comprises of four papers: 1) Temporal and spectral dependence between crude oil and agricultural commodities: A wavelet-based copula approach, 2) Price volatility dynamics in aquaculture fish markets, 3) Dynamics of volatility spillover in commodity markets: Linking crude oil to agriculture, and 4) Stock market valuation revealing salmon price information.

1.4.1 Paper I: "Temporal and spectral dependence between crude oil and agricultural commodities: A wavelet-based copula approach" (with Atle Oglend and Roy Endré Dahl)

This paper investigates the temporal and frequency domain connectedness between the price of crude oil and ten major agricultural commodities. We decompose returns into short-, medium- and long-run movements using the MODWT and investigate cross-commodities dependence structures in the decomposed returns using a DCC-student-t copula. The method allows us to analyze variation in dependencies across time as well as frequencies of return movements. Structural variation is considered through subsample analysis. Consistent with previous research, we find that connectedness between oil and agricultural products increases post-2006 across all considered frequencies of return movements. However, the rate of increase is higher for longer investment horizons. The wavelet decomposition reveals that interconnectedness as a function of investment horizon is negative during the pre-2006, but positive during the post-2006 subsample. These findings support stronger connectedness primarily due to stronger connection between long-run return movements. Analysis of connectedness dynamics shows no strong pre- and post-2006 differences, suggesting that the recent higher connectedness is primarily a correlation level effect. We do find that persistence of connectedness variation is higher for long-run return movements. Overall, we document a more connected crude oil and agricultural commodities complex after 2006, with lower commodities diversification benefits in general, and higher correlation risk for longer investment horizons.

1.4.2 Paper II: "Dynamics of volatility spillover in commodity markets: Linking crude oil to agriculture" (with Atle Oglend and Roy Endré Dahl)

This paper examines spillover effects among markets of crude oil and ten major agricultural commodities by employing the Diebold and Yilmaz (2009, 2012) spillover frameworks to returns and EGARCH filtered volatilities. We account for structural variations in data by dividing the data into two subsamples: from July 1986 to December 2005 (pre-2006 subsample) and from January 2006 to June 2016 (post-2006 subsample). Our findings indicate that there is minuscule information transmission among crude oil and agricultural commodities over the pre-2006 subsample, however, crude oil becomes the net receiver of information over the post-2006 subsample. Second, our findings indicate asymmetric and bidirectional flow of information among crude oil and agricultural commodities that intensifies during periods of financial and economic turmoil. Last, net volatility spillover increases in periods of large declines in the crude oil price, such as in 2008 and later in 2014. Overall, we document a more detailed insight into channels of connectedness among the underlying commodities, which may assist developing policy recommendation, portfolio designs, and risk management decisions.

1.4.3 Paper III: "Price volatility dynamics in aquaculture fish markets" (with Roy Endré Dahl)

In this paper, a time-varying student-t copula is used to capture information on price volatility dependence in the short-, medium-, and long-run horizon in the US market for frozen and fresh salmon, trout, tilapia and catfish. Using monthly data from July 1992 to March 2017, the volatility dynamics for these aquaculture species are assessed. The analysis allows indicating significant differences in the volatility relationships, depending on time-frequency. While short-run volatility has limited dependency, there is significant dependency in both the medium- and long-run, indicating that market integration is stronger in the long-run. The information is particularly important to buyers and producers utilizing the futures markets, as contracts are typically traded using a set of frequencies, and may help them manage and reduce price risk.

1.4.4 Paper IV: "Stock Market Valuation Revealing Salmon Price Information" (with Atle Oglend and Roy Endré Dahl)

This paper investigates the relationship between one of the primary price indices of farmed salmon (the Fish Pool index, FPI) and the stock prices of major publically traded salmon companies. We document that prices of exchange traded salmon stocks reflect the flow of salmon market information earlier than the price index. Forward looking stock prices are predictive of the backward looking price index. Furthermore, the predictive value is greater for the larger companies. The price discovery role of stock prices introduces a potential bias in the salmon futures design utilizing the price index to settle futures contracts as well as reducing hedging efficiency due to lagged reflection of company relevant market information in the price index.

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2 Paper I: Temporal and Spectral dependence between crude oil and agricultural commodities

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Temporal and spectral dependence between crude oil and agricultural commodities: A wavelet-based copula approach

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ABSTRACT

This paper investigates the temporal and frequency domain connectedness between the price of crude oil and ten major agricultural commodities. We decompose returns into short-, medium- and long-run movements using the MODWT and investigate cross-commodities dependence structures in the decomposed returns using a DCC-Student-t copula. The method allows us to analyze variation in dependencies across time as well as frequencies of return movements. Structural variation is considered through subsample analysis. Consistent with previous research, we find that connectedness between oil and agricultural products increases post-2006 across all considered frequencies of return movements. However, the rate of increase is higher for longer investment horizons. The wavelet decomposition reveals that interconnectedness as a function of investment horizon is negative during the pre-2006, but positive during the post-2006 subsample. These findings support stronger connectedness primarily due to stronger connection between long-run return movements. Analysis of connectedness dynamics shows no strong pre- and post-2006 differences, suggesting that the recent higher connectedness is primarily a correlation level effect. We do find that persistence of connectedness variation is higher for long-run return movements. Overall, we document a more connected crude oil and agricultural commodities complex after 2006, with lower commodities diversification benefits in general, and higher correlation risk for longer investment horizons.

1. Introduction

World agricultural and energy commodity indexes have experienced exceptionally volatile periods throughout the last decade. The prices of some key agricultural commodities – wheat, soybeans, soybean oil, corn, sugar, and canola – significantly increased from early-2005 to mid-2008. Several studies provide evidence of shock and volatility transmission from crude oil as a dominant cause of the 2007/2008 "global food crisis" (Reboredo, 2012; Cabrera and Schulz, 2016). Co-movement between crude oil and agricultural commodities was also observed when crude oil prices swiftly dropped to a low of around $32 barrel in December 2008. The connectedness persisted as crude oil prices steadily increased post-2008 and continued until mid-2013. This raises uncertainty and concern for countries heavily dependent on agricultural imports and for stakeholders in general with a wide commodities exposure.

There are several reasons why crude oil is connected to food prices. The first, and perhaps most obvious, is the biofuels channel. Higher crude oil prices raise the demand for corn- and soybeans-based biofuels, which results in increased prices of feedstock (Pal and Mitra, 2017). This leads farmers to allocate more land and resources towards production of fuel crops, leading to an increase in food prices. Furthermore, an increase in crude oil price results in higher production cost of agricultural commodities, such as increased cost of fertilizers, chemicals, inbound and outbound transportation, and processing of food items, resulting in higher food prices (Hanson et al., 1993). The prosperity and growth in world population necessitates an increase in production of feedstock, and the rapid economic expansion in many developing and emerging countries leads to an increase in consumption and thereby driving up the demand and price of agricultural commodities. Lastly, the inflow and outflow of speculative investment in commodity markets can also contribute to connecting crude oil and agricultural commodity prices (Bekiros et al., 2017; Gorton and Rouwenhorst, 2006; Bhardwaj et al., 2015).

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In terms of empirical analysis, several studies have shown that large swings in crude oil prices are often followed by changes in prices of agricultural commodities (Nazlioglu et al., 2013; Wang and McPhail, 2014). However, there are dissenting studies that show no linkage (see e.g. Cabrera and Schulz, 2016; Nazlioglu and Soytas, 2011; Myers et al., 2014). Commodity markets are complex systems of several interacting agents with distinctive term objectives. Actors in commodity markets, such as industrial organizations, financial investors, and general population, have distinctive time-horizon objectives and operates at different frequencies. Hence, the resulting time series of market prices are formed by a combination of information from components operating at different frequencies. Accordingly, standard time series econometric methods that aggregate frequency components usually result in loss of information.

The aim of this paper is to contribute to this literature by investigating both the temporal and frequency domain connectedness between the price of crude oil and ten major agricultural commodities[1]. To do so, we decompose price returns into short-, medium- and long-run movements using the MODWT wavelet filter and investigate cross-commodities dependence structures in the decomposed returns using DCC-Student-t copula. This method allows us to analyze variation in dependencies across time as well as frequencies of return movements. Structural variation is considered through sub-sample analysis.

The objective is to detect and quantify the temporal and spectral connectedness in the prices of crude oil and agricultural commodities. The analysis aims to answer the following questions. First, what is the temporal and spectral contribution of oil price shock on the prices of agricultural commodities? Second, do periods of financial and economic turmoil change the dependence between crude oil and agricultural commodity prices? Third, has the recent decline in crude oil price changes the dependence structure with agricultural commodities? Finally, does connectedness dynamics between agricultural commodities and crude oil exhibit extreme tail co-movement across short-, medium-, and long-term investment horizons?

Meeting the objective requires specific attention to the frequency of price movements. The dependence between short run returns might differ substantially from dependence under longer investment horizons. We add to the study of Pal and Mitra (2017), Mensi et al. (2017), Wang and McPhail (2014) and Koirala et al. (2015) by analyzing the dependence structure of decomposed return series across different investment horizons, and by modeling the static and dynamic connectedness between using static and time-varying copula. The novel feature of wavelet analysis is that it allows decomposing a unidimensional time series data into bivariate time-frequencies scales. This allows us to separately evaluate the short-, medium-, and long-term connectedness between the commodities using copulas. To the best of our knowledge, this is the first study to estimate temporal and frequential dependence between a broad set of agricultural commodities and crude oil prices using a discrete-type wavelet decomposition and time-varying copulas. The paper complements and augments the findings of previous studies on the oil-food nexus by highlighting temporal and spectral connectedness across time.

Consistent with previous research, our results reveal that connectedness between oil and agricultural products increases post-2006 across all frequencies of return movements. However, the rate of increase is higher for longer investment horizon. The frequency decomposition reveals declining correlation in investment horizon pre-2006 but increasing correlation post-2006. This supports stronger dependence between crude oil and food commodities primarily due to a stronger connection between long-run return movements. Analysis of connectedness dynamics shows no strong pre- and post-2006 differences, suggesting that the recent higher dependence is primarily a level effect. We do find that persistence of correlation variation is higher for long-run return movements. Overall, we document a more connected crude oil and agricultural commodities complex after 2006, with lower commodities diversification benefits in general, and higher correlation risk for longer investment horizons. The findings of this study have important implications for policy risk management and portfolio optimization. We show and discuss the implications of our findings in terms of portfolio weights, hedge ratios and VaR outcomes.

The remainder of this article is structured as follows. Section 2 presents the literature review. The empirical methodology is presented in Section 3. The data and preliminary statistics are presented in Section 4. Section 5 reports and discusses the empirical findings along with policy and portfolio risk implications. Section 6 concludes the paper.

2. Literature review

Studies on the connectedness between crude oil and agricultural commodities has increased significantly over the recent years. In an early study, Hanson et al. (1993) employ a computable general equilibrium (CGE) model and reports that agricultural commodities affected by oil price shock not just through direct and indirect cost but also through foreign borrowing and exchange rate.

Successive literature in the field further elucidate the connectedness dynamics by employing different econometric methodologies such as different versions of GARCH, VAR, and VECM models. In addition, several tests are utilized to evaluate linkage such as non-parametric causality tests, causality in variance test, and impulse response functions. However, these studies provide divergent evidence of linkage. Some studies demonstrate a significant relationship between crude oil and agricultural commodities. For example, Du and McPhail (2012) employ a GARCH model using daily data between 2005 and 2011, and reports significant volatility transmission from crude oil to agricultural commodities. In a later study, Wang and McPhail (2014) employ a VAR model using annual data from 1948 to 2011 and report mixed evidence of spillover from energy prices to agricultural prices. Koirala et al. (2015) use copulas method to study dependence between energy and two agricultural commodities (corn and soybeans). Their findings indicate strongly positive and significant correlation between energy and the two agricultural commodity prices.

In contrast, several studies document non-significant linkage between oil and agricultural nexus. For example, Kaltalioglu et al. (2011) use a VAR model using monthly data from 1980 to 2008 and report insignificant linkage between crude oil and agricultural commodities. Reboredo (2012) also reports weak connectedness and tail dependence between oil and three agricultural commodities (corn, soybean, and wheat). In a later study, Nazlioglu et al. (2013) report no evidence of volatility spillover during the period of 1986 to 2005. However, they show significant transmission between crude oil and agricultural commodities between 2006 and 2011. Liu (2014) shows that the cross-correlations are significant but weak for the smaller time scales between oil, corn, and soybeans returns. Whereas, the cross-correlations are not significant for the larger scales. Cabrera and Schulz (2016) study the relation between crude oil, rapeseed, and biodiesel prices. Their findings indicate that the production of biodiesel does not explain price linkage between agricultural feedstock and crude oil. In a recent study, Fowowe (2016) evaluates the linkage between oil and agricultural commodities prices using structural breaks co-integration and nonlinear causality tests. His findings indicate that the prices of agricultural commodities are neutral to oil price change.

[1] The agricultural commodities in our sample comprise wheat (W), sugar (SB), soybean (S), soybean oil (BO), cotton (CT), corn (C), coffee (KC), cocoa (CC), canola (WC), and soybeans meal (SM).

Table 1
Literature on connectedness between crude oil and other commodities.

Study	Assets/Markets	Data	Method	Results
Hanson et al. (1993)	Crude oil and agricultural commodities	1986–1991 (Annual)	CGE	Significant
Du and McPhail (2012)	Energy and agricultural	2005–2011 (Daily)	GARCH SVAR	Significant
Wang and McPhail (2014)	Energy price shocks, agricultural prices	1948–2011 (Annual)	VAR	Mixed
Koirala et al. (2015)	Energy commodities, corn, cattle, and soybeans futures	2011–2012 (Daily)	Copula	Significant
Kaltalioglu et al. (2011)	Oil price, agricultural commodities and food items	1980–2008 (Monthly)	VAR	Insignificant
Reboredo (2012)	Oil, corn, soybean, and wheat	1998–2011 (Weekly)	Copula	Insignificant
Nazlioglu et al. (2013)	Crude oil, wheat, sugar soybeans, and corn	1986–2011 (Daily)	CIV test	Mixed
Liu (2014)	Oil, soybean, oat, wheat, and corn	1994–2012 (Daily)	DCCA	Insignificant
Cabrera and Schulz (2016)	crude oil, rapeseed, and biodiesel	2003–2012 (Weekly)	AGARCH MVM	Insignificant
Fowowe (2016)	Oil, maize, soybeans, and sunflower	2003–2014 (Weekly)	JC NPCT	Insignificant
Vacha and Barunik (2012)	Energy commodities	1993–2010 (Daily)	CWT	significant
Kristoufek et al. (2016)	Crude oil, ethanol, sugar, and corn	2004–2014 (Weekly)	CWT	significant
Mensi et al. (2017)	Implied volatility indexes Crude oil, wheat, and corn	2012–2016 (Daily)	WBCP	significant
Pal and Mitra (2017)	Crude oil, dairy, cereals, vegetable oil, sugar indexes	1990–2016 (Monthly)	JC, TY CWT	significant

Notes. Computable General Equilibrium model (CGE), Structural Vector Autoregressive (SVAR), Detrended cross-correlation analysis (DCCA), Asymmetric dynamic conditional correlation GARCH (AGARCH), Multiplicative volatility model (MVM), Johansen co-integration (JC), Continuous wavelet transform (CWT), Wavelet-based copula (WBCP), Toda-Yamamoto (TY), Diks–Panchenko non-parametric causality test (NPCT), and Causality in variance test (CIV). Significant indicates that a study reports crude oil has positive effect on the price dynamics of agricultural commodities, and vice versa for insignificant. Mixed reflects bidirectional connectedness between crude oil and the underlying agricultural commodities.

These studies provide estimates of connectedness based on standard time-series techniques. However, a key limitation of such methodologies lies in their inability to account for information pertaining in the frequency domain (Huang et al., 2016; Pal and Mitra, 2017). Huang et al. (2015) show that the information pertaining in the frequency domain is one of the leading cause of nonlinearity in assessment of time-series data. Vacha and Barunik (2012) were the first to employ a continuous type wavelet analysis to explore the connectedness between energy commodities in the time-frequency domain. The novel feature of this approach is the decomposition of univariate time series data into bi-dimensional time-frequency sphere (Pal and Mitra, 2017). Kristoufek et al. (2016) investigate the relation between ethanol prices to the price of corn and sugar by employing a continuous wavelet coherence analysis. They report that ethanol prices are affected by the prices of feedstock. In their study, Berger and Uddin (2016) provide evidence of weak dependence over short-term and strong dependence over the long-run between equity market and commodities by employing a discrete-type wavelet-based copulas. In a recent study, Mensi et al. (2017) examine the dependence structure between implied volatility indexes of crude oil, wheat, and corn by employing a wavelet-based copula approach. Their findings support evidence of time-varying asymmetric tail dependence between the commodities. Pal and Mitra (2017) examine connectedness dynamics using a continuous-type wavelet transform and reported co-movement over short- and long-run between crude oil and five food related indexes. Our paper complements the study of Pal and Mitra (2017), Mensi et al. (2017), Wang and McPhail (2014) and Koirala et al. (2015) as we utilized futures prices of crude oil and 10 different agricultural commodities and by utilizing discrete-type wavelet transform analysis, which is a natural extension to continuous wavelet transform. In this regard, our study provides a more comprehensive analysis of dependence between crude oil and agricultural commodities.

To summarize, regardless of theoretical underpinnings, the empirical findings of previous literature provide mixed evidence regarding temporal connectedness between crude oil and agricultural commodities (Table 1). In addition, the studies evaluating time-spectral linkage structure between crude oil and agricultural commodities are limited. Furthermore, the recent decline in crude oil price necessitates a strong urge to reevaluate the connectedness dynamics using a broader set of agricultural commodities and improved methodology.

3. Methodology

Previous literature on connectedness dynamics mainly relies on standard time series models to evaluate linkage structure. One major shortcoming of these approaches is that they do not fully consider how dependence might vary over the frequency of price variation. In this study, we first employ a discrete-type wavelet transform (DWT), which enables us to decompose the underlying return series into discrete wavelets reflecting information pertaining to the frequency domain. Secondly, we employ univariate EGARCH models on individual frequencies to standardize the series. Finally, we estimate the dependence dynamics in each frequency component using a static and time-varying Student-t copula. In the proceeding subsection, we briefly present basic idea of wavelets before introducing the employed methodologies. We refer interested readers to Gençay et al. (2001), Percival and Walden (2000) and Gallegati and Semmler (2014) for detailed overview of wavelet analysis. We follow the diligence outlined by Berger and Uddin (2016) to implement the wavelet-based copula through the following stages:

1. Decomposition of returns series using maximal overlap discrete wavelet transform (MODWT)
2. Standardization of both returns and decomposed series using marginal distribution models
3. Dependence dynamics in each frequency using static and time-varying copula

3.1. The wavelet

A wavelet can be expressed as a wave-like oscillation, which begins at zero, increases over time and then revert to zero. Wavelets allow us to determine the dominant modes of variability and to study each component with a resolution that matches to its scales (Torrence and Webster, 1999; Graps, 1995). As such, wavelets last through a certain periods of space or time and have defined number of oscillations at each scale (Crowley, 2007). Wavelets help to simultaneously evaluate information contained in the frequency and the time domain of a time series.

3.2. Maximal overlap discrete wavelet transform (MODWT)

The first step is the employment of wavelet transform on the underlying returns series to decompose it into discrete signals. Percival and Walden (2000) and Gençay et al. (2001) introduced discrete wavelet transform to decompose the returns series into a set of underlying trends and triggered a growing field of literature dealing with the decomposition of returns[2] series into short-run and long-run seasonalities.[3] Wavelet transform analysis enable us to provide a multi-resolution decomposition of the underlying time series. The output of wavelet transform reveal relationships that are not apparent on "scale aggregated" data (Gallegati and Semmler, 2014). There are two types of wavelet transforms: discrete and continuous. Based on the purpose of our research, feature extraction, we use the prior in this study. Discrete wavelet transform (DWT) allows for the decomposition of a time series vector into a set of different frequencies reflecting information from low to high frequency fluctuations of prices. The DWT decomposes the underlying time series based on two types of filters called the scaling filter and the wavelet filter. Following Percival and Walden (2000) and Percival and Mofjeld (1997), let $\{g_l : l = 0, \ldots, L-1\}$ represent the scaling filter and $\{h_l : l = 0, \ldots, L-1\}$ the wavelet filter. By definition, a real-valued wavelet filter $\{h_l\}$ of length $L \in \mathbb{N}$ satisfies the following three properties:

$$\sum_{l=0}^{L-1} h_l = 0, \qquad \sum_{l=0}^{L-1} h_l^2 = 1, \qquad \text{and} \qquad \sum_{l=0}^{L-1} h_l, h_{l+2n} = 0, \qquad \forall \quad n \in \mathbb{N}. \tag{1}$$

These properties ensures that for any length $L \in \mathbb{N}$ the filter has zero mean, produces unit energy, and is orthogonal to its even shifts (Percival and Walden, 2000; Gençay et al., 2001). The low- and high-pass filters are defined as quadrature mirror filters (QMfs) satisfying:

$$h_l = (-1)^l g_{L-1-l}, \qquad \textit{or} \qquad g_l = (-1)^{l+1} h_{L-1-l}, \qquad l = 0, \ldots, L-1. \tag{2}$$

Similar to wavelet filter, the scaling filter satisfies the following conditions:

$$\sum_{l=0}^{L-1} g_l = \sqrt{2}, \qquad \sum_{l=0}^{L-1} g_l^2 = 1, \qquad \text{and} \qquad \sum_{l=0}^{L-1} g_l, g_{l+2n} = 0, \qquad \forall \quad n \in \mathbb{N}. \tag{3}$$

The wavelet and scaling coefficients, $W_{j,t}$ and $V_{j,t}$, of DWT at the jth level $(j = 1, \ldots, J)$ are defined as:

$$W_{j,t} = \sum_{l=0}^{L-1} h_l X_{t-1} \qquad \text{and} \qquad V_{j,t} = \sum_{l=0}^{L-1} g_l X_{t-1}, \tag{4}$$

where $X_t : t = 0, \ldots, N-1$ is the underlying time series. We apply the modified version of discrete wavelet transform namely maximal overlap discrete wavelet transform (MODWT) as introduced by Percival and Walden (2000) to decompose the underlying returns series. The MODWT is an extension of DWT and it does not suffer from the pitfalls facing DWT.[4] We refer interested readers to Percival and Walden (2000) and Gençay et al. (2001) for a detailed discussion of the choice of wavelet transform.

We chose Daubechies (1992) least asymmetric wavelet filters in MODWT to obtain the wavelet and scaling coefficients due to their better ability to capture the time and scale variations in a time series. Furthermore, Daubechies least asymmetric (LA(8)) wavelet filter is most favored in the financial literature due to approximate linear phase and near symmetric properties (Percival and Walden, 2000). Phase linearity reflects that the events and the sinusoidal components in the scaling and wavelet coefficients can be aligned, at all levels, with the original time series. This alignment of coefficients in the MODWT is achieved by circularly shifting the wavelet and scaling coefficients by an amount estimated by the phase delay property of basic filter (Percival and Mofjeld, 1997; Cornish et al., 2006). The LA(8) do not have a closed form and have been tabulated by Daubechies (1992, Sec. 6.2) and Percival and Walden (2000, Sec. 4.8).

Let X_t be a time series $t = 0, \ldots, N-1$ with length N. The wavelet transform leads to a decomposition of time series into different frequency bands by successive low- and high-pass filtering of the signal. More specifically, the original return series is decomposed into a set of wavelet coefficients $(\tilde{W}_{j,t})$ and low-pass filtered versions $(\tilde{V}_{j,t})$ of the signal. As we incorporate the MODWT, we utilize the rescaled scaling and wavelet filters obtained directly from DWT as follows:

$$\tilde{h}_{j,l} = \frac{h_{j,l}}{2^{j/2}} \qquad \text{and} \qquad \tilde{g}_{j,l} = \frac{g_{j,l}}{2^{j/2}}, \qquad j = 0, \ldots, J, \tag{5}$$

where J is the total number of levels. Following Mallat (1989), we obtained $\tilde{W}_{j,t}$ and $\tilde{V}_{j,t}$ by applying the pyramid algorithm to log returns series of each commodity. We require three inputs for each iteration of the MODWT pyramid algorithm, i.e., the data vector X_t, the scaling filter $\tilde{g}$, and the wavelet filter $\tilde{h}$. The first iteration begins by convolving (filtering) the data with wavelet and scaling filters to obtain the following wavelet and scaling coefficients as follows:

$$\tilde{W}_{1,t} = \sum_{l=0}^{L-1} \tilde{h}_l X_{t-l} \qquad \text{and} \qquad \tilde{V}_{1,t} = \sum_{l=0}^{L-1} \tilde{g}_l X_{t-l}, \tag{6}$$

where $t = 0, \ldots, N-1$. In the second step of MODWT pyramid algorithm, the scaling coefficients from the first iteration becomes the input data vector and we apply filtering operations to obtain the second level wavelet and scaling coefficients as follows:

$$\tilde{W}_{2,t} = \sum_{l=0}^{L-1} \tilde{h}_l \tilde{V}_{1,t-l \bmod N} \qquad \text{and} \qquad \tilde{V}_{2,t} = \sum_{l=0}^{L-1} \tilde{g}_l \tilde{V}_{1,t-l \bmod N}. \tag{7}$$

where $t = 0, \ldots, N-1$. Similarly, the jth level MODWT wavelet and scaling coefficients of a time series $X_t : t = 0, \ldots, N-1$ are defined as:

$$\tilde{W}_{j,t} = \sum_{l=0}^{L-1} \tilde{h}_l X_{t-1 \bmod N} \qquad \text{and} \qquad \tilde{V}_{j,t} = \sum_{l=0}^{L-1} \tilde{g}_l X_{t-1 \bmod N}. \tag{8}$$

[2] The wavelet decomposition of return series brings about a decomposition of both the risk of the underlying asset (conditional variance component) and the diversification effect between the assets (covariance component). Since we are interested in evaluating the co-movement (covariance component) based on the conditional variance between crude oil and agricultural, it would be appropriate to carry out decomposition at raw returns data instead of applying wavelets to the filtered data.

[3] Several of the recent studies in the field of wavelet analysis utilize wavelet decomposition on returns series data, see for example, Gallegati (2012), In and Kim (2013), Dewandaru et al. (2015), Berger (2015), Berger and Uddin (2016), and Berger and Gençay (2018), among others.

[4] The discussion on advantages and drawbacks between DWT and MODWT is beyond the subject of this study.

$\tilde{W}_{j,t}$ is the decomposed signals that are utilized for further analysis to evaluate dependence over varying frequencies. Following Gençay et al. (2001) and Percival and Walden (2000), we determine the level $J = 8$ for the MODWT decomposition level, which is given by, $J \leq \log_2\left(\frac{T}{L-1}+1\right)$, where L and T are the length of the filter and the time series. We refer to Percival and Walden (2000), Burrus et al. (1997) and Gençay et al. (2001) for further description of the employed framework.[5]

3.3. Marginal distribution models

The marginal distribution models are fundamental to estimate copulas. We estimate the marginal distribution models for each returns and decomposed series and determine the well-suited marginal model from various GARCH-type specifications (GARCH, GJR-GARCH, and EGARCH) to capture the dynamics in crude oil and agricultural commodities. Based on Log-likelihood and AIC criterion, our results indicate that an ARMA(1,0)-EGARCH(1,1) specification as the most suitable marginal model for the underlying return and decomposed series. Furthermore, the EGARCH model assumes the asymmetric effects of positive and negative shocks on conditional volatility (Nelson, 1991). The general form of EGARCH(P,Q) conditional variance process, σ_t^2, is represented by the following expression:

$$\log\sigma_t^2 = \kappa+\sum_{i=1}^{P}\beta_i\log\sigma_{t-i}^2+\sum_{j=1}^{Q}\alpha_j\left[\frac{|\varepsilon_{t-j}|}{\sigma_{t-j}}-E\left\{\frac{|\varepsilon_{t-j}|}{\sigma_{t-j}}\right\}\right]+\sum_{j=1}^{Q}\xi_j\left(\frac{\varepsilon_{t-j}}{\sigma_{t-j}}\right) \tag{9}$$

where κ is variance intercept parameter, α_j and β_i are the parameters of ARCH and GARCH volatility components, respectively, and ξ_j captures the leverage effect. For $\xi_j < 0$, the future conditional variance will increase relatively more following a negative shock than following a positive shock of the equal magnitude. The EGARCH models are appropriate when positive and negative shocks od same magnitude do not contribute equally to the volatility (Tsay, 2005).

3.4. Time-varying copula

To evaluate the time-varying dependence between crude oil and agricultural commodities, we employ bivariate DCC-Student-t copula. Copula models are found to be effective and flexible in characterizing and modeling dependence (Bekiros et al., 2017). Furthermore, it decouples the choice of marginal return distribution from dependence modeling, which provides further flexibility and accuracy in selection of marginal models and copula functions (Sklar, 1959). We employ time-varying DCC-Student-t copula as it take into account joint extreme movements, which are observed in financial and commodity returns data. The Student t-copula can be seen as the representation of the dependence structure implicit in a multivariate t-distribution (Demarta and McNeil, 2005).

Let X_t and Y_t denotes the crude oil and agricultural commodities futures returns series, respectively. Furthermore, let $F_X(x)$ and $F_Y(y)$ be the marginal distribution functions for the series and a joint distribution $F_{XY}(x, y)$. The foundation of copula theory is the Sklar (1959) theorem (Patton, 2006), which states that the joint distribution function, $F_{XY}(x, y)$, of two continuous random variables X and Y can be presented in terms of marginal distribution functions of the variables, $F_X(x)$ and $F_Y(y)$, and a copula function as:

$$F_{XY}(x, y) = C(F_X(x), F_Y(y)), \tag{10}$$

where $C(u, v)$ with $u = F_X(x)$ and $v = F_Y(y)$ is a bivariate copula function. Therefore, a copula is a multivariate function with uniform marginals, which represents the connectedness structure between two continuous random variables (Cherubini et al., 2004). In terms of construction, a copula connects the marginals to a multivariate distribution function, which then can be decomposed into univariate marginal distributions and a copula capturing the connectedness structure. The joint probability density, $f_{XY}(x, y)$, can be obtained from the product between the copula density, $c(u, v) = \frac{\partial^2 C(u,v)}{\partial u \partial v}$, and the univariate marginal distributions of crude oil and agricultural commodities futures returns, $f_X(x)$ and $f_Y(y)$ as:

$$f_{XY}(x, y) = c(u, v)f_X(x)f_Y(y), \tag{11}$$

where $f_X(x)$ and $f_Y(y)$ represent the marginal densities of variables X and Y, respectively. Therefore, in order to portray the joint probability density of two random variables, we require information on marginal densities and the copula density.

We apply the Student-t copula to account for extreme tail dependence in returns series. The Student-t copula generalizes the Gaussian copula by allowing for increased probability of joint extreme events. The Student-t copula for the bivariate case is defined as:

$$C_{d,\rho}(u, v) = t_{d,\rho}\left(t_d^{-1}(u), t_d^{-1}(v)\right), \tag{12}$$

where ρ is the correlation coefficient and d is degrees of freedom parameter. The general multivariate case of Student-t copula can be expressed as:

$$C_{d,\rho}(u_1, \ldots, u_n) = t_{d,R}\left(t_d^{-1}(u_1), \ldots, t_d^{-1}(u_n)\right) \tag{13}$$

$$= \int_{-\infty}^{t_d^{-1}(u_1)}, \ldots, \int_{-\infty}^{t_d^{-1}(u_n)} \frac{\Gamma\left(\frac{d+n}{2}\right)|\rho|^{-\frac{1}{2}}}{\Gamma\left(\frac{d}{2}\right)(\pi v)^{\frac{n}{2}}}\left(1+\frac{1}{d}z^T\rho^{-1}z\right)^{-\frac{d+n}{2}} \mathrm{d}z_1, \ldots, \mathrm{d}z_n, \tag{14}$$

where d refers to degrees of freedom, t_d^{-1} represents the inverse of univariate t distribution and the symmetric tail dependency influenced by d, $t_{d,\rho}$ characterizes the multivariate t distribution with ρ as the correlation matrix. Following Berger and Uddin (2016), we capture the time-varying dependence between commodities by substituting the linear correlation coefficients ρ by the dynamic conditional correlation (DCC) model of Engle (2002), which can be expressed as:

$$R_t = \mathrm{diag}\left(\tilde{Q}_t\right)^{-1} Q_t \; \mathrm{diag}\left(\tilde{Q}_t\right)^{-1}, \tag{15}$$

$$Q_t = (1-\alpha-\beta)\bar{R} + \alpha\epsilon_{t-1}\epsilon_{t-1}' + \beta Q_{t-1}, \tag{16}$$

where $\bar{Q}$ represents the sample covariance of ϵ_t, $\tilde{Q}_t$ is $p \times p$ square matrix with diagonal elements as square root of Q_t and zeros as

[5] We carried out all the calculations of wavelet decomposition in MATLAB R2018a (The MathWorks Inc.). We utilize the WMTSA wavelet toolkit for MATLAB available at http://www.atmos.washington.edu/wmtsa/ for wavelet decomposition.

off-diagonal elements, and ϵ_t refers to the volatility adjusted returns originating from univariate ARMA(1,0)-EGARCH(1,1) model.

3.5. Estimation

Following Joe and Xu (1996) and Joe (1997), we estimate the copula parameters using a two-step maximum likelihood procedure called the inference functions for margins (IFM). The first step comprises of estimating the GARCH margins' parameters $\hat{\theta}_1$ by estimation of univariate marginal distributions as:

$$\hat{\theta}_1 = \arg\max_{\theta_1} \sum_{t=1}^{T} \sum_{j=1}^{n} \ln\ f_j\left(u_{jt}; \theta_1\right). \tag{17}$$

In the second step, given $\hat{\theta}_1$, we estimate DCC-Student-t copula parameters $\hat{\theta}_2$ using:

$$\hat{\theta}_2 = \arg\max_{\theta_2} \sum_{t=1}^{T} \ln\ c\left(F_1(u_{1t}), F_2(u_{2t}), \ldots, F_n(u_{nt}); \theta_2, \hat{\theta}_1\right). \tag{18}$$

We refer interested readers to Patton (2009), Cherubini et al. (2004), and Joe (1997) for detailed description and application of copulas.

4. Data and descriptive statistics

4.1. Data selection

Our study utilizes daily data on futures prices of crude oil and ten agricultural commodities over the period of July 1986 to June 2016, which exhibits a total number of 7593 observations for each commodity. The chosen data is extracted from the Commodity Research Bureau (CRB), which is an industry leader due to its comprehensive database in commodity markets' price history. Agricultural commodities are selected based on their high trading volume and liquidity. Overall, crude oil and agricultural commodities represents a significant proportion of the S&P GSCI and S&P GSCI agricultural commodity index, which are widely accepted instruments to measure the investment performance in commodity and agricultural markets, and as economic indicators.

The investigated time span covers several periods of financial and economic turmoil, which enable us to evaluate the impact of these episodes on the linkage between crude oil and agricultural commodities. Particularly, our selected period includes: the "Black Monday" of 1987, the Gulf war 1990–1991, the Asian financial crisis during 1997–1998, the dot–com bubble burst in 2001, the Gulf War during in 2003, the world food price crisis of 2006–2008, the 2007 U.S. sub-prime mortgage crisis, the global financial crisis of 2008, the European debt crisis of 2010–2012, and the decline in crude oil prices since 2014. The choice of daily data would enable us to better capture the connectedness dynamics, which are often too low or high when undertaking weekly or monthly observations. In addition, using daily data would enable us to capture the price and volatility day-of-the-week effect prevalent in many time series.

The commodities in our sample comprises of crude oil (CL), wheat (W), sugar (SB), soybean (S), soybean oil (BO), cotton (CT), corn (C), coffee (KC), cocoa (CC), canola (WC), and soybeans meal (SM). Crude oil trades on New York Mercantile Exchange (NYMEX), while the agricultural commodities trades on the Intercontinental Exchange (Sugar, Cotton, Coffee, Cocoa, and Canola) and Chicago Board of Trade (Wheat, Soybeans, Soybean oil, Corn, and Soybean meal). The development in daily futures prices and continuously compounded returns for the underlying commodities are presented in Fig. 1. Interestingly, nearly all the agricultural prices increase during 1995 and 1996, which is followed by a decline between 1998 and 1999. In addition, an increasingly upward trend is apparent for nearly all the agricultural commodities during 2005. The price of crude oil and for nearly all the underlying agricultural commodities peaked during 2008, which is followed by a sharp decline due to the global financial crisis of 2008. This might be due to higher risk perceived by the market participants in these assets and prefer to hold securities with less risk, a phenomenon refers as the flight-to-quality. Visual inspection of Fig. 1 indicates that the commodities are non-stationary in levels, but the log-returns of the series are stationary. In addition, all the return series exhibits volatility clustering with periods of tranquility and turmoil. Following Nazlioglu et al. (2013), Du et al. (2011), Wang et al. (2014) and Baumeister and Kilian (2014), we divide the full sample into two subsamples to account for the impact of food price crisis. Furthermore, a higher price of crude oil, together with federal support policies lead to a rapid growth in corn-based ethanol production during mid-2006. In addition, an increased demand of feedstock lead to increase in prices of corn and other agricultural commodities thus leading to a structural change or fundamental shift in the market for major agricultural commodities (Du et al., 2011). Therefore, the first subsample is for the period from July 1986 to December 2005 and the second subsample covers the period from January 2006 to June 2016. The second subsample now contains the recent turmoil periods associated with the financial crisis, the food price crisis and the oil price drop in 2014. Relative to these large market innovations, the first sub-sample period is a less turmoil period. Splitting the sample allows us to investigate structural changes in connectedness.

4.2. Descriptive statistics

The continuously compounded return for each commodity is estimated as the logarithmic difference of two consecutive prices at time t and $t-1$: $r_{i,t} = \ln(P_{i,t}/P_{i,t-1})$. Table 2 provides the descriptive statistics of full-sample, pre-2006, and post-2006 sample.[6] The results of full-sample statistics in Panel A of Table 2 shows that the average annualized return of agricultural commodities ranges between −1.0 % for coffee and 3.6% for sugar, respectively, and the standard deviation varies from 20.4% for canola to 37.2% for coffee, respectively. Whereas, the mean annualized return and standard deviation of crude oil is 4.5% and 35.0%, respectively. In terms of reward-to-risk, soybean meal provides the highest return proportionate to risk of 0.057 and coffee provides the lowest Sharpe (1994) ratio of −0.08 and the reward-to-risk estimate for crude oil is 0.073.[7] The returns distribution for more than half of the underlying commodities exhibits negative skewness. Moreover, the value of kurtosis is larger than 3 for all the commodities. Overall, our findings indicate that all the return series exhibit skewed and leptokurtic distributions, which indicates that the distributions are asymmetrical and have fatter tails than normal distribution. A formal Jarque-Bera test affirms this non-Gaussian pattern and strongly reject the null-hypotheses of normality for all the commodities. The test-statistics of Ljung-Box test on returns and squared returns with 20 lags are significant, thus rejecting the null-hypothesis of independence at 1% threshold level, which indicates that both series are serially

[6] Mean and standard deviation is annualized by multiplying each with 252 and $\sqrt{252}$, respectively.

[7] The risk-free rate in the Sharpe ratio is T-bill rate collected from CRSP database. The daily average risk-free rate for full-sample and pre-2006 subsample is estimated to be 2% and the risk-free rate for post-2006 subsample is 1%.

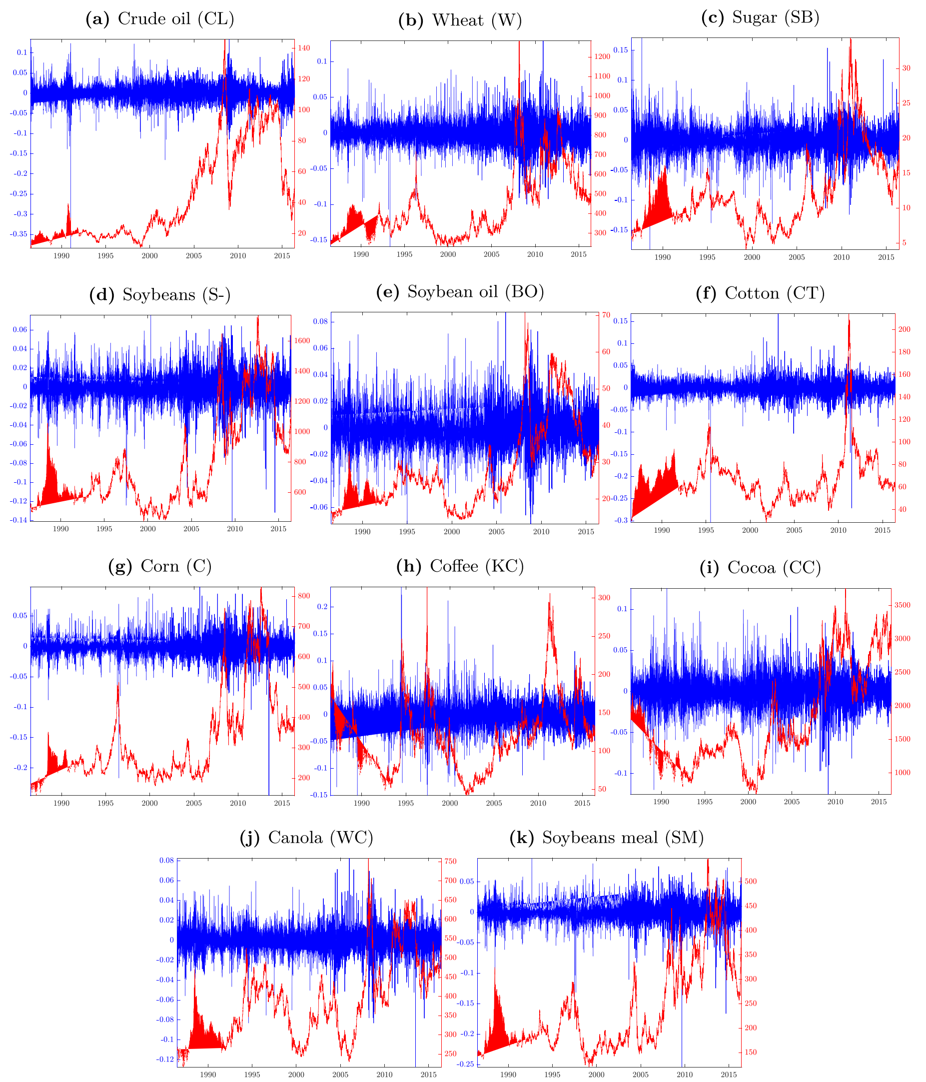

Fig. 1. Development in futures prices and returns: The figure portrays the development in nearby daily futures prices and continuously compounded returns for crude oil and agricultural commodities. All the price series exhibit an increasingly upward trend post-2006 and after 2009. Furthermore, visual inspection for all series suggest that all commodities are non-stationary in levels and stationary at first difference.

correlated. The ARCH test (Engle, 1982) with 20 lags rejects the null-hypothesis of homoscedasticity for all commodities, thus advocating the employment of GARCH-type model to capture the stylized facts, for instance, temporal dynamics and volatility clustering.

The results of pre- and post-2006 are presented in Panels B and C of Table 2. Although the annualized standard deviation of individual commodity does not differ significantly in both subsamples, the annualized mean changes dramatically in both subsamples. During

Table 2
Descriptive statistics.

	Mean (%)	SD	SR	Max	Min	Skew	Kurt	J–B	Q(20)	$Q^2(20)$	ARCH (20)
Panel A: Full sample statistics											
Crude oil	4.570	0.350	0.073	0.13	−0.38	−0.81	18.23	0.00	46.91*	599.35*	344.47*
Wheat	2.392	0.285	0.014	0.13	−0.16	0.07	6.87	0.00	33.87*	977.18*	400.26*
Sugar	3.602	0.339	0.047	0.17	−0.18	−0.07	7.53	0.00	36.72*	482.39*	248.96*
Soybean	2.696	0.235	0.030	0.08	−0.14	−0.67	8.90	0.00	33.87*	1068.32*	417.22*
Soybean oil	2.246	0.230	0.011	0.09	−0.07	0.16	5.15	0.00	34.55*	2152.13*	694.21*
Cotton	2.225	0.283	0.008	0.17	−0.30	−1.01	24.25	0.00	33.84*	58.41*	43.62*
Corn	2.754	0.265	0.028	0.10	−0.25	−0.50	15.37	0.00	59.41*	210.09*	130.31*
Coffee	−0.991	0.372	−0.080	0.24	−0.15	0.22	9.60	0.00	41.46*	1119.02*	639.65*
Cocoa	1.718	0.299	−0.009	0.13	−0.13	0.04	6.20	0.00	39.68*	371.71*	200.95*
Canola	2.215	0.204	0.011	0.08	−0.13	−0.27	8.25	0.00	76.90*	1370.64*	529.41*
Soybeans meal	3.522	0.268	0.057	0.09	−0.25	−1.02	14.94	0.00	44.34*	240.08*	142.77*
Panel B: Pre-2006 sample statistics											
Crude oil	8.081	0.344	0.177	0.12	−0.38	−1.33	26.06	0.00	45.40*	217.14*	165.28*
Wheat	1.732	0.246	−0.011	0.09	−0.16	0.04	8.61	0.00	35.47*	129.60*	84.38*
Sugar	4.267	0.336	0.067	0.17	−0.18	−0.15	7.92	0.00	42.21*	367.02*	189.74*
Soybean	0.942	0.220	−0.048	0.08	−0.12	−0.54	8.39	0.00	31.86*	1107.80*	394.60*
Soybean oil	1.344	0.225	−0.029	0.08	−0.07	0.19	4.96	0.00	40.69*	886.63*	356.47*
Cotton	2.569	0.270	0.021	0.17	−0.30	−0.86	27.16	0.00	30.62*	8.25	7.37
Corn	0.877	0.231	−0.049	0.10	−0.22	−0.21	16.26	0.00	71.23*	211.79*	133.81*
Coffee	−2.377	0.399	−0.110	0.24	−0.15	0.25	10.10	0.00	36.01*	713.21*	429.05*
Cocoa	−0.902	0.307	−0.095	0.13	−0.12	0.24	5.96	0.00	31.67*	182.93*	109.30*
Canola	−0.661	0.194	−0.137	0.07	−0.08	0.00	5.91	0.00	50.54*	764.01*	322.53*
Soybeans meal	1.649	0.242	−0.015	0.09	−0.15	−0.56	9.40	0.00	43.10*	466.01*	216.83*
Panel C: Post-2006 sample statistics											
Crude oil	−2.071	0.362	−0.085	0.13	−0.11	0.04	6.14	0.00	39.27*	2483.24*	550.80*
Wheat	3.641	0.347	0.076	0.13	−0.10	0.08	4.93	0.00	30.13*	390.13*	160.14*
Sugar	2.346	0.345	0.039	0.15	−0.12	0.07	6.85	0.00	18.90*	139.50*	83.32*
Soybean	6.014	0.262	0.192	0.06	−0.14	−0.82	8.90	0.00	23.54*	192.83*	96.82*
Soybean oil	3.954	0.240	0.123	0.09	−0.07	0.10	5.37	0.00	22.19*	1255.69*	405.85*
Cotton	1.573	0.306	0.019	0.10	−0.27	−1.20	20.13	0.00	24.95*	70.60*	44.48*
Corn	6.304	0.320	0.166	0.09	−0.25	−0.69	12.62	0.00	29.15*	21.41*	15.89*
Coffee	1.631	0.316	0.020	0.12	−0.11	0.11	4.95	0.00	34.84*	211.50*	125.44*
Cocoa	6.674	0.284	0.200	0.08	−0.13	−0.45	6.74	0.00	28.95*	240.68*	133.89*
Canola	7.656	0.220	0.302	0.08	−0.13	−0.62	10.70	0.00	81.04*	513.56*	222.18*
Soybeans meal	7.065	0.311	0.195	0.08	−0.25	−1.40	17.24	0.00	24.42*	36.52*	28.00*

Notes. Annualized figures of mean and standard deviation are presented. SR refers to the Sharpe ratio and J–B provides the p-values from Jarque-Bera normality test. Q(20) and $Q^2(20)$ correspond to the Ljung-Box test statistics for serial autocorrelation on returns and squared returns with 20 lags. ARCH(20) provides the statistics of Engle (1982) test for conditional heteroscedasticity with 20 lags. The notation *, **, and *** indicate the rejection of the null hypothesis of normality, no autocorrelation, and conditional homoscedasticity at the 1%, 5%, and 10% threshold levels.

pre-2006 subsample, the average annualized reward-to-risk measure for agricultural commodities ranges between −0.14 and 0.07 for canola and sugar, respectively. Whereas, during post-2006, the Sharpe ratio ranges between 0.02 and 0.3 for cotton and canola, correspondingly. Interestingly, canola exhibits the lowest and highest reward-to-volatility measure during pre- and post-2006 subsamples, respectively. The average Sharpe ratio for crude oil is 0.18 and −0.08 during pre- and post-2006 subsamples, respectively. More than half of the agricultural commodities are negatively skewed and exhibiting leptokurtic distributions during both subsamples indicating deviations from the normal distribution. The Jarque-Bera test of normality affirms this non-Gaussian pattern as the null hypothesis is strongly rejected in all series. The Ljung-Box portmanteau test with 20 lags is significant for returns and squared returns thus exhibiting the presence of serial correlation. This illustrates that information contains in the previous returns is crucial for future forecasting. Additionally, the ARCH effect with 20 lags rejects the homoscedasticity null-hypothesis for all the commodities in both subsamples.[8]

Table 3 shows the unconditional correlation between crude oil and agricultural commodities according to Pearson, Kendall, and Spearman tests (so that we have correlation results from parametric and non-parametric tests) for full-sample, pre- and post-2006 subsamples. All the agricultural commodities shows strong dependence with crude oil during post-2006 subsample, for instance, soybeans oil and corn exhibits linear dependence of 48.9% and 28.0%, respectively. Whereas, for the full-sample analysis, most of the agricultural commodities are characterized by moderately positive linkage with crude oil, for instance, soybean oil and corn show positive relation of 18.8% and 14.8%. In contrast, during pre-2006 subsample, all the agricultural commodities exhibit minimal linear dependence with crude oil. As an example, the correlation between crude oil and soybeans oil is 1.0% and that of corn is 4.9%. The estimates are consistent across all three correlation tests. Furthermore, we evaluate whether the correlation coefficients during pre- and post-2006 subsamples are significantly different from each other by employing Fisher (1921) r to z transformation. The sign ‡ indicates that correlation coefficient between the two subsamples are statistically different from each other. This supports our hypothesis that in comparison to the pre-2006 period, the post-2006 subsample is characterized by strong positive dependence between crude oil and agricultural commodities. Furthermore, this reflects that the potential to attain diversification benefits has significantly reduced over the post-2006 subsample.

[8] The estimates from Dickey-Fuller (ADF) (Dickey and Fuller, 1979) and Phillips-Perron (PP) (Phillips and Perron, 1988) unit-root tests indicate that return series follow an I(1) process in both subsamples. For the sake of brevity, we chose not to report these estimates. These results are available from authors upon request.

Table 3
Correlation analysis based on undecomposed returns series.

Commodity	Full sample			Pre-2006			Post-2006		
	Pearson	Kendall	Spearman	Pearson	Kendall	Spearman	Pearson	Kendall	Spearman
Wheat	12.864	6.711	9.949	3.833‡	2.611‡	3.882‡	24.690‡	13.626‡	20.019‡
Sugar	10.251	6.675	9.877	3.125‡	2.139‡	3.144‡	22.719‡	14.873‡	21.984‡
Soybean	15.745	9.373	13.875	3.185‡	2.427‡	3.630‡	34.819‡	21.712‡	31.745‡
Soybean oil	18.812	10.778	15.889	1.016‡	0.093‡	0.145‡	48.869‡	30.784‡	44.144‡
Cotton	11.480	7.367	10.992	3.771‡	2.996‡	4.503‡	23.739‡	15.145‡	22.446‡
Corn	14.831	8.837	13.069	4.917‡	3.302‡	4.889‡	28.012‡	17.889‡	26.306‡
Coffee	7.242	6.116	9.101	−0.190‡	0.846‡	1.257‡	24.342‡	16.501‡	24.407‡
Cocoa	8.652	5.725	8.488	1.166‡	1.417‡	2.088‡	23.249‡	14.033‡	20.673‡
Canola	10.510	5.757	8.593	1.226‡	1.036‡	1.539‡	25.251‡	14.517‡	21.476‡
Soybeans	10.620	6.734	10.004	3.576‡	3.280‡	4.877‡	20.578‡	12.732‡	18.874‡

Notes. The table presents correlation coefficients from Pearson, Kendall, and Spearmann for the undecomposed returns series between crude oil and agricultural commodities. We test whether the correlation coefficients are statistically different between pre-2006 and post-2006 subsamples by utilizing Fisher (1921) r to z transformation. ‡ indicates that the correlation coefficients are significantly different between pre- and post-2006 subsamples at 1% significance level.

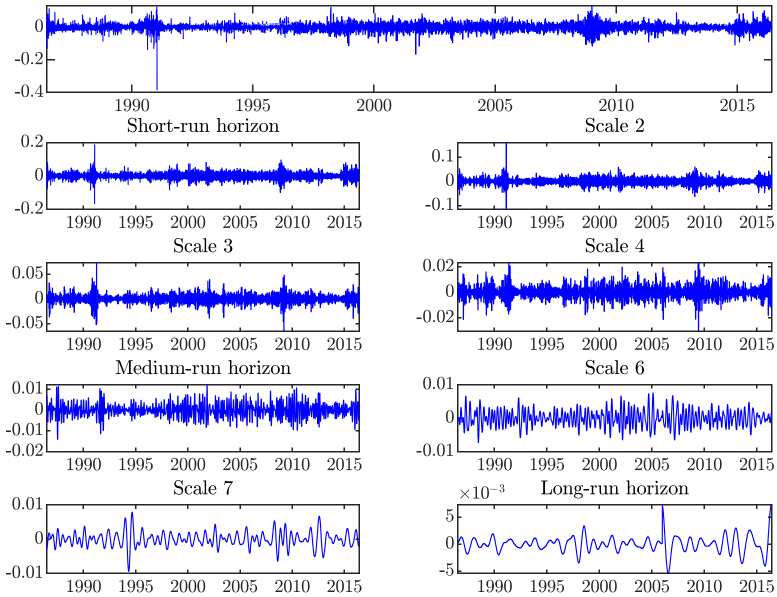

Fig. 2. Original and decomposed return series of crude oil. Notes. The figure presents the decomposition of underlying returns series into subsequent wavelets corresponding to the short-, medium-, and long-run trends.

5. Empirical analysis

We first examine the multi-scale dependence between crude oil and agricultural commodities by employing unconditional correlation measures on the decomposed returns series from the wavelet analysis (Panels B, C, and D of Table 5). We then employ time-varying copulas on the decomposed series to evaluate the dependence structure in short-, medium-, and long-run trends.

5.1. *Multi-scale unconditional correlation analysis*

In addition to the unconditional correlation analysis of original (undecomposed) return series, we examine multi-scale dependence dynamics by employing unconditional connectedness measures on decomposed returns series: short-, medium-, and long-run trends (Fig. 2). Table 4 provides a definition behind the applied setup. Specifically, short-run series reflects the variations over short-term horizon due to shocks occurring between 2 and 4 succeeding days (daily effects), medium-run captures dependence dynamics between 32 and 64 days (approximately one to two-month effects), and long-run trend characterized to show variations in connectedness structure between 256 and 512 succeeding days (approximately one to two year effects). Panels B, C, and D of Table 5 provide the estimates of multi-scale connectedness.[9] In general, the short-run dependence

[9] The correlation estimates for all frequencies are available upon request.

Table 4
Decomposed returns series.

Component	Time-horizon	Definition
Scale 1	2–4 days	Short-run
Scale 2	4–8 days	Short-run
Scale 3	8–16 days	Short-run
Scale 4	16–32 days	Medium-run
Scale 5	32–64 days	Medium-run
Scale 6	64–128 days	Long-run
Scale 7	128–256 days	Long-run
Scale 8	256–512 days	Long-run

Notes. The table provides intuition behind the applied setup. Scale 1 – Scale 3 represents the variations over daily, weekly, and fortnight which can then be represented as low scales. Scale 4 and 5 captures the changes between one and two months and can be interpreted as intermediate scales. Scale 7 and 8 represents variations over one and two year period and characterize as high scale data.

dynamics presented in Panel B closely follows the similar pattern as of original returns series during full-sample and both subsamples.

The dependence structure of medium-run variations provides evidence of relatively weaker connectedness than short-run and undecomposed returns series during full-sample and post-2006 subsample. Although, the pre-2006 linkage structure of undecomposed return series is characterize by weak level of connectedness, it is noteworthy that nearly all agricultural commodities exhibit negative correlation with crude oil in the medium-run trend.[10] This reflects that during pre-2006, addition of these agricultural commodities with crude oil over the middle-run investment horizon would enable market participants to minimize the risk of their portfolio.

The long-run estimates in Panel D indicate stronger dependence structure between crude oil and most of the agricultural commodities. The linkage structure between crude oil and all of the agricultural commodities during pre-2006 subsample exhibits negative dependence with crude oil.[11] Specifically, wheat, corn, canola, cotton, and soybean oil exhibit largest degree of negative correlation during pre-2006 subsample ($\rho = -27.9\%$, -24.3%, -12.5%, -7.5 %, and -6.7 %, respectively) and the linkage structure changes significantly during post-2006 subsample ($\rho = 24.9\%$, 43.9%, 57.9%, 61.9%, and 74.5%, respectively). Likewise, the correlation with sugar, soybean, coffee, cocoa, and soybean meal changes from ($\rho = -2.2\%$, -4.1%, -6.4 %, 21.9% and 0.2%) during pre-2006 to ($\rho = 55.4\%$, 58.3%, 37.1%, 59.0%, and 48.3%) during post-2006 subsample. In general, the long-run estimates of pre-2006 subsample indicate that the linkage structure is strongly negative for nearly all the commodities. Whereas, the full-sample and post-2006 subsample dependence estimates indicate strong and positive connectedness between crude oil and agricultural commodities over long-run.[12]

We evaluate whether the correlation coefficients are significantly different in the undecomposed and decomposed returns series by employing Fisher (1921) r to z transformation. As expected, our estimates indicate that the dependence structure of original returns and short-run trend are not significantly different from each other in all the samples. This is because short-run trend closely follows the original returns series. For the medium-run trend, the dependence structure is significantly different from the original series for nearly all the commodities over the three samples. Whereas, for the long-run horizon, the dependence dynamics for all the commodities are significantly different from the linkage structure in original return series. Similarly, we employ Fisher (1921) r to z transform to evaluate whether the dependence dynamics are significantly different between pre- and post-2006 subsamples. Our findings indicate that the correlation coefficients are significantly different between the two subsamples in all the decomposed series.

5.2. Marginal distribution models

We follow two-step procedure to estimate the time-varying copula parameters. The first step comprise of parameter estimations of univariate marginal model for returns and decomposed series. Table 6 provides the estimated parameters of the ARMA(1,0)-EGARCH(1,1) specification for the returns series.[13,14] The lagged autoregressive coefficients, AR(1), of the mean equation are insignificant for nearly half of the commodities during pre-2006 and for nearly all the commodities over the post-2006 subsample. This indicates that the past information (past returns) is not instantaneously embodied in the current returns thus showing lack of one-step ahead predictability for these commodities. The ARCH component (α) is significant at 1% threshold level for all the underlying series during pre- and post-2006 subsamples thus indicating that the current conditional volatility is affected by the one-period lagged squared shocks. The coefficients on lagged conditional variance (β) is significant for all the commodities over both subsamples indicating persistence in conditional volatility for all series.

The parameter capturing the leverage effect (θ) on conditional volatility is significant for nearly half of the underlying commodities, indicating that good and bad news have asymmetric effect on conditional volatility of these underlying commodities. Furthermore, the tail dependence parameter (Student-df) is strongly significant at 1% threshold level in both subsamples with values exceeding two for all the commodities showing that fat tails characterize the distribution and potential for co-movement in the tails of the joint distribution. This advocates the importance and relevance of employing Student-t error distribution to estimate the parameters for crude oil and agricultural commodities. In addition, the results of diagnostic tests also indicate that the ARMA(1,0)-EGARCH(1,1) specification with Student-t errors distribution is appropriate to capture the dynamics in returns of crude oil and agricultural commodities. The estimated residuals exhibit no autocorrelation and no remaining ARCH effects for nearly all the commodities over the pre- and post-2006 subsamples, suggesting the stability of our marginal distribution models.

5.3. Estimation results of copula functions

Based on filtered returns from the EGARCH framework, we assess the dependence structure between crude oil and agricultural commodities using static and time-varying Student-t copula. Panels A and B of Table 7 presents the static and time-varying copula estimates based on original (undecomposed) returns series for the pre-2006 subsample. The dependence parameter is low and significant for most of the underlying commodities for both static and time-varying copula functions. The parameter β is significant at 1% threshold level for more than half of the commodities thus implying that the dependence is time-varying for these commodities. However, the AIC values are lower for the time-invariant Student-t copula thereby suggesting to utilize the static model to capture the underlying dependence structure between crude oil and agricultural commodities over the pre-2006 subsample. The level of connectedness (ρ) are almost same for both functions. For the static model, the dependence ranges from 0.4% (soybean oil) to 4.5% (cotton). Whereas, in the case of time-varying Student-t model, the level of dependence

[10] With exception of wheat and soybeans meal, which exhibit weak positive linkage.
[11] With exception of cocoa and soybeans meal, which exhibit positive dependence with crude oil.
[12] Except for wheat, which exhibits close to zero correlation over the full-sample.
[13] We determine the well-suited marginal model from various GARCH-type specifications (GARCH, GJR-GARCH, and EGARCH) to model crude oil and agricultural commodities returns.
[14] For the sake of brevity, we report the EGARCH parameters of returns series. The marginal estimates for all the decomposed series are available upon request.

Table 5
Multi-scale correlation analysis between crude oil and agricultural commodities.

Short-run	Full sample			Pre-2006			Post-2006		
	Pearson	Kendall	Spearman	Pearson	Kendall	Spearman	Pearson	Kendall	Spearman
Panel A: Dependence of decomposed series S1									
Wheat	15.453	7.346	10.924	3.781‡	1.712‡	2.568‡	29.885‡	16.775‡	24.668‡
Sugar	9.706	6.991	10.397	1.755‡	2.276‡	3.403‡	23.081‡	15.795‡	23.216‡
Soybean	17.902	10.447	15.481	4.912‡	3.188‡	4.760‡	36.936‡	23.340‡	34.016‡
Soybean oil	20.559	11.568	17.063	2.391‡	0.726‡	1.093‡	49.776‡	31.994‡	45.771‡
Cotton	12.756	7.777	11.569	3.674‡	2.510‡	3.769‡	26.948‡	17.228‡	25.489‡
Corn	18.334	9.995	14.861	7.730‡	4.377‡	6.546‡	31.479‡	19.324‡	28.368‡
Coffee	6.001	4.368	6.559	−1.625‡	−1.259‡	−1.859‡	22.521‡	15.445‡	23.022‡
Cocoa	8.460	5.090	7.557	0.623‡	0.963‡	1.443‡	23.206‡	13.258‡	19.577‡
Canola	11.912	6.564	9.811	2.764‡	1.454‡	2.181‡	26.069‡	15.944‡	23.600‡
Soybeans meal	12.759	7.624	11.339	5.704‡	3.942‡	5.868‡	22.359‡	13.909‡	20.595‡
Medium-run	Full sample			Pre-2006			Post-2006		
	Pearson	Kendall	Spearman	Pearson	Kendall	Spearman	Pearson	Kendall	Spearman
Panel B: Dependence of decomposed series S5									
Wheat	15.002	10.051†	14.966†	7.398‡	6.292‡	9.584†,‡	24.780‡	15.717‡	23.262‡
Sugar	9.960	6.104	9.170	−4.602†,‡	−4.399†,‡	−6.509†,‡	36.846†,‡	25.007†,‡	37.458†,‡
Soybean	18.044	12.814†	18.911†	−2.001†,‡	2.317‡	3.554‡	48.228†,‡	30.636†,‡	44.460†,‡
Soybean oil	11.802†	9.149	13.630	−10.366†,‡	−4.179†,‡	−6.209†,‡	48.017‡	32.225‡	47.152‡
Cotton	3.973†	2.722†	4.050†	−1.724†,‡	−1.737†,‡	−2.630†,‡	12.173†,‡	10.123‡	14.825†,‡
Corn	11.138†	5.152†	7.693†	−6.950†,‡	−4.175†,‡	−6.231†,‡	33.628†,‡	19.680‡	29.256‡
Coffee	2.357†	2.165†	3.229†	−11.595†,‡	−7.083†,‡	−10.701†,‡	31.550†,‡	20.700‡	30.436†,‡
Cocoa	9.794	7.865	11.505	−6.817†,‡	−1.814‡	−2.605†,‡	38.203†,‡	25.305†,‡	36.608†,‡
Canola	4.216†	2.483†	3.797†	−7.270†,‡	−3.040†,‡	−4.427†,‡	24.299‡	12.419‡	18.591‡
Soybeans meal	16.777†	11.416†	16.957†	3.001‡	3.730‡	5.638‡	37.258†,‡	24.303†,‡	35.650†,‡
Long-run	Full sample			Pre-2006			Post-2006		
	Pearson	Kendall	Spearman	Pearson	Kendall	Spearman	Pearson	Kendall	Spearman
Panel C: Dependence of decomposed series S8									
Wheat	3.852†	−3.774†	−5.226†	−27.997†,‡	−22.220†,‡	−32.418†,‡	24.952‡	17.515‡	27.496†,‡
Sugar	33.211†	16.537†	24.404†	−2.237†,‡	0.854‡	1.123‡	55.461†,‡	39.456†,‡	56.518†,‡
Soybean	31.530†	12.382	18.507†	−4.117†,‡	−5.270†,‡	−7.996†,‡	58.318†,‡	34.848†,‡	50.675†,‡
Soybean oil	40.187†	15.929†	23.439†	−6.692†,‡	−4.699†,‡	−7.008†,‡	74.556†,‡	45.951†,‡	64.553†,‡
Cotton	35.344†	21.801†	31.959†	−7.519†,‡	−0.651‡	−0.809†,‡	61.957†,‡	49.772†,‡	70.815†,‡
Corn	18.473†	2.100†	3.300†	−24.269†,‡	−14.801†,‡	−22.067†,‡	43.891†,‡	23.823†,‡	35.177†,‡
Coffee	12.307†	4.810	7.488	−6.401†,‡	−8.038†,‡	−11.064†,‡	37.092†,‡	25.597†,‡	38.522†,‡
Cocoa	40.778†	20.431†	30.029†	21.988†,‡	11.034†,‡	16.890†,‡	59.040†,‡	34.150†,‡	49.571†,‡
Canola	28.484†	9.791†	14.935†	−12.482†,‡	−10.283†,‡	−15.518†,‡	57.924†,‡	36.046†,‡	52.680†,‡
Soybeans meal	28.253†	13.142†	19.516†	0.224‡	−1.104†,‡	−2.063†,‡	48.275†,‡	30.833†,‡	45.300†,‡

Notes. The table presents correlation coefficients from Pearson, Kendall, and Spearmann for the decomposed series. Panels A, B, and C presents the coefficients of dependence from the short-, medium-, and long-run trends, respectively. We tested whether the correlation coefficients in the decomposed returns are statistically different from correlations in undecomposed returns by utilizing Fisher (1921) r to z transformation. In addition, we employ Fisher (1921) r to z transformation to evaluate whether the coefficients in pre- and post-2006 subsamples are statistically different from each other. † indicates that the dependence coefficients in the decomposed series are significantly different from coefficients in the undecomposed returns at 5% threshold level. Whereas, ‡ indicates that the correlation coefficients are significantly different between pre- and post-2006 subsamples at 1% significance level.

varies from −0.5 % (coffee) to 4.4% (cotton). The low magnitude of the dependence parameters supports the hypothesis that adding agricultural commodities with crude oil helps in attaining diversification benefits during the pre-2006 subsample. Furthermore, the degrees of freedom (DoF) parameters are low and significant for more than half of the commodities reflecting tail dependence and joint extreme movements of these commodities with crude oil.

Table 8 provides the copula parameters of original (undecomposed) returns for the post-2006 subsample. In contrast to the pre-2006 estimates, the post-2006 subsample is characterized by strong dependence as indicated by statistically significant and positive values of ρ. By comparing the static and time-varying copula specifications, the estimates Table 8 indicates strong evidence that the time-varying Student-t copula offer the best fit for crude oil and agricultural commodities. Soybean oil (44.2%), soybeans (32.1%), and corn (25.8%) exhibits strongest level of dependence with crude oil, which is due to increased diversion of these commodities towards production of biofuels over the post-2006 subsample. The parameter β is significant at 1% threshold level for all the commodities thus supporting evidence of time-varying dependence structure. Furthermore, the degrees of freedom are low and significant at 1% and 5% threshold level for most of the commodities thereby indicating joint extreme movements and strong tail dependence behavior over the post-2006 subsample. The positivity and higher magnitude of dependence parameters during post-2006 subsample provide evidence of information transmission from crude oil significantly effects the price dynamics of agricultural commodities. In addition, Fig. 3 shows the time-varying dependence parameter of the DCC-Student-t

Table 6
EGARCH parameters for crude oil and agricultural commodities.

Pre-2006	Crude oil	Wheat	Sugar	Soybeans	Soybeans oil	Cotton	Corn	Coffee	Cocoa	Canola	Soybeans meal
Panel A: Pre-2006 EGARCH estimates											
Mean equation estimates											
Const. (%)	0.018	−0.020	0.028	0.022	−0.014	0.000	−0.030‡	0.011	−0.036	−0.013	−0.009
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
AR(1)	−0.032‡	0.028‡	−0.065†	−0.033‡	0.027	−0.010	0.034‡	−0.021	−0.022	0.037†	0.010
	(0.014)	(0.013)	(0.013)	(0.014)	(0.014)	(0.013)	(0.013)	(0.013)	(0.014)	(0.014)	(0.013)
GARCH process estimates											
Const. (Ω)	−0.086†	−0.109†	−0.034‡	−0.096†	−0.199†	−0.059†	−0.148†	−0.173†	−0.052†	−0.218†	−0.092†
	(0.023)	(0.034)	(0.013)	(0.026)	(0.046)	(0.018)	(0.038)	(0.035)	(0.018)	(0.049)	(0.023)
GARCH (β)	0.989†	0.987†	0.996†	0.989†	0.977†	0.993†	0.983†	0.977†	0.993†	0.976†	0.989†
	(0.003)	(0.004)	(0.002)	(0.003)	(0.005)	(0.002)	(0.004)	(0.005)	(0.002)	(0.005)	(0.003)
ARCH (α)	0.128†	0.084†	0.082†	0.141†	0.125†	0.073†	0.157†	0.163†	0.073†	0.170†	0.126†
	(0.014)	(0.012)	(0.010)	(0.013)	(0.015)	(0.010)	(0.017)	(0.016)	(0.010)	(0.017)	(0.013)
Leverage (θ)	−0.019‡	0.013	−0.001	0.045†	0.035†	−0.002	0.006	0.051†	0.014‡	0.002	0.044†
	(0.008)	(0.008)	(0.006)	(0.008)	(0.009)	(0.006)	(0.010)	(0.011)	(0.007)	(0.009)	(0.008)
Student-df	5.793†	5.990†	4.295†	5.927†	6.654†	4.955†	4.340†	4.074†	5.392†	6.213†	4.854†
	(0.452)	(0.378)	(0.279)	(0.471)	(0.660)	(0.319)	(0.247)	(0.274)	(0.412)	(0.471)	(0.331)
Log(L)	12,708	14,017	12,671	14,857	14,385	13,735	14,679	11,891	12,918	15,261	14,402
AIC	−25,402	−28,021	−25,328	−29,700	−28,755	−27,457	−29,343	−23,768	−25,822	−30,508	−28,790
BIC	−25,357	−27,975	−25,282	−29,654	−28,710	−27,411	−29,298	−23,722	−25,776	−30,462	−28,745
Skewness	−0.348	−0.208	−0.208	−0.135	0.262	−0.923	0.847	0.158	0.281	0.196	0.029
Kurtosis	6.406	11.074	7.254	5.793	4.483	24.829	11.083	6.771	5.647	6.335	8.883
Q (15)	16.6	25.1**	25.5**	20.5	28.3**	32.3**	20.7	24.4	23.9	18.9	19.7
Q^2(15)	31.1**	4.8	13.0	10.6	15.2	2.0	12.4	30.2**	9.6	15.1	5.1
ARCH (15)	32.3**	4.9	13.4	10.8	15.8	2.0	12.8	31.3**	9.9	15.6	5.3
Post-2006	Crude oil	Wheat	Sugar	Soybeans	Soybeans oil	Cotton	Corn	Coffee	Cocoa	Canola	Soybeans meal
Panel B: Post-2006 EGARCH parameters											
Mean equation estimates											
Const. (%)	0.000	0.000	−0.001‡	0.001†	0.000	0.000	0.000	0.000	0.001	0.001†	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
AR(1)	−0.038‡	−0.007	−0.026	−0.010	0.018	0.028	0.022	−0.047‡	−0.005	0.037‡	0.000
	(0.019)	(0.020)	(0.019)	(0.019)	(0.020)	(0.019)	(0.018)	(0.019)	(0.018)	(0.018)	(0.019)
GARCH process estimates											
Const. (Ω)	−0.046†	−0.079†	−0.032	−0.082‡	−0.062‡	−0.107†	−0.088†	−0.119‡	−0.029	−0.244†	−0.106†
	(0.017)	(0.027)	(0.017)	(0.035)	(0.028)	(0.036)	(0.028)	(0.047)	(0.016)	(0.071)	(0.041)
GARCH (β)	0.994†	0.990†	0.996†	0.990†	0.993†	0.987†	0.989†	0.985†	0.996†	0.972†	0.987†
	(0.002)	(0.004)	(0.002)	(0.004)	(0.003)	(0.004)	(0.004)	(0.006)	(0.002)	(0.008)	(0.005)
ARCH (α)	0.096†	0.102†	0.077†	0.117†	0.098†	0.132†	0.118†	0.067†	0.067†	0.147†	0.113†
	(0.015)	(0.017)	(0.013)	(0.018)	(0.015)	(0.018)	(0.018)	(0.016)	(0.013)	(0.023)	(0.018)
Leverage (θ)	−0.055†	0.033†	0.010	0.014	−0.010	0.003	−0.002	0.039†	−0.004	−0.009	0.034†
	(0.009)	(0.010)	(0.008)	(0.011)	(0.008)	(0.012)	(0.011)	(0.009)	(0.009)	(0.013)	(0.011)
Student-df	11.946†	8.675†	5.572†	5.149†	12.091†	5.760†	5.988†	6.246†	5.744†	4.452†	5.514†
	(2.044)	(1.248)	(0.545)	(0.483)	(2.475)	(0.571)	(0.524)	(0.880)	(0.663)	(0.363)	(0.546)
Log(L)	6631	6498	6598	7357	7489	7021	6774	6667	7086	7883	6905
AIC	−13,249	−12,982	−13,181	−14,701	−14,963	−14,028	−13,534	−13,320	−14,159	−15,753	−13,795
BIC	−13,208	−12,941	−13,140	−14,660	−14,922	−13,987	−13,492	−13,279	−14,118	−15,712	−13,754
Skewness	−0.214	0.178	0.537	−0.706	0.208	−0.491	−1.077	0.048	−0.436	−0.598	−0.540
Kurtosis	4.103	4.594	8.197	8.858	3.813	9.266	18.985	4.311	5.717	11.963	7.470
Q (15)	5.4	17.5	10.9	12.0	10.3	13.9	18.2	13.0	19.6	28.0**	12.1
Q^2(15)	20.3	12.2	3.8	4.9	8.6	5.9	2.3	20.4	19.5	2.0	7.3
ARCH (15)	19.9	12.5	3.8	4.9	11.4	5.9	2.3	18.5	18.6	1.8	7.1

Notes: This table presents the estimates of EGARCH model for each return series. Standard errors are presented in parenthesis. Q(15), Q^2(15), and ARCH(15) are empirical statistics of Ljung-Box test for autocorrelation with 15 lags in residuals and squared residuals, and the ARCH effects test by Engle (1982) with 15 lags, respectively.
$^{+}$ indicates the significance at 10% threshold level.
‡ indicates the significance at 5% threshold level.
† indicates the significance at 1% threshold level.
* The rejection of null hypothesis of independence and conditional homoscedasticity at 10% threshold level.
** The rejection of null hypothesis of independence and conditional homoscedasticity at 5% threshold level.
*** The rejection of null hypothesis of independence and conditional homoscedasticity at 1% threshold level.

copula for the pre- and post-2006 subsamples. [15] Notably, in comparison with the DCC parameter for pre-2006 subsample, the graphs for post-2006 subsample indicates strong time-varying dependence structure between crude oil and the studied agricultural commodities. Furthermore, it is noteworthy that the financial and economic turmoil significantly influence the relationship in oil-fuel nexus. For instance, the dependence parameter for all commodities peaked around 2008–09, which is the period associated to the global financial crisis. Moreover, similar structure can be observed during the period of European debt crisis of 2010–12. This is indicative that the conditional dependence between crude oil and the agricultural commodities are higher during bearish and lower during bullish periods.

[15] For the sake of brevity, we report the DCC-Student-t copula parameters for wheat, soybean oil, and corn. The estimates for crude oil and other agricultural commodities are available from authors upon request.

Table 7
Copula estimates of undecomposed series for pre-2006 subsample.

	Wheat	Sugar	Soybeans	Soybeans oil	Cotton	Corn	Coffee	Cocoa	Canola	Soybeans meal
Panel A: Static Student-t copula parameters										
ρ	0.035‡	0.035‡	0.033‡	0.004	0.045†	0.043†	0.008	0.021	0.017	0.043†
	(−0.016)	(−0.016)	(−0.016)	(0.004)	(−0.015)	(−0.015)	(0.045)	(−0.019)	(−0.023)	(−0.015)
DoF	17.460†	25.628*	21.783†	31.295	24.793†	11.675†	21.909†	31.222	45.349	18.721†
	(5.152)	(14.254)	(7.328)	(38.306)	(8.507)	(2.180)	(7.362)	(49.494)	(34.729)	(6.848)
Log(L)	11.26	8.01	6.93	2.43	9.13	20.45	4.67	2.84	1.45	9.61
AIC	−20.52	−14.02	−11.85	−2.86	−16.25	−38.91	−7.34	−3.68	−0.90	−17.22
Panel B: DCC-Student-t copula parameters										
ρ	0.035†	0.044†	0.030†	−0.001	0.044†	0.042†	−0.005†	0.013†	0.013†	0.036†
	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
DoF	17.592†	25.949‡	22.690†	31.693	24.843†	11.689†	23.118†	31.997‡	45.902	18.987‡
	(4.301)	(10.883)	(7.402)	(60.515)	(9.467)	(2.055)	(8.374)	(14.661)	(5349.250)	(6.314)
α	0.009	0.018	0.010	0.005	0.000	0.000	0.003	0.003	0.000	0.000†
	(0.015)	(0.016)	(0.008)	(0.002)	(0.012)	(0.011)	(0.005)	(0.002)	(60.939)	(0.000)
β	0.030	0.000	0.865†	0.990†	0.305†	0.339†	0.989†	0.989†	0.380	0.079†
	(0.900)	(0.596)	(0.055)	(0.007)	(0.013)	(0.038)	(0.026)	(0.007)	(171.465)	(0.006)
Log(L)	11.44	8.81	7.91	7.06	9.12	20.42	6.34	4.31	1.48	9.61
AIC	−16.89	−11.62	−9.83	−8.12	−12.24	−34.85	−6.67	−2.63	3.04	−13.21

Notes: This table reports the estimates of static and DCC-Student-t copula for the pre-2006 subsample based on original returns series. The standard errors are presented in parenthesis.
* indicates the significance at 10% threshold level.
‡ indicates the significance at 5% threshold level.
† indicates the significance at 1% threshold level.

In general, all the agricultural commodities follow similar dependence structure. Furthermore, the decline in crude oil price from the last quarter of 2014 leads to a slight increase in dependence soybean oil and corn. The co-movement between crude oil and wheat over this period is rather neutral varying between 0 and 10%. Whereas, in the case of soybean oil and corn, the decline in crude oil price lead to an increase in connectedness for these commodities. These findings indicate that the positive co-movement between the agricultural commodities is also apparent in the case of decline in crude oil price especially for the crops being utilized to produce biofuel.

We explore the temporal and spectral dependence dynamics by employing MODWT and least asymmetric wavelet filter (LA(8)) proposed by Daubechies (1992) to decompose the original returns series into a set of subsequent wavelets. Table 9 provides the pre-2006 static and time-varying copula estimates based on the decomposed series capturing the short-run trend, i.e. variations over 2 and 4 consecutive days. These estimates closely follow the dependence parameters of original returns series for both copula functions. This evidence is consistent with the idea that, over the pre-2006 subsample, the effect of crude oil price shocks diminishes rapidly and does not transmit information to agricultural commodity prices over shorter horizons. Based on the AIC values, the time-varying copula function offers the best fit for all the underlying pairs. The connectedness measure ρ is significant at 1% level for nearly all the commodities and ranges from −1.7 % (coffee) to 5.7% (soybeans meal) during pre-2006 subsample. The tail dependence parameter is high thus reflecting the lack of joint extreme movement during pre-2006 subsample. The parameter α is significant for nearly all the underlying commodities indicating asymmetric impact of shocks on conditional dependence. However, the coefficient β is low and

Table 8
Copula estimates of undecomposed series for post-2006 subsample.

	Wheat	Sugar	Soybeans	Soybeans oil	Cotton	Corn	Coffee	Cocoa	Canola	Soybeans meal
Panel A: Static Student-t copula parameters										
ρ	0.181†	0.211†	0.313†	0.432†	0.225†	0.256†	0.242†	0.193†	0.208†	0.187†
	(0.019)	(0.019)	(0.019)	(0.018)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)
DoF	9.786†	18.216†	14.116†	14.191†	56.897‡	17.176†	13.096†	30.387‡	12.888†	14.188†
	(2.203)	(6.880)	(4.729)	(4.300)	(25.100)	(6.345)	(3.647)	(13.031)	(3.671)	(4.837)
Log(L)	61.76	66.47	154.60	300.29	73.24	98.60	87.17	55.24	77.01	58.46
AIC	−121.52	−130.95	−307.20	−598.59	−144.47	−195.19	−172.34	−108.47	−152.01	−114.91
Panel B: DCC-Student-t copula parameters										
ρ	0.187†	0.214†	0.321†	0.442†	0.234†	0.258†	0.238†	0.200†	0.227†	0.195†
	(0.003)	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)	(0.001)
DoF	12.679†	21.559*	16.353†	15.900†	76.828	19.768‡	17.634†	32.053	16.697†	15.763†
	(3.756)	(11.978)	(5.782)	(5.929)	(98.767)	(8.578)	(6.649)	(19.075)	(6.338)	(5.834)
α	0.018	0.029	0.008†	0.008†	0.005*	0.011	0.011†	0.005*	0.008*	0.006†
	(0.011)	(0.034)	(0.003)	(0.003)	(0.003)	(0.020)	(0.003)	(0.003)	(0.004)	(0.003)
β	0.976†	0.913†	0.989†	0.990†	0.990†	0.984†	0.985†	0.990†	0.990†	0.988†
	(0.017)	(0.171)	(0.005)	(0.004)	(0.007)	(0.039)	(0.005)	(0.006)	(0.008)	(0.005)
Log(L)	90.22	73.80	169.88	323.98	77.56	114.37	105.05	58.56	96.46	64.14
AIC	−174.44	−141.61	−333.76	−641.96	−149.11	−222.74	−204.11	−111.11	−186.92	−122.27

Notes: This table reports the estimates of static and DCC-Student-t copula for the post-2006 subsample based on original returns series. The standard errors are presented in parenthesis.
* indicates the significance at 10% threshold level.
‡ indicates the significance at 5% threshold level.
† indicates the significance at 1% threshold level.

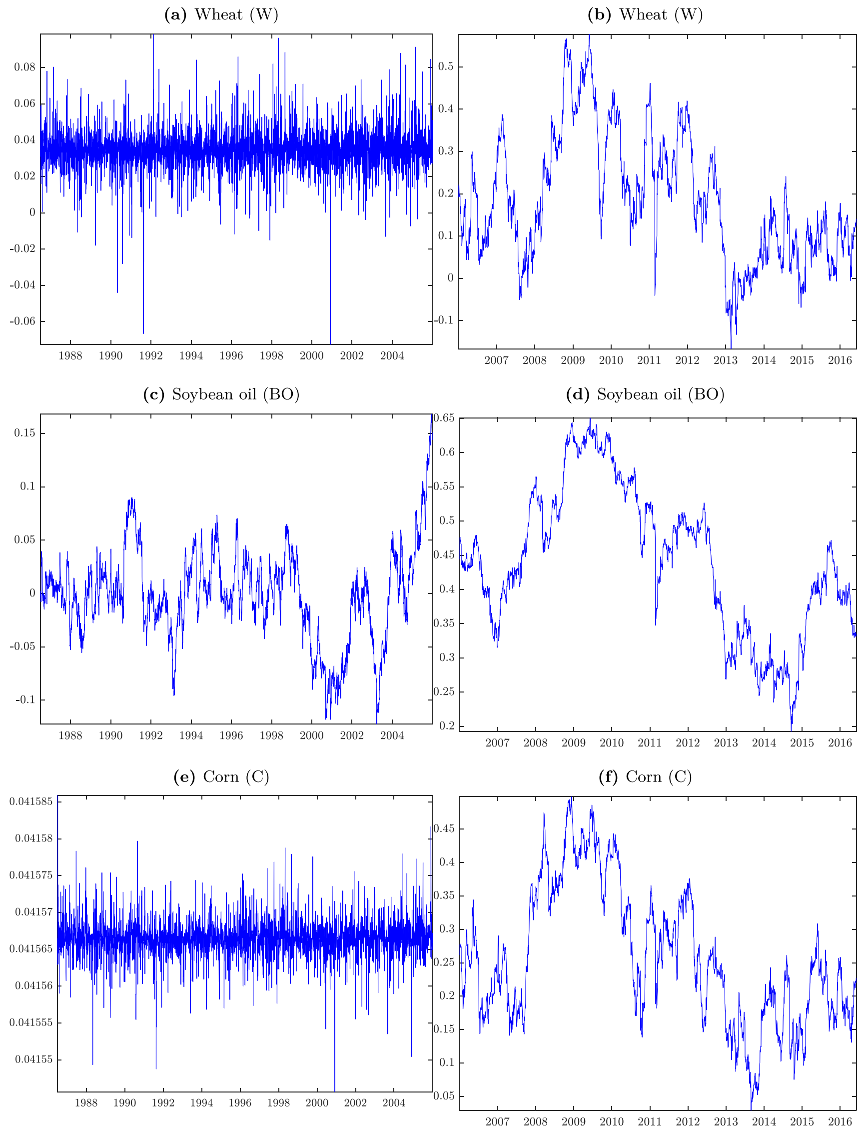

Fig. 3. Time-varying copula dependence parameter for pre- and post-2006 subsample. **Notes.** The figure presents an overview of change in dependence dynamics between crude oil and three agricultural commodities for the pre- and post-2006 subsamples. The time period presented on x-axis and y-axis shows the temporal variation in dependence coefficient. The graphs for all the agricultural commodities can be obtained from authors upon request.

insignificant reflecting the lack of persistence. The short-run estimates of static and time-varying copula functions for the post-2006 subsample are presented in Table 10. Similar to pre-2006 subsample, the copula estimates for short-run trend over the post-2006 subsample follows dependence dynamics of undecomposed returns series. The connectedness parameter ranges from 18.6% (cocoa) to 43.2%

Table 9
Copula estimates of short-run trend for pre-2006.

	Wheat	Sugar	Soybeans	Soybeans oil	Cotton	Corn	Coffee	Cocoa	Canola	Soybeans meal
Panel A: Static Student-t copula parameters										
ρ	0.024	0.038‡	0.043†	0.012	0.039‡	0.060†	-0.015	0.012	0.026	0.055†
	(−0.018)	(−0.016)	(−0.015)	(−0.043)	(−0.016)	(−0.015)	(0.027)	(−0.053)	(−0.017)	(−0.015)
DoF	44.502†	199.999†	172.848†	85.514	127.219†	199.999‡	93.562	27.904‡	199.999	73.239
	(60.587)	(1.435)	(1.771)	(105.550)	(15.337)	(92.075)	(128.225)	(14.077)	(142.329)	(50.766)
Log(L)	3.07	3.12	4.75	0.69	4.13	10.30	1.07	2.80	1.31	9.15
AIC	−4.13	−4.25	−7.50	0.63	−6.26	−18.59	−0.13	−3.60	−0.63	−16.29
Panel B: DCC-Student-t copula parameters										
ρ	0.027†	0.036†	0.043†	0.012†	0.039†	0.062†	−0.017†	0.008‡	0.026†	0.057†
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)	(0.004)	(0.003)	(0.003)
DoF	199.710†	199.987†	199.988†	199.988†	199.986	199.999†	199.949†	199.647	199.776†	199.970
	(9.807)	(5.865)	(5.041)	(20.801)	(133.494)	(3.137)	(17.727)	(918.655)	(2.746)	(648.798)
α	0.317†	0.331†	0.330†	0.330†	0.300†	0.336†	0.329†	0.338	0.326†	0.325
	(0.016)	(0.016)	(0.016)	(0.016)	(0.024)	(0.016)	(0.016)	(0.203)	(0.017)	(0.537)
β	0.005	0.000	0.000	0.000	0.000	0.086‡	0.070	0.010	0.024	0.000
	(0.080)	(0.024)	(0.214)	(0.039)	(0.057)	(0.042)	(0.042)	(0.886)	(0.047)	(10.773)
Log(L)	208.99	208.68	228.37	214.13	185.66	220.64	210.83	236.84	194.96	219.79
AIC	−411.98	−411.35	−450.73	−422.26	−365.31	−435.28	−415.66	−467.68	−383.92	−433.57

Notes: This table reports the estimates of static and DCC-Student-t copula based on decomposed return series characterizing the short-run investment horizon for the pre-2006 subsample. Also, see notes of Table 7.

Table 10
Copula estimates of short-run trend for post-2006.

	Wheat	Sugar	Soybeans	Soybeans oil	Cotton	Corn	Coffee	Cocoa	Canola	Soybeans meal
Panel A: Static t-copula post-2006										
ρ	0.226†	0.216†	0.323†	0.433†	0.251†	0.266†	0.217†	0.185†	0.220†	0.203†
	(0.019)	(0.019)	(0.019)	(0.018)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)
DoF	20.938‡	11.517†	10.485†	12.819†	81.698†	15.263†	38.251	27.996	19.947‡	10.614†
	(8.963)	(2.872)	(2.284)	(3.274)	(23.093)	(5.404)	(32.301)	(21.191)	(8.730)	(2.585)
Log(L)	79.59	73.84	162.21	292.77	87.49	108.28	64.50	50.38	70.86	69.78
AIC	−157.18	−145.67	−322.43	−583.53	−172.97	−214.55	−126.99	−98.76	−139.71	−137.55
Panel B: DCC t-copula post-2006										
ρ	0.231†	0.212†	0.321†	0.432†	0.248†	0.267†	0.213†	0.186†	0.219†	0.203†
	(0.005)	(0.005)	(0.005)	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)
DoF	30.471	27.023	26.691‡	72.810	199.968†	29.910	199.983†	199.918†	106.889	22.183‡
	(18.847)	(31.373)	(11.034)	(95.046)	(3.791)	(25.427)	(57.856)	(6.005)	(126.803)	(10.767)
α	0.355†	0.360†	0.365†	0.341†	0.341†	0.367†	0.375†	0.363†	0.348†	0.410†
	(0.025)	(0.023)	(0.022)	(0.025)	(0.021)	(0.025)	(0.021)	(0.022)	(0.025)	(0.023)
β	0.000	0.064	0.065	0.057	0.000	0.048	0.072	0.000	0.034	0.067
	(0.076)	(0.061)	(0.055)	(0.063)	(0.097)	(0.047)	(0.050)	(0.023)	(0.076)	(0.040)
Log(L)	209.17	212.24	305.32	431.23	211.04	242.05	212.41	190.25	201.70	230.95
AIC	−412.33	−418.49	−604.64	−856.45	−416.07	−478.10	−418.83	−374.51	−397.40	−455.90

Notes: The table reports the estimates of static and DCC-Student-t copula based on decomposed return series characterizing the short-run investment horizon for the post-2006 subsample. Also, see notes of Table 7.

(soybean oil). However, unlike the estimates from undecomposed series, the short-run estimates are not characterized by tail dependence behavior.

Tables 11 and 12 provide static and time-varying copula estimates characterizing the middle-run trend (32–64 days) for pre- and post-2006 subsamples. The magnitude and direction of dependence follows the middle-run linear correlation parameters presented in Table 5 over both subsamples. Similar to the estimates of short-run trend, the AIC values indicate that the time-varying Student-t copula specifications offer the best fit between crude oil and agricultural commodities. The dependence parameter ρ is negative and significant at 1% threshold level for more than half of the commodities. In addition, the magnitude of the parameter tends to be stronger over the medium-run trend thereby supporting the hypothesis of adding agricultural commodities with crude oil over the middle-term investment horizon helps in attaining diversification benefits. The degrees of freedom parameter is large indicating that the middle-run trend is not characterized by tail-dependence over both subsamples.[16] It is interesting to note that the dependence between crude oil and wheat exhibits significant and relatively strong linkage over the middle-run investment horizon as oppose to short-run frequency during pre-2006. Consistent with post-2006 estimates of original returns and short-run investment horizon, the medium-run is characterized by significant and strongly positive dependence structure. Furthermore, the time-varying component of DCC-copula functions β indicate that the dependence measure is time-varying over both subsamples. The magnitude and direction of connectedness over the medium-run change from weakly negative to moderately positive from pre-2006 to post-2006 subsample.

The static and time-varying copula estimates representing the long-run trend (256–512 days) of return series for pre- and post-2006 subsamples are presented in Tables 13 and 14, respectively. Similar to previous copula functions, the time-varying Student-t copula specification offers the best fit between crude oil and agricultural commodities over both subsamples. Unlike the linkage parameters of original and short-run trend, the direction and magnitude of connectedness in some of the agricultural commodities is negative and comparatively strong during pre-2006 subsample thus suggesting stronger negative dependence over long-run trend for these

[16] With exception of wheat, soybeans, soybean oil, and soybeans meal over the post-2006 subsample.

Table 11
Copula estimates of medium-run trend for pre-2006.

	Wheat	Sugar	Soybeans	Soybeans oil	Cotton	Corn	Coffee	Cocoa	Canola	Soybeans meal
Panel A: Static t-copula post-2006										
ρ	0.104†	−0.075†	0.015	−0.054†	−0.028	−0.090†	−0.077†	0.004	−0.047†	0.015
	(−0.014)	(0.015)	(−0.028)	(0.015)	(0.017)	(0.014)	(0.014)	(0.005)	(0.015)	(−0.028)
DoF	49.109‡	199.999†	199.989†	199.999†	21.268‡	199.999†	199.999†	32.225†	200.000†	199.999†
	(21.164)	(43.909)	(36.669)	(44.030)	(8.338)	(28.801)	(14.537)	(8.980)	(1.649)	(20.025)
Log(L)	18.25	13.89	−0.31	8.33	6.82	22.69	14.39	2.25	9.19	−1.20
AIC	−34.51	−25.77	2.61	−14.66	−11.64	−43.38	−26.77	−2.49	−16.38	4.40
Panel B: DCC t-copula post-2006										
ρ	0.092†	−0.068†	0.009	−0.053†	−0.027†	−0.089†	−0.071†	0.006	−0.048†	0.007
	(0.007)	(0.006)	(0.007)	(0.007)	(0.007)	(0.006)	(0.006)	(0.008)	(0.007)	(0.007)
DoF	199.998†	199.988†	200.000†	199.989†	199.996†	200.000†	200.000†	23.928‡	199.987†	199.998†
	(1.693)	(7.069)	(10.013)	(4.640)	(26.035)	(12.535)	(9.474)	(9.682)	(2.306)	(20.744)
α	0.500†	0.500†	0.500†	0.500†	0.500†	0.500†	0.500†	0.160†	0.500†	0.500†
	(0.021)	(0.019)	(0.025)	(0.019)	(0.026)	(0.012)	(0.014)	(0.011)	(0.028)	(0.023)
β	0.289†	0.265†	0.295†	0.274†	0.320†	0.252†	0.281†	0.824†	0.277†	0.287†
	(0.033)	(0.032)	(0.042)	(0.032)	(0.042)	(0.029)	(0.026)	(0.015)	(0.051)	(0.038)
Log(L)	1174.31	1105.82	1148.59	1087.70	1263.79	1076.07	1045.88	1174.52	1095.97	1098.30
AIC	−2342.61	−2205.64	−2291.18	−2169.40	−2521.58	−2146.14	−2085.77	−2343.03	−2185.95	−2190.61

Notes: This table reports the parameters of static and DCC-Student-t copula based on decomposed return series characterizing the medium-run investment horizon for the pre-2006 subsample. Also, see notes of Table 7.

commodities. Notably, the dependence between crude oil and wheat increases from 3.5% in the case of undecomposed series to −33.8 %. This indicates that adding these agricultural commodities with crude oil over the long-term investment horizon helps in attaining diversification benefits during pre-2006 subsample. Furthermore, the parameters α and β are significant at 1% threshold level indicating asymmetric impact of shocks and persistence in conditional dependence. The DoF parameter is significant for nearly half of the agricultural commodities thus reflecting extreme co-movement between these commodities and crude oil. As oppose to negative dependence structure during pre-2006, the post-2006 subsample is characterized by strongly positive and significant dependence structure. Specifically, cotton, soybean oil, canola, corn, and sugar exhibit the largest degrees of dependence with crude oil. The copula estimates of long-run trend support the hypothesis that crude oil prices significantly changes the price dynamics of agricultural commodities over the long-term investment horizon. The positive dependence structure during post-2006 subsample might be a result of increased employment of agricultural commodities towards production of biofuels.

5.4. Discussion and implications

In this paper, we study the temporal and spectral dependence dynamics between crude oil and some of the key agricultural commodities. We divide our data into two subsets to account for structural change and fundamental shift in market for major agricultural commodities during 2006. Our findings of linear correlation analysis indicate that the increase in investment horizon results in stronger dependence structure over both subsamples. Furthermore, the parameters from static and time-varying Student-t copula functions provide further validation to these findings. In addition, our analysis indicates that the diversification and hedging benefits diminishes with the increase in frequency horizon over the post-2006 subsample.

The results of this study add to the findings of Pal and Mitra (2017), Mensi et al. (2017), Wang and McPhail (2014) and Koirala et al. (2015) as the application of wavelet-based copulas provides key insights into fuel-food dependence dynamics. Specifically, with regard to temporal and spectral contribution of oil price shock on agricultural commodities, our analysis indicate that the

Table 12
Copula estimates of medium-run trend for post-2006.

	Wheat	Sugar	Soybeans	Soybeans oil	Cotton	Corn	Coffee	Cocoa	Canola	Soybeans meal
Panel A: Static t-copula post-2006										
ρ	0.197†	0.336†	0.399†	0.443†	0.141†	0.275†	0.282†	0.314†	0.135†	0.297†
	(0.019)	(0.019)	(0.019)	(0.018)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)
DoF	8.536	200.000†	10.288†	199.999†	22.415	23.770†	126.754†	27.947†	28.301†	30.270†
	(1.781)	(160.550)	(2.220)	(8.484)	(8.882)	(11.999)	(263.925)	(12.300)	(20.092)	(92.367)
Log(L)	59.99	117.37	233.49	252.74	21.88	100.49	87.57	107.49	27.14	119.13
AIC	−117.98	−232.74	−464.98	−503.49	−41.76	−198.97	−173.14	−212.98	−52.28	−236.26
Panel B: DCC t-copula post-2006										
ρ	0.178†	0.303†	0.369†	0.414†	0.135†	0.254†	0.255†	0.285†	0.133†	0.259†
	(0.011)	(0.007)	(0.010)	(0.009)	(0.012)	(0.010)	(0.008)	(0.008)	(0.009)	(0.011)
DoF	15.321†	200.000†	24.480‡	13.758†	162.885	28.923	199.996†	199.996†	200.000†	26.241‡
	(4.183)	(2.393)	(11.540)	(3.939)	(244.187)	(17.359)	(49.490)	(4.050)	(3.955)	(10.995)
α	0.205†	0.500†	0.116†	0.128†	0.152†	0.167†	0.500†	0.500†	0.500†	0.123†
	(0.016)	(0.034)	(0.006)	(0.013)	(0.005)	(0.019)	(0.044)	(0.051)	(0.053)	(0.008)
β	0.775†	0.191†	0.868†	0.857†	0.836†	0.809†	0.264†	0.205‡	0.280†	0.866†
	(0.020)	(0.061)	(0.008)	(0.016)	(0.007)	(0.027)	(0.086)	(0.098)	(0.095)	(0.009)
Log(L)	751.78	566.10	762.14	673.87	687.84	660.55	639.80	621.84	648.05	653.51
AIC	−1497.57	−1126.20	−1518.29	−1341.73	−1369.69	−1315.09	−1273.60	−1237.68	−1290.10	−1301.01

Notes: This table reports the parameters of static and DCC-Student-t copula based on decomposed return series characterizing the medium-run investment horizon for the post-2006 subsample. Also, see notes of Table 7.

Table 13
Copula estimates of long-run trend for pre-2006.

	Wheat	Sugar	Soybeans	Soybeans oil	Cotton	Corn	Coffee	Cocoa	Canola	Soybeans meal
Panel A: Static t-copula post-2006										
ρ	−0.346†	−0.054†	−0.022	−0.038†	0.077†	−0.048†	−0.083†	0.139†	−0.158†	0.026*
	(−0.014)	(−0.014)	(−0.014)	(−0.013)	(0.014)	(−0.013)	(−0.014)	(0.014)	(−0.014)	(0.014)
DoF	29.781	199.930†	8.741†	10.546†	7.377†	18.690†	5.168†	200.000†	27.768*	11.394†
	(22.699)	(48.070)	(1.353)	(1.678)	(0.943)	(5.565)	(0.480)	(2.878)	(15.513)	(2.000)
Log(L)	314.19	13.16	23.77	19.00	47.79	7.82	85.37	47.95	72.04	15.03
AIC	−626.38	−24.32	−45.54	−36.01	−93.58	−13.65	−168.74	−93.89	−142.07	−28.05
Panel B: DCC t-copula post-2006										
ρ	−0.338†	−0.029†	−0.034†	−0.055†	0.030†	−0.039†	−0.089†	0.133†	−0.170†	0.026†
	(0.007)	(0.008)	(0.009)	(0.008)	(0.009)	(0.007)	(0.010)	(0.006)	(0.009)	(0.007)
DoF	199.988	199.966†	8.037†	199.985†	29.276†	198.175†	9.387†	200.000	60.522‡	198.482†
	(179.662)	(49.160)	(0.928)	(19.892)	(10.596)	(18.854)	(1.006)	–	(27.301)	(35.766)
α	0.026†	0.034†	0.030†	0.019†	0.023†	0.069†	0.036†	0.296	0.035†	0.142†
	(0.005)	(0.002)	(0.001)	(0.001)	(0.001)	(0.013)	(0.001)	–	(0.001)	(0.018)
β	0.971†	0.963†	0.970†	0.980†	0.975†	0.909†	0.963†	0.576	0.963†	0.800†
	(0.007)	(0.002)	(0.001)	(0.001)	(0.001)	(0.019)	(0.001)	–	(0.002)	(0.027)
Log(L)	1513.15	1266.53	1415.91	1261.03	1397.93	1271.81	1681.88	987.83	1572.87	1286.17
AIC	−3020.31	−2527.05	−2825.82	−2516.06	−2789.87	−2537.62	−3357.76	−1969.65	−3139.75	−2566.33

Notes: This table reports the parameters of static and DCC-Student-t copula based on decomposed return series characterizing the long-run investment horizon for the pre-2006 subsample. In the case of cocoa, the numerical Hessian which is used in calculation of standard errors is not positive definite resulting in too large standard errors. Also, see notes of Table 7.

connectedness between oil and agricultural commodities increases over the post-2006 subsample across all frequencies of return movements. However, the rate of increase is higher for longer investment horizon. The wavelet decomposition reveals declining correlation over short-, medium-, and long-run horizons during pre-2006 subsample but increasing dependence during post-2006.

The temporal dependence parameter indicate that all agricultural commodities exhibits significantly higher co-movement with crude oil over the period of global financial crisis in 2008–09 and European debt crisis of 2010–12. Whereas, the level of dependence is relatively low and stable during periods of economic prosperity. Furthermore, the recent decline in crude oil price lead to an increase in dependence crude oil and agricultural commodities. However, the rate of increase is more pronounced for the agricultural commodities being utilized to produce biofuel. With regard to extreme tail co-movement in underlying undecomposed and decomposed series, our analysis indicates the tail dependence tends to diminish with the increase of investment horizon. Specifically, the large values of DoF parameter over the medium- and long-run trend indicates that the Student-t distribution gets closer to the standard normal distribution.

5.4.1. Policy implications

Due to environment-friendly energy policies and increased prices of energy commodities, the linkage structure between crude oil and agricultural commodities tend to be stronger. Therefore, designing sound energy and agricultural policies requires identification of connectedness structure over short-, medium-, and long-run horizons. The findings of this study clearly indicate that evaluation of temporal and spectral connectedness between crude oil and agricultural commodities is crucial for policymakers, regulatory agencies, producers, and market participants to design and implement strategies.

The favorable environment-friendly policies and increased prices of agricultural commodities utilized in biofuel production led producers to divert their resources by increasing production of these

Table 14
Copula estimates of long-run trend for post-2006.

	Wheat	Sugar	Soybeans	Soybeans oil	Cotton	Corn	Coffee	Cocoa	Canola	Soybeans meal
Panel A: Static t-copula post-2006										
ρ	0.205†	0.345†	0.285†	0.563†	0.774†	0.269†	0.167†	0.256†	0.467†	0.238†
	(0.019)	(0.019)	(0.019)	(0.018)	(0.000)	(0.019)	(0.019)	(0.019)	(0.018)	(0.019)
DoF	144.175	22.236†	11.775†	199.999†	199.999	19.264†	44.619†	9.577†	199.999†	199.999†
	(288.438)	(6.552)	(2.093)	(4.409)	(154.261)	(5.183)	(16.853)	(1.809)	(13.048)	(3.213)
Log(L)	32.77	141.62	92.90	414.69	840.99	87.21	18.70	77.26	234.67	44.14
AIC	−63.54	−281.23	−183.81	−827.38	−1679.97	−172.41	−35.40	−152.52	−467.35	−86.29
Panel B: DCC t-copula post-2006										
ρ	0.178†	0.310†	0.268†	0.526†	0.708†	0.248†	0.156†	0.211†	0.423†	0.211†
	(0.009)	(0.008)	(0.008)	(0.005)	(0.002)	(0.009)	(0.009)	(0.011)	(0.006)	(0.008)
DoF	199.996†	198.111†	199.997†	199.687†	199.986†	200.000†	199.997†	199.960†	199.998†	199.989†
	(2.991)	(10.126)	(10.422)	(17.400)	(2.758)	(1.689)	(3.395)	(13.622)	(11.441)	(19.057)
α	0.500†	0.104†	0.402†	0.192‡	0.345†	0.226†	0.162†	0.022†	0.247†	0.500†
	(0.058)	(0.022)	(0.065)	(0.088)	(0.016)	(0.050)	(0.018)	(0.001)	(0.061)	(0.108)
β	0.270†	0.847†	0.408†	0.619†	0.000	0.669†	0.779†	0.976†	0.573†	0.273
	(0.087)	(0.034)	(0.095)	(0.184)	(0.008)	(0.071)	(0.024)	(0.001)	(0.104)	(0.159)
Log(L)	583.83	724.47	681.19	789.40	1077.77	716.32	666.15	741.45	582.12	462.50
AIC	−1161.67	−1442.94	−1356.37	−1572.80	−2149.54	−1426.65	−1326.30	−1476.89	−1158.24	−919.01

Notes: This table reports the parameters of static and DCC-Student-t copula based on decomposed return series characterizing the long-run investment horizon for the pre-2006 subsample. Also, see notes of Table 7.

commodities. Consequently, this leads to reduction in cultivation and production of other agricultural commodities that helps in meeting the needs of growing population. The higher price variability of food items would harm the poor as a greater fraction of their income would be spent on food. Therefore, it is important to design and implement short- and medium-run policies by offering food subsidies to the poor that would help in reducing price shocks from agricultural commodities. To reduce volatility and attain stability, governments should offer subsidies and price control tariffs to producers to invest more in food commodities.

The agricultural sector accounts for an important part of employment and total production in underdeveloped and developing countries. The prices of agricultural commodities play a significant role in land allocation for agricultural production. The increased demand of agricultural commodities can be attributed to increased production of biofuels. Concurrently, the prices of agricultural commodities utilized in biofuel production will be a crucial determinant towards land allocation of agricultural commodities, influencing the production and supply of other crops. These nations should design integrated energy and agricultural policies to account for the increased connectedness structure between these markets.

5.4.2. Portfolio designs

Assessment of temporal and spectral dependence dynamics is essential for portfolio allocation and risk management decisions. To study the implications of our copula estimates, we estimate and quantify portfolio weights and hedge ratios for investment in crude oil and agricultural markets. To estimate the portfolio weights, we follow the diligence provided by Kroner and Ng (1998) as it minimizes risk without lowering expected returns. Given the frequent fluctuations and substantial volatility in the prices of crude oil and agricultural commodities, we suppose an investor who wishes to minimize his investment risk by holding long/short positions in the futures market of crude oil and agricultural commodities. The portfolio weights of the holdings of agricultural commodities (AC)/crude oil (CO) is given by:

$$w_t^{AC,CO} = \frac{h_t^{CO} - h_t^{AC,CO}}{h_t^{AC} - 2h_t^{AC,CO} + h_t^{CO}} \tag{19}$$

$$w_t^{AC,CO} = \begin{cases} 0 & \text{if } \quad w_t^{AC,CO} < 0 \\ w_t^{AC,CO} & \text{if } \; 0 \le w_t^{AC,CO} \le 1 \\ 1 & \text{if } \quad w_t^{AC,CO} > 1 \end{cases}$$

where $w_t^{AC,CO}$ is the proportion of one dollar to be invested in two underlying assets (agricultural commodities, crude oil) at time t, h_t^{CO} and h_t^{AC} is the conditional variance of crude oil and agricultural commodities, and $h_t^{AC,CO}$ is the conditional covariance at time t between agricultural commodities and crude oil. The weight of crude oil in the underlying portfolio is $1 - w_t^{AC,CO}$. Table 15 provides summary statistics for the bivariate portfolio weights computed from ARMA(1,0)-EGARCH(1,1) and DCC-Student-t copula. Specifically, the time-varying dependence parameter from the Student-t copula function is utilized along with the conditional variance measures to estimate weights.

The data indicate that the average portfolio weight for wheat/crude oil is 0.621 for the pre-2006 period, indicating that for a $1 portfolio, 62.1 cents should be invested in wheat, and 37.9 (1–0.621) cents should be invested in crude oil. Whereas, the average portfolio weight of wheat/crude oil for the post-2006 subsample is 0.467, indicating that for a $1 portfolio, 46.7 cents should be invested in wheat, and 53.3 (1-0.467) cents should be invested in crude oil. The portfolio weights for the short-run trend closely follows the weights in undecomposed series. However, the medium- and long-run trend shows changes in portfolio weights from the original returns and short-run trend for the pre- and post-2006 subsamples. For instance, the average portfolio weight of wheat/crude oil over the long-run increases from 0.467 to 0.625 during the post-2006 subsample, indicating that for a $1 portfolio, 62.5 cents should

Table 15
Summary statistics for the portfolio weights and hedge ratios.

Commodity	Returns				Short-run			
	$w_{t,pre}^{AC,CO}$	$\beta_{t,pre}^{AC,CO}$	$w_{t,post}^{AC,CO}$	$\beta_{t,post}^{AC,CO}$	$w_{t,pre}^{AC,CO}$	$\beta_{t,pre}^{AC,CO}$	$w_{t,post}^{AC,CO}$	$\beta_{t,post}^{AC,CO}$
Wheat	0.621	0.028	0.467	0.207	0.626	0.022	0.477	0.269
Sugar	0.481	0.049	0.476	0.236	0.477	0.041	0.479	0.249
Soybean	0.684	0.021	0.644	0.265	0.683	0.032	0.647	0.271
Soybean oil	0.649	−0.001	0.744	0.327	0.654	0.011	0.725	0.323
Cotton	0.586	0.039	0.564	0.223	0.591	0.036	0.582	0.238
Corn	0.659	0.031	0.516	0.258	0.684	0.047	0.528	0.283
Coffee	0.407	−0.007	0.508	0.236	0.427	−0.025	0.504	0.232
Cocoa	0.515	0.012	0.573	0.184	0.512	0.012	0.578	0.176
Canola	0.715	0.009	0.721	0.151	0.719	0.017	0.733	0.151
Soybeans meal	0.642	0.028	0.536	0.193	0.652	0.047	0.558	0.201

Commodity	Medium-run				Long-run			
	$w_{t,pre}^{AC,CO}$	$\beta_{t,pre}^{AC,CO}$	$w_{t,post}^{AC,CO}$	$\beta_{t,post}^{AC,CO}$	$w_{t,pre}^{AC,CO}$	$\beta_{t,pre}^{AC,CO}$	$w_{t,post}^{AC,CO}$	$\beta_{t,post}^{AC,CO}$
Wheat	0.523	0.122	0.439	0.281	0.510	−0.778	0.625	0.275
Sugar	0.474	−0.232	0.519	0.497	0.422	−0.460	0.609	2.049
Soybean	0.587	−0.062	0.568	0.454	0.543	−0.010	0.546	0.128
Soybean oil	0.562	−0.144	0.570	0.511	0.538	0.615	0.666	1.185
Cotton	0.541	−0.012	0.503	0.263	0.465	0.464	0.527	3.904
Corn	0.562	−0.138	0.470	0.393	0.425	0.192	0.559	−0.340
Coffee	0.377	−0.201	0.453	0.464	0.349	−1.382	0.622	−0.012
Cocoa	0.452	−0.049	0.489	0.512	0.536	0.812	0.599	−2.264
Canola	0.599	−0.112	0.644	0.131	0.498	0.281	0.645	2.068
Soybeans meal	0.544	−0.055	0.530	0.373	0.586	−0.139	0.553	−1.431

Notes. The table reports average weights and hedge ratios for investment in crude oil and agricultural markets. $w_t^{AC,CO}$ is the proportion of one dollar to be invested in two underlying assets (agricultural commodities (AC), crude oil (CO)) at time t, $\beta_t^{AC,CO}$ is the risk-minimizing hedge ratios for investment in CO and AC.

be invested in wheat, and 37.5 cents should be invested in crude oil. Similar variations in portfolio weights can be observed for pre- and post-2006 subsamples for the medium- and long-run trends. These results indicate how our employed framework could be utilized by the market participants in the financial and commodity markets for making optimal portfolio allocation decisions.

5.4.3. Hedge ratios

In addition to optimal portfolio weights, we follow Kroner and Sultan (1993) to estimate risk-minimizing hedge ratios for a portfolio of two assets, i.e. crude oil and agricultural commodities. To minimize the risk of the underlying portfolio that is $1 long in agricultural commodities, the investor should short $\$\beta$ of crude oil. We can estimate the risk-minimizing hedge ratios as follows:

$$\beta_t^{AC,CO} = \frac{h_t^{AC,CO}}{h_t^{CO}} \tag{20}$$

where $h_t^{AC,CO}$ is the conditional covariance between agricultural commodities and crude oil, and h_t^{CO} is the conditional variance of crude oil at time t. Table 15 provides summary statistics for the hedge ratio, $\beta_{t,pre}^{AC,CO}$ and $\beta_{t,post}^{AC,CO}$, for returns and decomposed series. It is noteworthy that the hedge ratios for the pre-2006 subsample are relatively low thus indicating the hedging effectiveness of involving crude oil and agricultural commodities is quite good. This is consistent with our hypothesis that the inclusion of agricultural commodities along with crude oil in a diversified portfolio over the pre-2006 subsample increases the risk-adjusted performance of the portfolio. Whereas, the values of hedge ratio over the post-2006 subsample are significantly higher indicating that the hedging becomes expensive over the post-2006 subsample.

The values of hedge ratio for the pre-2006 subsample ranges from −0.007(coffee/crude oil portfolio) to 0.049 (sugar/crude oil). These results indicate that a $1 long position in wheat can be hedged with a 2.8 cents short position in the crude oil. Likewise, in the case of soybean oil/crude oil portfolio, a $1 long position in soybean oil can be hedged with a 0.1 cent long position in crude oil. On the contrary, the estimates of hedge ratio are significantly higher for the post-2006 subsample thus indicating that the hedging would be expensive over post-2006 period. For instance, a long position of $1 in soybean oil can be hedged with a 32.7 cents short position in crude oil. The estimates of hedge ratio over the short-run trend closely follow the hedge ratio of undecomposed series. However, the medium- and long-run trend indicate significant increase in hedge ratio over both subsamples thus reflecting additional cost to hedge the position due to increased dependence structure over these periods. Overall, the increased connectedness between crude oil and agricultural commodities over the post-2006 subsample lead to an increase in the estimates of hedge ratios, indicating that the hedging cost increase with the increase of investment horizon.

Risk management, using e.g. Value-at-Risk (VaR), is concerned with measuring variation and deviations from expected trends. The increasing hedge ratio indicates higher risk post-2006, and consequently VaR in this period is higher. More specifically, when assessing the same portfolio pre- and post-2006, VaR would increase post-2006. In addition, the increased dependence structure, in particular for the medium- and long-run trends, further emphasizes the consequences for VaR and risk management in this period.

6. Conclusion

This paper investigates the dependence dynamics between crude oil and the agricultural commodities using wavelet analysis and copula approach. The core objective of this work is to evaluate how the connectedness varies over time and across different spectral horizons. Hence, we combine a multi-resolution wavelet transform analysis and DCC-Student-t copula model to evaluate the underlying phenomenon. Specifically, a bivariate ARMA(1,0)-EGARCH(1,1)-DCC-Student-t copula model is employed with MODWT and least asymmetric LA(8) as wavelet filter to capture the dependence dynamics across various investment horizons. Furthermore, we incorporate daily data spanning from July 1986 to June 2016. To account for structural changes, we divide the sample into two subsamples spanning from July 1986 to December 2005 (pre-2006 subsample) and from January 2006 to June 2016 (post-2006 subsample). This paper aims to reveal the development in temporal and spectral connectedness between crude oil and agricultural commodities during pre-2006 and post-2006 subsamples.

Our empirical results are as follows. First, we find evidence of temporal and spectral dependence between crude oil and agricultural commodities over both subsamples. In addition, the empirical findings from Student-t copula indicate that the short-run horizon is characterized by tail-dependence behavior. This indicate that the tendency of joint extreme movements is highly probable over the short-run than over the medium- and long-run investment horizon. Second, the dependence estimates from the frequency-domain analysis are significantly different and more distinct than the estimates from the undecomposed time-domain analysis thus suggesting the need to consider timespan before policy recommendations and investment allocation decisions. Furthermore, the results from parametric and nonparametric correlation analysis indicate that the dependence structure of the decomposed series are statistically different from the original returns. Third, the time-varying DCC parameter indicate that the connectedness between crude oil and the agricultural commodities intensify during the periods of financial and economic turmoil. Specifically, the dependence parameter spikes during the period of global financial crisis of 2008 and thereafter during the period of European debt crisis. This indicate that the temporal dependence in the oil-food nexus is less pronounced during the periods of economic prosperity. Lastly, our findings indicate that the dependence between crude oil and agricultural commodities is close to zero during the pre-2006 subsample over the short-run horizon. Furthermore, the connectedness increases negatively with the increase in investment horizon. However, the post-2006 subsample is characterized by moderately positive dependence over the undecomposed series and the linkage increases positively with the increase in frequency. This indicate that the tendency to attain hedging and portfolio diversification has diminished over the post-2006 subsample.

The findings of this study are of promising interest to policymakers, producers, portfolio managers, and international investors. The dynamic temporal and spectral dependence structure between crude oil and agricultural commodities requires policymakers to formulate strategies that decouples the impact of information connectedness between these markets. Policymakers may devise a 'road map' of systematic risk and asymmetric tail dependence between crude oil and agricultural commodities to assist them in formulating strategies that can foster market stability and serve as protection mechanism against contagion risk. Therefore, an informed dependence structure would lead policymakers and regulatory agencies to formulate food subsidies and price control strategies to assist the poor. Furthermore, these measures would facilitate in evading the long-run effect of oil price and volatility shocks on the prices of agricultural commodities. Regarding portfolio managers and international investors, an assessment of dependence structure is crucial for formulating and implement investment allocation and hedging decisions. Therefore, it is important to consider tail-dependence and extreme co-movement as well as the temporal and spectral interconnectedness in oil-food nexus for devising risk management, asset pricing and allocation decisions.

In this study, we utilize bivariate analysis to evaluate the dependence dynamics between crude oil and agricultural commodities. A key drawback of bivariate analysis lies in their inability to accommodate relations among more than two commodities. Furthermore, it is noteworthy that the relationship among more than two commodities are complex and hard to interpret. While crude oil is a global commodity, some of the agricultural commodities are dominated by a small number of producing countries, which can impact the oil-food nexus. Therefore, in the future research, we propose to assimilate a multivariate approach to understand the relationship between crude oil and agricultural commodities at both global and domestic level. It would be interesting to evaluate whether crude oil directly impacts the local agricultural commodity prices or indirectly through global agricultural commodity prices.[17]

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eneco.2019.01.011.

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3 Paper II: Dynamics of volatility spillover in commodity markets

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Dynamics of volatility spillover in commodity markets: Linking crude oil to agriculture

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ABSTRACT

This paper examines spillover effects among markets of crude oil and ten major agricultural commodities by employing the Diebold and Yılmaz (2009, 2012) spillover frameworks to returns and EGARCH filtered volatilities. We account for structural variations in data by dividing the data into two subsamples: from July 1986 to December 2005 (pre-2006 subsample) and from January 2006 to June 2016 (post-2006 subsample). Our findings indicate that there is minuscule information transmission among crude oil and agricultural commodities over the pre-2006 subsample, however, crude oil becomes the net receiver of information over the post-2006 subsample. Second, our findings indicate asymmetric and bidirectional flow of information among crude oil and agricultural commodities that intensifies during periods of financial and economic turmoil. Last, net volatility spillover increases in periods of large declines in the crude oil price, such as in 2008 and later in 2014. Overall, we document a more detailed insight into channels of connectedness among the underlying commodities, which may assist developing policy recommendation, portfolio designs, and risk management decisions.

1. Introduction

Understanding the price and volatility dynamics of crude oil and agricultural commodities has received considerable attention following the surge in energy and food prices since 2006. The prices of these commodities have experienced sharp fluctuations and large swings over the last decade due to economic turmoil and financial crises, changes in macroeconomic uncertainties, and introduction of new regulations to combat climate change. The decline in crude oil price in 2014 has renewed interest in examining the evolution of connectedness between the markets of crude oil and agricultural commodities. Understanding the time-varying connectedness across these markets has several important implications for investment allocations, asset valuation, risk management, policy recommendations, and implementation. Although, there is a large strand of literature dedicated to estimating the variances and covariance of different assets, research on volatility spillover has received comparatively less attention (Nazlioglu et al., 2013).

Financial interdependence and increased connectedness of global markets are the main elements of volatility transmission between assets and markets (Aloui et al., 2011; Mensi et al., 2013). The recent upsurge in prices of agricultural commodities can be explained by several mechanisms. First, the crude oil and agricultural commodities became increasingly entwined due to increased production of biofuels. An increase in prices of energy commodities raises the demand for soybean- and corn-based biofuels (Pal and Mitra, 2017). Subsequently, this led farmers to allocate more resources and land towards production of fuel crops resulting in higher prices for other agricultural commodities. Second, due to the energy intensive nature of agriculture sector, an increase in crude oil price would result in

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higher cost of inputs for these commodities. Third, adverse weather conditions would affect the total production of agricultural commodities, which will eventually result in higher price and volatility for agricultural products. Finally, the financialization of commodity futures markets and flow of speculative investments can also contribute to higher prices of agricultural commodities and crude oil, which are primarily driven due to involvement of institutional investors during periods of high liquidity[1] (Gorton and Rouwenhorst, 2006; Bhardwaj et al., 2015; Basak and Pavlova, 2016; Ordu et al., 2018).

Several studies provide empirical evidence that crude oil often behaves as exogenous and transmit volatility to agricultural markets (see e.g. Serra, 2011; Du and McPhail, 2012; Nazlioglu et al., 2013). On the contrary, a number of studies appear to reject this notion of volatility transmission, and finds either negative or no spillover from crude oil to agriculture (see e.g. Kaltalioglu and Soytas, 2011; Du et al., 2011; Nazlioglu and Soytas, 2011; Gardebroek and Hernandez, 2013; Kang et al., 2017). As this literature indicates, the dynamics of volatility spillover between crude oil and agricultural commodities is opaque, and therefore further elucidation by employing different approaches and a broader set of data is needed. Understanding risk transmission is crucial in designing and selecting appropriate portfolio management and risk management techniques, in which negative or low dependence among the asset returns are essential for insuring large losses. Furthermore, it provides a reference for regulators and policymakers in deriving and implementing appropriate strategies for optimal risk management.

Although the theoretical underpinnings of previous studies are different, the empirical methodology converges to a common framework. The studies in the strand of spillover analysis mainly employs different specification of Multivariate Generalized Autoregressive Conditional Heteroscedasticity (MGARCH) models to analyze the dynamics and cross-dynamics of volatility transmission between assets. However, the main issue with the MGARCH is its inability to provide the direction of spillover.

The aim of this study is to provide a more comprehensive analysis of static and temporal volatility spillover between crude oil and ten agricultural commodities. We contribute to the existing literature by integrating an EGARCH specification with Diebold and Yılmaz (2009, 2012, 2014, 2015) (hereafter: DY) frameworks to examine conditional spillover between the underlying commodities. Specifically, we utilize an ARMA(1,0)-EGARCH(1,1) specification on returns series to extract the conditional volatility, which is used in the DY frameworks to estimate static and temporal spillover. Similar to return series in financial markets, commodity markets' return series exhibit volatility clustering, serial correlation, heteroscedasticity, leverage effects, and fat tails, which can be captured using an EGARCH framework. More specifically, the EGARCH model is an extension of standard GARCH model and assumes the asymmetric impact of positive or negative shocks on conditional volatility, which are embedded in the financial and commodity returns. To account for structural variation, we divide our sample into two subsamples, i.e. the calm period (pre-2006subsample) and turmoil period (post-2006 subsample).

The objective of this study is to empirically investigate the claim of volatility transmission from crude oil, being the dominant commodity, to the changes in volatility dynamics of agricultural commodities under different market conditions. We seek to answer whether the crude oil price really matters, and to what degree does the changes in price dynamics of crude oil shift the equilibrium in other commodity prices. Secondly, we seek to elucidate the spillover dynamics within agricultural sector and examine how the within sector relationship might influence the price dynamics of food commodities. Thirdly, we decompose the temporal volatility spillover index into bidirectional ('to' and 'from') spillovers to estimate the net volatility spillover index between the underlying commodity markets. The net spillover index provides an overview of the underlying assets that are net contributors and receivers of spillovers. Lastly, our selected timespan covers several periods of financial and economic turmoil, which would enable us to further elucidate the development in spillover dynamics during these periods and thus the discrepancy of mixed evidence of volatility spillover in previous literature.

Consistent with previous research, our results on static volatility spillover supports the neutrality hypothesis indicating no interconnectedness between crude oil and agricultural commodities over the pre-2006 subsample. Our analysis of post-2006 subsample shows negative spillover to crude oil, which rejects a hypothesis of significant volatility spillover from crude oil to agricultural commodities in this period. Furthermore, our findings indicate that the increased prices of agricultural commodities over periods of economic prosperity and turmoil are mainly due to within sector variations, not due to shifts in crude oil prices.

The remainder of this article is structured as follows. In section 2 we present previous literature relevant for volatility spillover in the commodity market. The empirical methodology and the dataset is presented in section 3 and 4, respectively. The obtained empirical results are presented and discussed in section 5. Section 6 concludes.

2. Literature review

Since the global financial crisis (GFC) during 2007–2008, an emerging strand of literature focuses on the connectedness dynamics between crude oil and agricultural commodities by employing different datasets and various econometric frameworks. Spillover can be defined as a shock in one asset that changes the price dynamics in other asset(s). Previous studies on the spillover dynamics has mainly evaluated the price level interdependence. Whereas, the volatility and transmission of volatility between markets has received less attention (Cabrera and Schulz, 2016).

Table 1 provides a review of relevant literature on spillover between crude oil and agricultural commodities. Serra (2011) employs a GARCH-type specification to evaluate the relationship between crude oil, ethanol, and sugar prices in Brazil using weekly data. They find significant information transmission between crude oil and the underlying commodities. Wang et al. (2014) examine the variations in agricultural commodity prices due to shocks in oil price using monthly data in a structural VAR analysis. Their findings indicate that

[1] We thank an anonymous referee for pointing this out.

Table 1
Literature on spillover between crude oil and agricultural commodities.

Study	Assets/Markets	Data	Method	Results
Serra (2011)	Crude oil, ethanol, and sugar prices in Brazil	2000–2009 (Weekly)	GARCH	Significant
Nazlioglu et al. (2013)	Oil and agricultural commodities	1986–2011 (Daily)	CIV IRF	Significant
Wang et al. (2014)	Crude oil and agricultural commodities	1980–2012 (Monthly)	SVAR	Significant
Liu (2014)	Crude Oil price and agricultural commodities	1984–2012 (Daily)	DCCA	Significant
Koirala et al. (2015)	Energy and agriculture futures	2011–2012 (Daily)	Copulas	Significant
Silvennoinen and Thorp (2016)	Crude oil and agriculture commodities	2011–2012 (Daily)	DSTCC-GARCH	Mixed
Lucotte (2016)	Crude oil and food	1990–2015 (Monthly)	VAR	Significant
Al-Maadid et al. (2017)	Energy and food prices	2003–2015 (Daily)	VAR-GARCH	Significant
Shahzad et al. (2018)	Oil and agri- cultural commodities	2000–2017 (Daily)	Copulas	Significant
Kaltalioglu and Soytas. (2011)	Oil, agricultural comm- odities and food items	1980–2008 (Monthly)	VAR	Insignificant
Wang and McPhail (2014)	Energy price shocks and agricultural prices	1948–2011 (Annual)	VAR	Mixed
Fowowe (2016)	Oil and agricultural prices	2003–2014 (Weekly)	Non-linear causality tests	Insignificant
Cabera and Schulz (2016)	Energy and agricultural markets	2003–2012 (Weekly)	DCC MVM	Insignificant
Gardebroek and Hernandez (2013)	Crude oil, ethanol, and corn prices	1997–2011 (Weekly)	MGARCH	Insignificant
Awartani et al. (2016)	Oil, equities, exchange rate, metals, agricultural commodities	2012–2015 (Daily)	DY (09, 12)	Insignificant
Kang et al. (2017)	Crude oil, gold, silver, corn, wheat, and rice	2002–2012 (Weekly)	DY (09, 12)	Insignificant

Notes. Generalized autoregressive conditional heteroscedasticity (GARCH), Causality in variance (CIV), Impulse response functions (IRF), Structural vector autoregressive (SVAR), Dynamic conditional correlation analysis (DCCA), Dynamic smooth transition conditional correlation (DSTCC-GARCH), Multivariate GARCH (MGARCH), Dynamic conditional correlation (DCC), Multiplicative volatility model (MVM), Diebold and Yılmaz (2009, 2012) DY(09, 12). Significant indicates if a study finds crude oil changes the price dynamics of agricultural commodities, and vice versa for the insignificant. Mixed reflects that crude oil and agricultural commodities are characterize by bidirectional volatility spillover.

the oil shocks can explain minor friction of variations in agricultural commodity prices before the food crisis of 2006–2008. However, the explanatory ability become much higher over the post-crisis period. Liu (2014) investigates the cross-correlation between crude oil and agricultural commodity markets by employing a detrended cross-correlation analysis (DCCA). Their findings indicate that the cross-correlations are multi-fractal and high oil prices partly contributes to the food crisis during 2006 to mid-2008. In their study, Koirala et al. (2015) investigate the dependence between energy futures prices and agricultural futures prices using various copula functions. Their findings highlight that an increase in energy price increases the price of agricultural commodities. Silvennoinen and Thorp (2016) evaluate the connectedness between crude oil and agricultural commodities by incorporating dynamic smooth transition conditional correlation (DSTCC-GARCH) model. Their findings indicate that the high correlation between crude oil and biofuel feedstock is more probable when the price levels for food and oil are high. Furthermore, they report limited contagion from energy to non-biofuel feedstock markets. In their study, Lucotte (2016) analyzes the dynamics of co-movement between food and crude oil prices using the correlations of VAR. They divide the sample into two subsamples. Their findings reveal strong positive co-movements between the underlying commodities in the aftermath of commodity boom (post-2007 subsample). Whereas, they report no significant co-movements over the pre-boom period. Al-Maadid et al. (2017) examine the linkage between food and energy prices by utilizing a bivariate VAR-GARCH(1,1) model. Their findings suggest significant linkage between food, oil, and ethanol prices. Furthermore, their results indicate significant shifts in volatility spillover between the underlying price series. In a recent study, Shahzad et al. (2018) evaluate the asymmetric risk spillovers between oil and agricultural commodities. Their findings indicate symmetry in tail dependence and asymmetry in the spillover dynamics from oil to the agricultural markets, which intensifies during periods of financial turmoil.

In contrast, several studies provide evidence of neutral interconnectedness structure between crude oil and agricultural commodities. Kaltalioglu and Soytas (2011) employ a VAR model using monthly data from 1980 to 2008 and found insignificant transmission of volatility between crude oil and agricultural and food items. Gardebroek and Hernandez (2013) evaluate the volatility transmission between oil, ethanol, and corn prices using a multivariate GARCH approach. Their findings indicate that energy markets do not influence the volatility in corn market. In a later study, Wang and McPhail (2014) employ the VAR model on annual data between 1948 and 2011 and report mixed evidence of volatility spillover between energy prices and agricultural prices. Similarly, Fowowe (2016) examines whether oil drive the agricultural commodity prices in South Africa by utilizing structural break cointegration and nonlinear causality tests. They report no evidence of long-run relationship between oil and agricultural commodity prices in South Africa.

Furthermore, the analysis of nonlinear causality tests also reflects no evidence of causal relationship between the underlying commodities. Cabrera and Schulz (2016) investigate the price and volatility risk linkage between the energy and agricultural markets in Germany by employing an asymmetric dynamic correlation GARCH model and multiplicative volatility model. Their findings indicate that in the long-run prices tend to move together and develop equilibrium with positive correlations during persistent market shocks. Furthermore, their results reveal that the biodiesel does not cause the high volatility in agricultural prices. Awartani et al. (2016) utilize the implied volatility indexes to examine the directional risk transmission from oil to US equities, Euro/Dollar exchange rates, precious metals, and agricultural commodities using the spillover index. Their findings indicate moderate level of risk transfer from oil to equity markets, precious metals, and Euro/Dollar exchange rate. Whereas, they find limited connectedness between crude oil and agricultural commodities. In a later study, Kang et al. (2017) examine the volatility spillover between six commodity futures markets (gold, silver, crude oil, corn, wheat, and rice) by employing a multivariate DECO-GARCH model and the spillover index using weekly data from 2002 to 2016. Their findings indicate bidirectional spillovers between commodity futures markets and crude oil as net receiver of volatility.

To summarize, regardless of theoretical underpinnings, the empirical findings of these studies provide mixed evidence regarding the importance of crude oil as a dominant asset in volatility transmission. The intensity and direction of volatility spillover between crude oil and commodity prices is opaque and suggests further investigation. Therefore, in this paper, we fill the gap by considering the temporal dynamics of conditional volatility spillover between crude oil and other commodities, by explicitly modeling the intensity and direction of transmission.

3. Methodology

This section describes the empirical methods employ in this study. We start with the univariate marginal distribution model, which measures the conditional volatility of crude oil and agricultural commodities. We estimate the static and dynamic spillover effects between the underlying commodities by employing the frameworks proposed by Diebold and Yılmaz (2009, 2012, 2014, 2015). To estimate optimal portfolio weights and hedge ratios, we estimate time-varying student-t copula specification.

3.1. Marginal model

Unlike the traditional body of literature, we follow Engle (2001) and estimate conditional volatility, which is then utilized as an input in the Diebold and Yılmaz (2009, 2012, 2014, 2015) (hereafter: DY) frameworks.[2] This is of particular interest, because the asset returns may exhibit properties (serial correlation, volatility clustering, heteroscedasticity, leverage effects, and fat tails) that are better able to capture using a GARCH-type specification (Cont, 2001). We determine the best-suited GARCH-type specification from GARCH, GJR-GARCH, and EGARCH models. Based on AIC and log-likelihood, the ARMA(1,0)-EGARCH(1,1) specification of Nelson (1991) is the most suitable marginal model to capture the stylized facts embedded in the underlying returns series. In addition, the EGARCH model is more flexible than the standard GARCH model and assumes that negative and positive shocks have asymmetric effects on conditional volatility. The specification of the marginal model for the returns r_t is:

$$r_t = \Omega + \sum_{i=1}^{m} \varphi_i r_{t-i} + \sum_{j=1}^{n} \theta_j \epsilon_{t-j} + \epsilon_t, \tag{1}$$

where φ_i and θ_j represents the AR and MA components with m and n lags, respectively. We assume the white noise process ϵ_t follows a student-t distribution with degrees of freedom υ specified as:

$$\sqrt{\frac{\upsilon}{\sigma_t^2(\upsilon-2)}}\epsilon_t \tilde{} \, i.i.d.t_\epsilon, \tag{2}$$

and with a conditional variance, σ_t^2, with time dynamics specified using the following expression:

$$\log \sigma_t^2 = \omega + \sum_{i=1}^{P} \beta_i \log \sigma_{t-i}^2 + \sum_{j=1}^{Q} \alpha_j \left[\frac{||\epsilon_{t-j}}{\sigma_{t-j}} - E\left\{ \frac{||\epsilon_{t-j}}{\sigma_{t-j}} \right\} \right] + \sum_{j=1}^{Q} \xi_j \left(\frac{\epsilon_{t-j}}{\sigma_{t-j}} \right) \tag{3}$$

where ω is the intercept of variance, β_i and α_j are the parameters of the GARCH and ARCH components of volatility, and ξ_j captures the leverage effects. For $\xi_j < 0$, the conditional volatility will increase proportionally less to a positive shock than following a negative shock of equal magnitude. The conditional volatility from the marginal distribution model is used as an input in the DY frameworks to estimate static and temporal volatility spillover between crude oil and agricultural commodities.

3.2. Spillover index frameworks

Following the work of Diebold and Yılmaz (2009, 2012, 2014, 2015), we briefly present the methodology for quantifying static and temporal directional volatility spillover in generalized VAR models. The primary advantage of applying DY frameworks compared to the

[2] The traditional literature estimate the daily variance by utilizing the daily high and low prices as: $\widetilde{\sigma}_{it}^2 = 0.361[\ln(P_{it}^{\max}) - \ln(P_{it}^{\min})]^2$.

more common approach of using impulse response functions with Cholesky factor decomposition is the elimination of order dependence in the obtained results.

To conduct a variance error decomposition, consider a generalized vector autoregressive (VAR) model as proposed by Koop et al. (1996) and Pesaran and Shin (1998) (KPPS). Let a set of data of N variables which is covariance stationary be represented by a VAR(p) model of the following specification:

$$x_t = \sum_{i=1}^{p} \varphi_i x_{t-i} + \epsilon_t \quad \text{where} \epsilon \tilde{} (0, \sigma). \tag{4}$$

Further, let the moving average representation be given as $x_t = \sum_{i=0}^{\infty} A_i \epsilon_{t-i}$. Here, the $N \times N$ coefficient matrix is recursively specified, $A_i = \varphi_1 A_{i-1} + \varphi_2 A_{i-2} + \cdots + \varphi_p A_{i-p}$ with $A_i = 0 \, \forall \, i < 0$. The next step constitutes of decomposing the variance of residual obtained from VAR model. Let the KPPS H-step-ahead generalized forecast error variance decompositions (FEVD) be given as:

$$\theta_{ij}^{g}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} \left(e_i' \Theta_h \sum e_j\right)^2}{\sum_{h=0}^{H-1} \left(e_i' \Theta_h \sum \Theta_h' e_i\right)}, \tag{5}$$

where $\theta_{ij}^{g}(H)$ is generalized form of forecast error variance decomposition, Θ_h is the coefficient matrix multiplying the $h-$lagged shock vector in the infinite moving-average representation of the non-orthogonalized VAR, $\sum$ is the covariance matrix of the shock vector in the non-orthogonalized VAR model, σ_{jj} is the j^{th} diagonal element of covariance matrix, and e_j is the selection vector with j^{th} element unity and zeros elsewhere. Equation (5) provides a spillover index of $N \times N$ matrix, $\theta_{ij}^{g}(H)$, where each element represents the contribution from asset j to the forecast error variance asset i. The diagonal elements of the spillover matrix provide own-variable contribution, whereas, the off-diagonal elements represents cross-variable contribution. Since the cross- and own-variable shares of variance contribution do not sum to 1 under the generalized decomposition, we normalize each entry of the variance decomposition matrix by its row sum as:

$$\tilde{\theta}_{ij}^{g}(H) = \frac{\theta_{ij}^{g}(H)}{\sum_{j=1}^{N} \theta_{ij}^{g}(H)}, \tag{6}$$

with $\sum_{j=1}^{N} \tilde{\theta}_{ij}^{g}(H) = 1$ and $\sum_{i,j=1}^{N} \tilde{\theta}_{ij}^{g}(H) = N$ by construction. The total volatility spillover index (TVI) can be constructed using the volatility contributions from KPPS variance decomposition:

$$S^{g}(H) = \frac{\sum_{\substack{i,j=1 \\ i \neq j}}^{N} \tilde{\theta}_{ij}^{g}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ij}^{g}(H)} \cdot 100 = \frac{\sum_{\substack{i,j=1 \\ i \neq j}}^{N} \tilde{\theta}_{ij}^{g}(H)}{N} \cdot 100. \tag{7}$$

The TVI measures the contribution of spillovers of volatility shocks across all markets to the total forecast error variance. Similarly, the directional volatility spillovers received by market i from all other markets j, and directional volatility spillovers transmitted by market i to all other markets j, respectively, as:

$$S_{i \leftarrow j}^{g}(H) = \frac{\sum_{\substack{j=1 \\ j \neq i}}^{N} \tilde{\theta}_{ij}^{g}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ij}^{g}(H)} \cdot 100 = \frac{\sum_{\substack{j=1 \\ j \neq i}}^{N} \tilde{\theta}_{ij}^{g}(H)}{N} \cdot 100, \tag{8}$$

and

$$S_{i \rightarrow j}^{g}(H) = \frac{\sum_{\substack{j=1 \\ j \neq i}}^{N} \tilde{\theta}_{ji}^{g}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ji}^{g}(H)} \cdot 100 = \frac{\sum_{\substack{j=1 \\ j \neq i}}^{N} \tilde{\theta}_{ji}^{g}(H)}{N} \cdot 100. \tag{9}$$

The net volatility spillover is the difference between the shocks transmitted to and those received from other markets. The net spillover from asset i to all other assets j as:

$$S_i^g(H) = S_{i\to j}^g(H) - S_{i\leftarrow j}^g(H). \tag{10}$$

The net volatility spillover analysis determine whether a market is source or recipient of spillovers.

4. Data and descriptive statistics

We consider daily closing futures prices of crude oil and ten agricultural commodities. The study span ranges from July 02, 1986 to June 03, 2016. The data is obtained from the Commodity Research Bureau (CRB). The selected agricultural commodities consist of wheat (W), sugar (SB), soybean (S), soybean oil (BO), cotton (CT), corn (C) coffee (KC), cocoa (CC), canola (WC), and soybeans meal (SM). We selected these agricultural commodities based on their high liquidity and trading volume. Overall, these agricultural commodities represent a significant proportion of S&P GSCI agricultural commodity index, which is a widely accepted instrument to measure the investment performance in agricultural markets and as an economic indicator (Yahya et al., 2019). The selected time frame allows us to evaluate the impacts of major economic and financial turmoil that occurred over the last three decades: the Gulf war 1990-1991, the dot-com bubble of 2001, the 2007 U.S. sub-prime mortgage crisis, the global financial crisis in 2008, the European debt crisis 2010–12, and the recent decline in crude oil prices. We choose to evaluate daily data as it better captures the dynamics of volatility transmission, which are often too high or low when using weekly or monthly observations. Further, stylized facts indicate that there tends to be both price and volatility day-of-the-week effect prevalent in many financial and commodity prices, which would be neglected when using weekly or monthly frequency.

Fig. 1 shows the development in daily futures prices and continuously compounded returns for crude oil and agricultural commodities. All the price and return series display important behaviors. The price series exhibits an increasingly upward trend during post-2006 for all the commodities. The figure portrays a spectacular increase in crude oil and several agricultural commodity prices in 2008, which is followed by a decline due to the global financial crisis in 2008 (GFC).

The continuously compounded daily futures returns is calculated as the logarithmic difference in two consecutive prices at time t and $t-1$ as: $r_{i,t} = \ln(P_{i,t}/P_{i,t-1})$. Visual inspection appears to suggest that all commodities are non-stationary in levels and stationary at first-difference. Furthermore, the return series appears to reflect stylized facts (e.g., volatility clustering) for both the crude oil and agricultural commodities. The price of crude oil and agricultural commodities experienced sharp increase over the period from 2006 to mid-2008, which led researchers to suspect that the food crisis in 2006–2008 was due to increase in crude oil price (Harri and Hudson, 2009; Ji and Fan, 2012; Wang et al., 2014; Nazlioglu et al., 2013; Du et al., 2011). Therefore, following Nazlioglu et al. (2013); Du et al. (2011) and Wang and McPhail (2014), we divide our data into two subsamples. Furthermore, the introduction of federal support policies in 2006, together with high crude oil prices lead to a rapid growth in biofuel, which lead to an increase in prices of agricultural products. The prime explanation is attributed to the latter, that is, the substitutive effect between fossil fuel and biofuels. The upsurge in crude oil prices lead to the development of alternative energy sources. The biodiesel and biofuel extracted from soybean and corn, respectively, are considered as the suitable substitute of crude oil. Thus, an increase in crude oil price can lead to an upsurge in price of soybean and corn, which may eventually lead to the increase in prices of other agricultural commodities due to limited planting acreage in a certain period of time (Wang et al., 2014). Therefore, to account for this structural change or fundamental shift, we split our data into two subsamples: pre-2006 subsample (July 1986 to December 2005) and post-2006 subsample (January 2006 to June 2016).

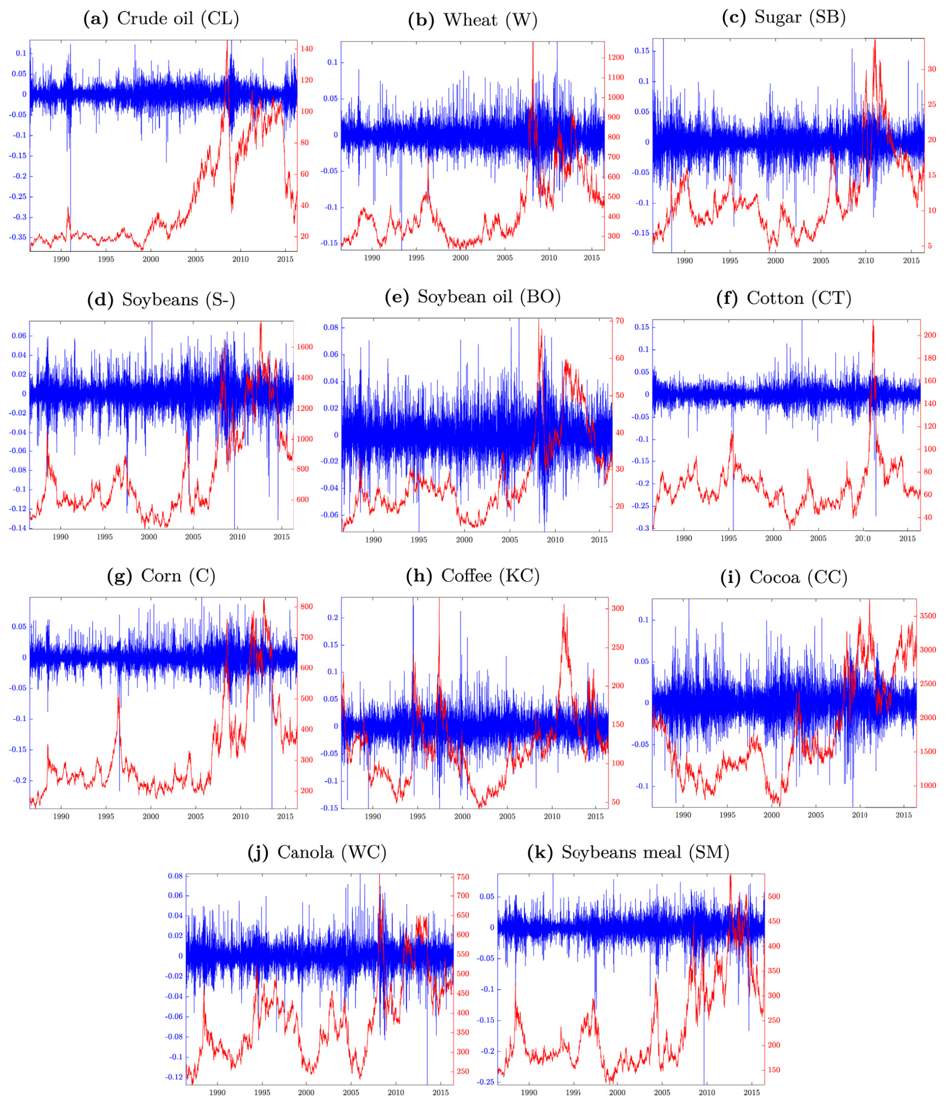
Table 2 shows descriptive statistics for the pre-2006 and post-2006 subsamples for crude oil and agricultural commodities.[3] Panel A and B of Table 2 reports the estimates for the pre- and post-2006 subsamples. The annualized mean significantly differs over both subsamples. The average return for crude oil changes from 8.1% to −2.1% from pre-to post-2006 subsample. Whereas, the mean returns for agricultural commodities increased significantly over the post-2006 subsample. The reward-to-risk measure (SR) (Sharpe, 1994) for the pre-2006 subsample is negative for nearly all the agricultural commodities, however, the post-2006 subsample indicate significant increase in reward-to-risk measure of agricultural commodities.[4] Notably, the SR for canola changes from −0.14 to 0.3 from pre-to post-2006 subsample. Whereas, the SR for crude oil changes from 0.177 to −0.085 from pre-to post-2006 subsample. The skewness values are negative and positive over both subsamples and the values of kurtosis are over three times the values of normal distribution. These findings indicate that the returns over both subsamples exhibits skewed and leptokurtic distributions, suggesting that the distribution is asymmetric and have fatter tails than normal distribution. The estimates from the Jarque-Bera test affirms the non-normality of the return distribution indicating the non-Gaussian distribution. The Ljung-box test with is significant at 1% threshold level for returns and squared returns for both pre- and post-2006 subsample exhibiting presence of serial correlation. Furthermore, the ARCH test (Engle, 1982) with 20 lags rejects the null-hypothesis of homoscedasticity for the underlying commodities over both subsamples suggesting the employment of a GARCH-type model to capture the underlying stylized facts.[5]

Table 3 reports the test statistics from unit root tests for level and logarithmic returns by applying Augmented Dickey-Fuller (ADF) (Dickey and Fuller, 1979), Phillips-Perron (PP) (Phillips and Perron, 1988), and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) (Kwiatkowski et al., 1992) unit-root tests. The estimates of ADF and PP are insignificant at levels for both subsamples thus unable to reject the null hypothesis of unit root. Similarly, the estimates of KPSS are significant at levels over both subsamples thus rejecting the null

[3] Mean and standard deviation is annualized by multiplying each with 250 and $\sqrt{250}$, respectively.

[4] The average risk-free rate is estimated to be 2% for pre-2006 subsample, and 1% for the post-2006 subsample.

[5] The Ljung-Box estimate for cotton are insignificant for squared returns and ARCH.



Notes. The figure portrays the development in nearby daily futures prices and continuously compounded returns for crude oil and agricultural commodities. All the price series exhibits an increasingly upward trend post-2006 and after 2009.

Fig. 1. Development in futures prices and returns: Notes. The figure portrays the development in nearby daily futures prices and continuously compounded returns for crude oil and agricultural commodities. All the price series exhibits an increasingly upward trend post-2006 and after 2009.

Table 2
Descriptive statistics.

	Mean (%)	SD	SR	Max	Min	Skew	Kurt	J–B	Q(20)	$Q^2(20)$	ARCH (20)
Panel A: Pre-2006 sample statistics											
Crude oil	8.081	0.344	0.177	0.12	−0.38	−1.33	26.06	0.00	45.40*	217.14*	165.28*
Wheat	1.732	0.246	−0.011	0.09	−0.16	0.04	8.61	0.00	35.47*	129.60*	84.38*
Sugar	4.267	0.336	0.067	0.17	−0.18	−0.15	7.92	0.00	42.21*	367.02*	189.74*
Soybean	0.942	0.220	−0.048	0.08	−0.12	−0.54	8.39	0.00	31.86*	1107.80*	394.60*
Soybean oil	1.344	0.225	−0.029	0.08	−0.07	0.19	4.96	0.00	40.69*	886.63*	356.47*
Cotton	2.569	0.270	0.021	0.17	−0.30	−0.86	27.16	0.00	30.62*	8.25	7.37
Corn	0.877	0.231	−0.049	0.10	−0.22	−0.21	16.26	0.00	71.23*	211.79*	133.81*
Coffee	−2.377	0.399	−0.110	0.24	−0.15	0.25	10.10	0.00	36.01*	713.21*	429.05*
Cocoa	−0.902	0.307	−0.095	0.13	−0.12	0.24	5.96	0.00	31.67*	182.93*	109.30*
Canola	−0.661	0.194	−0.137	0.07	−0.08	0.00	5.91	0.00	50.54*	764.01*	322.53*
Soybeans meal	1.649	0.242	−0.015	0.09	−0.15	−0.56	9.40	0.00	43.10*	466.01*	216.83*
Panel B: Post-2006 sample statistics											
Crude oil	−2.071	0.362	−0.085	0.13	−0.11	0.04	6.14	0.00	39.27*	2483.24*	550.80*
Wheat	3.641	0.347	0.076	0.13	−0.10	0.08	4.93	0.00	30.13*	390.13*	160.14*
Sugar	2.346	0.345	0.039	0.15	−0.12	0.07	6.85	0.00	18.90*	139.50*	83.32*
Soybean	6.014	0.262	0.192	0.06	−0.14	−0.82	8.90	0.00	23.54*	192.83*	96.82*
Soybean oil	3.954	0.240	0.123	0.09	−0.07	0.10	5.37	0.00	22.19*	1255.69*	405.85*
Cotton	1.573	0.306	0.019	0.10	−0.27	−1.20	20.13	0.00	24.95*	70.60*	44.48*
Corn	6.304	0.320	0.166	0.09	−0.25	−0.69	12.62	0.00	29.15*	21.41*	15.89*
Coffee	1.631	0.316	0.020	0.12	−0.11	0.11	4.95	0.00	34.84*	211.50*	125.44*
Cocoa	6.674	0.284	0.200	0.08	−0.13	−0.45	6.74	0.00	28.95*	240.68*	133.89*
Canola	7.656	0.220	0.302	0.08	−0.13	−0.62	10.70	0.00	81.04*	513.56*	222.18*
Soybeans meal	7.065	0.311	0.195	0.08	−0.25	−1.40	17.24	0.00	24.42*	36.52*	28.00*

Notes. Annualized figures of mean and standard deviation are presented. SR refers to the Sharpe ratio and J–B provides the p-values from Jarque-Bera normality test. Q(20) and $Q^2(20)$ correspond to the Ljung-Box test statistics for serial autocorrelation on returns and squared returns with 20 lags. ARCH(20) provides the statistics of Engle (1982) test for conditional heteroscedasticity with 20 lags. The notation *, **, and *** indicates the rejection of the null hypothesis of normality, no autocorrelation, and conditional homoscedasticity at the 1%, 5%, and 10% threshold level.

hypothesis of stationarity to alternative of unit root. However, the estimates of ADF and PP are significant for the returns suggesting that the first-difference of underlying commodities follows a stationary process. Likewise, the estimates of KPSS test are insignificant over both subsamples suggesting that the returns series follows a trend-stationary process.

5. Empirical analysis

5.1. Marginal distribution model

In order to examine the volatility spillover dynamics between crude oil and agricultural commodities, we first estimate univariate marginal distribution model for each of the underlying series. Table 4 presents the estimation results for the well-suited marginal

Table 3
Unit root tests for crude oil and agricultural commodities.

	Crude oil	Wheat	Sugar	Soybeans	Soybeans oil	Cotton	Corn	Coffee	Cocoa	Canola	Soybeans meal
Panel A: Pre-2006 Unit-root tests in level											
ADF	0.91	−0.39	0.00	−0.42	−0.38	−0.44	−0.53	−1.33	−0.86	−0.54	−0.39
PP	0.88	−0.37	−0.03	−0.41	−0.36	−0.43	−0.49	−1.38	−0.86	−0.52	−0.37
KPSS	30.53*	12.40*	14.91*	7.43*	15.67*	20.98*	16.58*	14.54*	18.28*	21.60*	5.51*
Panel B: Post-2006 Unit-root tests in level											
ADF	−0.62	−0.50	−0.37	−0.06	−0.24	−0.60	−0.31	−0.43	0.10	0.14	−0.01
PP	−0.60	−0.48	−0.40	−0.03	−0.19	−0.56	−0.29	−0.43	0.11	0.20	0.01
KPSS	11.86*	9.19*	20.51*	17.06*	17.62*	14.80*	17.60*	15.29*	13.44*	12.30*	13.21*
Panel C: Pre-2006 Unit-root tests in first differences											
ADF	−51.38*	−50.70*	−52.34*	−49.38*	−50.76*	−51.14*	−48.66*	−51.55*	−51.33*	−49.60*	−49.09*
PP	−70.78*	−68.09*	−72.52*	−69.27*	−67.33*	−69.11*	−65.55*	−70.09*	−70.29*	−66.52*	−67.70*
KPSS	0.04	0.04	0.08	0.04	0.04	0.06	0.03	0.05	0.03	0.04	0.04
Panel D: Post-2006 Unit-root tests in first differences											
ADF	−36.63*	−36.91*	−37.20*	−36.44*	−35.39*	−35.42*	−36.71*	−36.48*	−35.87*	−37.27*	−35.77*
PP	−53.85*	−51.39*	−52.73*	−50.41*	−50.20*	−48.48*	−49.97*	−52.96*	−51.09*	−48.67*	−49.93*
KPSS	0.05	0.04	0.08	0.05	0.06	0.06	0.05	0.04	0.03	0.08	0.03

Notes: This table presents test statistics of unit root test by applying Augmented Dickey-Fuller (ADF) (Dickey and Fuller, 1979), Phillips-Perron (PP) (Phillips and Perron, 1988), and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) (Kwiatkowski et al., 1992) unit-root tests. The estimates indicate that the returns series follows a stationary process.

Table 4
EGARCH parameters for crude oil and agricultural commodities.

Pre-2006	Crude oil	Wheat	Sugar	Soybeans	Soybeans oil	Cotton	Corn	Coffee	Cocoa	Canola	Soybeans meal
Panel A: Pre-2006 EGARCH estimates											
Mean equation estimates											
Const. (%)	0.018	−0.020	0.028	0.022	−0.014	0.000	−0.030[a]	0.011	−0.036	−0.013	−0.009
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
AR(1)	−0.032[a]	0.028[a]	−0.065[b]	−0.033[a]	0.027	−0.010	0.034[a]	−0.021	−0.022	0.037[b]	0.010
	(0.014)	(0.013)	(0.013)	(0.014)	(0.014)	(0.013)	(0.013)	(0.013)	(0.014)	(0.014)	(0.013)
GARCH process estimates											
Const. (Ω)	−0.086[b]	−0.109[b]	−0.034[a]	−0.096[b]	−0.199[b]	−0.059[b]	−0.148[b]	−0.173[b]	−0.052[b]	−0.218[b]	−0.092[b]
	(0.023)	(0.034)	(0.013)	(0.026)	(0.046)	(0.018)	(0.038)	(0.035)	(0.018)	(0.049)	(0.023)
GARCH (β)	0.989[b]	0.987[b]	0.996[b]	0.989[b]	0.977[b]	0.993[b]	0.983[b]	0.977[b]	0.993[b]	0.976[b]	0.989[b]
	(0.003)	(0.004)	(0.002)	(0.003)	(0.005)	(0.002)	(0.004)	(0.005)	(0.002)	(0.005)	(0.003)
ARCH (α)	0.128[b]	0.084[b]	0.082[b]	0.141[b]	0.125[b]	0.073[b]	0.157[b]	0.163[b]	0.073[b]	0.170[b]	0.126[b]
	(0.014)	(0.012)	(0.010)	(0.013)	(0.015)	(0.010)	(0.017)	(0.016)	(0.010)	(0.017)	(0.013)
Leverage (ξ)	−0.019[a]	0.013	−0.001	0.045[b]	0.035[b]	−0.002	0.006	0.051[b]	0.014[a]	0.002	0.044[b]
	(0.008)	(0.008)	(0.006)	(0.008)	(0.009)	(0.006)	(0.010)	(0.011)	(0.007)	(0.009)	(0.008)
Student-df	5.793[b]	5.990[b]	4.295[b]	5.927[b]	6.654[b]	4.955[b]	4.340[b]	4.074[b]	5.392[b]	6.213[b]	4.854[b]
	(0.452)	(0.378)	(0.279)	(0.471)	(0.660)	(0.319)	(0.247)	(0.274)	(0.412)	(0.471)	(0.331)
Log(L)	12708.1	14017.5	12671.0	14856.8	14384.7	13735.4	14678.7	11890.8	12917.9	15261.0	14402.0
AIC	−25402	−28021	−25328	−29700	−28755	−27457	−29343	−23768	−25822	−30508	−28790
BIC	−25357	−27975	−25282	−29654	−28710	−27411	−29298	−23722	−25776	−30462	−28745
Skewness	−0.348	−0.208	−0.208	−0.135	0.262	−0.923	0.847	0.158	0.281	0.196	0.029
Kurtosis	6.406	11.074	7.254	5.793	4.483	24.829	11.083	6.771	5.647	6.335	8.883
Q (15)	16.6	25.1**	25.5**	20.5	28.3**	32.3**	20.7	24.4	23.9	18.9	19.7
Q^2(15)	31.1**	4.8	13.0	10.6	15.2	2.0	12.4	30.2**	9.6	15.1	5.1
ARCH (15)	32.3**	4.9	13.4	10.8	15.8	2.0	12.8	31.3**	9.9	15.6	5.3
Post-2006	**Crude oil**	**Wheat**	**Sugar**	**Soybeans**	**Soybeans oil**	**Cotton**	**Corn**	**Coffee**	**Cocoa**	**Canola**	**Soybeans meal**
Panel B: Post-2006 EGARCH parameters											
Mean equation estimates											
Const. (%)	0.000	0.000	−0.001[a]	0.001[b]	0.000	0.000	0.000	0.000	0.001	0.001[b]	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
AR(1)	−0.038[a]	−0.007	−0.026	−0.010	0.018	0.028	0.022	−0.047[a]	−0.005	0.037[a]	0.000
	(0.019)	(0.020)	(0.019)	(0.019)	(0.020)	(0.019)	(0.018)	(0.019)	(0.018)	(0.018)	(0.019)
GARCH process estimates											
Const. (Ω)	−0.046[b]	−0.079[b]	−0.032	−0.082[a]	−0.062[a]	−0.107[b]	−0.088[b]	−0.119[a]	−0.029	−0.244[b]	−0.106[b]
	(0.017)	(0.027)	(0.017)	(0.035)	(0.028)	(0.036)	(0.034)	(0.047)	(0.016)	(0.071)	(0.041)
GARCH (β)	0.994[b]	0.990[b]	0.996[b]	0.990[b]	0.993[b]	0.987[b]	0.989[b]	0.985[b]	0.996[b]	0.972[b]	0.987[b]
	(0.002)	(0.004)	(0.002)	(0.004)	(0.003)	(0.004)	(0.004)	(0.006)	(0.002)	(0.008)	(0.005)
ARCH (α)											

(*continued on next page*)

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Table 4 (*continued*)

Pre-2006	Crude oil	Wheat	Sugar	Soybeans	Soybeans oil	Cotton	Corn	Coffee	Cocoa	Canola	Soybeans meal
	0.096[b]	0.102[b]	0.077[b]	0.117[b]	0.098[b]	0.132[b]	0.118[b]	0.067[b]	0.067[b]	0.147[b]	0.113[b]
	(0.015)	(0.017)	(0.013)	(0.018)	(0.015)	(0.018)	(0.018)	(0.016)	(0.013)	(0.023)	(0.018)
Leverage (ξ)	−0.055[b]	0.033[b]	0.010	0.014	−0.010	0.003	−0.002	0.039[b]	−0.004	−0.009	0.034[b]
	(0.009)	(0.010)	(0.008)	(0.011)	(0.008)	(0.012)	(0.011)	(0.009)	(0.009)	(0.013)	(0.011)
Student-df	11.946[b]	8.675[b]	5.572[b]	5.149[b]	12.091[b]	5.760[b]	5.988[b]	6.246[b]	5.744[b]	4.452[b]	5.514[b]
	(2.044)	(1.248)	(0.545)	(0.483)	(2.475)	(0.571)	(0.524)	(0.880)	(0.663)	(0.363)	(0.546)
Log(L)	6631.4	6497.9	6597.7	7357.5	7488.6	7021.1	6773.8	6667.2	7086.3	7883.4	6904.6
AIC	−13249	−12982	−13181	−14701	−14963	−14028	−13534	−13320	−14159	−15753	−13795
BIC	−13208	−12941	−13140	−14660	−14922	−13987	−13492	−13279	−14118	−15712	−13754
Skewness	−0.214	0.178	0.537	−0.706	0.208	−0.491	−1.077	0.048	−0.436	−0.598	−0.540
Kurtosis	4.103	4.594	8.197	8.858	3.813	9.266	18.985	4.311	5.717	11.963	7.470
Q (15)	5.4	17.5	10.9	12.0	10.3	13.9	18.2	13.0	19.6	28.0**	12.1
Q^2(15)	20.3	12.2	3.8	4.9	8.6	5.9	2.3	20.4	19.5	2.0	7.3
ARCH (15)	19.9	12.5	3.8	4.9	11.4	5.9	2.3	18.5	18.6	1.8	7.1

Notes: This table presents the estimates of EGARCH model for each return series. Standard errors are presented in parenthesis. Q(15), Q^2(15), and ARCH(15) are empirical statistics of Ljung-Box test for autocorrelation with 15 lags in residuals and squared residuals, and the ARCH effects test by Engle (1982) with 15 lags, respectively.

* The rejection of null hypothesis of independence and conditional homoscedasticity at 10% threshold level.

** The rejection of null hypothesis of independence and conditional homoscedasticity at 5% threshold level.

*** The rejection of null hypothesis of independence and conditional homoscedasticity at 1% threshold level.

[+] indicates the significance at 10% threshold level.

[a] Indicates the significance at 5% threshold level.

[b] Indicates the significance at 1% threshold level.

Table 5
Static return spillover between crude oil and agricultural commodities.

To/From	Crude oil	Wheat	Sugar	Soybean	Soybean oil	Cotton	Corn	Coffee	Cocoa	Canola	Soybeans meal
Panel A: Pre-2006 static spillovers											
Crude oil	99.02	0.15	0.10	0.11	0.02	0.16	0.26	0.00	0.02	0.02	0.14
Wheat	0.08	55.71	0.55	8.69	6.75	0.60	15.62	0.34	0.20	5.13	6.33
Sugar	0.18	0.98	93.25	1.08	0.86	0.28	1.26	0.49	0.46	0.58	0.59
Soybean	0.06	4.93	0.35	31.51	15.80	0.51	11.44	0.17	0.19	11.68	23.35
Soybean oil	0.03	4.95	0.28	20.41	40.79	0.62	10.10	0.10	0.20	14.55	7.96
Cotton	0.16	0.99	0.22	1.46	1.41	92.04	1.26	0.13	0.08	1.18	1.06
Corn	0.16	11.71	0.47	15.06	10.34	0.57	41.38	0.41	0.14	8.79	10.97
Coffee	0.01	0.67	0.39	0.53	0.27	0.15	0.91	95.16	1.26	0.17	0.49
Cocoa	0.03	0.37	0.56	0.62	0.44	0.10	0.39	1.26	95.52	0.36	0.34
Canola	0.02	4.02	0.30	16.42	15.79	0.55	9.27	0.07	0.19	43.63	9.74
Soybeans	0.08	4.45	0.25	28.90	7.63	0.45	10.31	0.18	0.11	8.59	39.05
To others	0.81	33.21	3.47	93.26	59.31	4.01	60.82	3.15	2.86	51.06	60.97
From others	0.98	44.29	6.75	68.49	59.21	7.96	58.62	4.84	4.48	56.37	60.95
Net spillover	−0.17	−11.08	−3.28	24.77	0.10	−3.95	2.20	−1.70	−1.62	−5.31	0.02
Total spillover index:											33.902%
To/From	Crude oil	Wheat	Sugar	Soybean	Soybean oil	Cotton	Corn	Coffee	Cocoa	Canola	Soybeans meal
Panel B: Post-2006 static spillovers											
Crude oil	54.82	3.31	2.83	6.55	13.00	3.14	4.28	3.35	2.98	3.44	2.30
Wheat	2.83	43.72	2.49	8.51	8.42	2.28	17.17	2.30	0.85	6.09	5.34
Sugar	3.41	3.73	65.49	3.41	4.21	2.86	4.11	5.72	2.69	2.82	1.53
Soybean	3.44	5.54	1.46	28.44	13.65	1.98	10.28	1.34	0.97	10.70	22.20
Soybean oil	7.95	6.40	2.18	16.05	33.45	3.44	8.18	2.44	1.46	12.68	5.76
Cotton	3.69	3.39	2.88	4.42	6.50	64.65	4.32	2.73	2.00	3.03	2.40
Corn	2.91	14.51	2.32	13.39	9.05	2.48	37.01	1.69	0.77	6.44	9.44
Coffee	3.99	3.56	5.78	3.20	4.93	2.82	3.03	66.17	3.40	1.70	1.43
Cocoa	4.04	1.70	3.20	2.70	3.37	2.39	1.87	3.92	74.47	0.84	1.51
Canola	2.52	5.57	1.72	15.08	15.10	1.92	7.12	0.99	0.45	40.09	9.44
Soybeans	1.58	4.57	0.83	28.81	6.37	1.37	9.40	0.80	0.71	8.61	36.95
To others	36.36	52.27	25.69	102.12	84.59	24.69	69.76	25.29	16.27	56.35	61.33
From others	45.18	56.28	34.51	71.56	66.55	35.35	62.99	33.83	25.53	59.91	63.05
Net spillover	−8.82	−4.01	−8.82	30.56	18.05	−10.67	6.77	−8.54	−9.25	−3.56	−1.71
Total spillover index:											50.429%

Notes: This table shows all the possible bivariate relations of directional static spillover between crude oil and the agricultural commodities. The underlying variance decomposition is based on VAR of order 1 (as determined by log-likelihood and AIC) and 70-steps-ahead forecasts of error variance decomposition. Each diagonal entry ($S_{ii}^{g}(H)$) of the table shows the self-caused variation within the given market. The element "From others" represents the gross directional spillover received by commodity i ($S_{i\leftarrow j}^{g}(H)$) from all other markets. The element "To others" indicates the gross directional spillover transmitted by commodity i to all other markets ($S_{i\rightarrow j}^{g}(H)$). The net spillover ($S_{i}^{g}(H)$) is the difference between spillover transmitted and spillover received, which is informative of whether the underlying commodity is a net receiver or transmitter of spillover. The average spillover between the commodities, the total volatility index ($S^{g}(H)$), can be approximated as the ratio of "To others" and the total number of assets.

distribution model for crude oil and agricultural commodities. The optimal model is selected that produces the lowest AIC and highest log-likelihood values from GARCH, GJR-GARCH, and EGARCH model.[6] Based on our estimates, the ARMA(1,0)-EGARCH(1,1) specification is best-suited to capture the dynamics for all the underlying series. Panel A and B of Table 4 reports the estimates of ARMA(1,0)-EGARCH(1,1) for the pre- and post-2006 subsamples.

The lagged autoregressive parameter, AR(1), is insignificant for nearly half of the underlying commodities over the pre-2006 subsample, and for nearly all the commodities over the post-2006 subsample, indicating that the past returns (past information) is not embodied in current returns. This suggests the lack of one-step ahead predictability for these commodities. The GARCH (β) and ARCH (α) components of the variance equation are significant at 1% threshold level for all the commodities. This indicates that the current conditional volatility is significantly affected by the lagged squared shocks of the previous period and also the persistence in conditional volatility for all the underlying series. The leverage effect (ξ) is significant for more than half of the commodities over the pre-2006 subsample, while it is significant for four of the commodities over the post-2006 subsample, indicating asymmetric impact of bad and good news on conditional volatilities for these commodities. For storable commodities, an increase in price might reflect scarcity in commodity availability depletion, which results in increased volatility (Stigler, 2011). In the prices of agricultural commodities, the conditional volatility reacts stronger to an increase in prices (bad news) than to a decrease in prices (good news).

[6] Although, we have not utilized the range estimate of volatility, we utilize several GARCH models (GARCH, GJR-GARCH-, and EGARCH) with different specifications to measure volatility and used these as inputs in the DY frameworks. The results of spillover index are qualitatively similar with minor fluctuation in magnitude of spillover. We thank an anonymous referee for suggestion to include different volatility inputs to provide robustness in empirical results. For the sake of brevity, we report only the estimates from the best-suited GARCH-framework. The estimates of other frameworks can be obtained from the authors upon request.

Table 6
Static volatility spillover between crude oil and agricultural commodities.

To/From	Crude oil	Wheat	Sugar	Soybean	Soybean oil	Cotton	Corn	Coffee	Cocoa	Canola	Soybeans meal
Panel A: Pre-2006 static spillovers											
Crude oil	95.41	0.66	0.15	0.15	0.01	0.16	0.37	0.03	1.64	0.82	0.60
Wheat	0.48	49.47	0.26	12.56	6.13	2.42	11.69	0.32	0.27	3.76	12.64
Sugar	2.80	2.93	86.17	0.47	3.06	0.36	1.35	1.22	0.12	1.32	0.18
Soybean	0.05	5.39	0.25	37.09	10.45	0.22	9.36	0.22	0.32	8.33	28.31
Soybean oil	0.03	3.97	0.77	21.16	41.02	2.14	7.85	0.97	0.34	11.28	10.46
Cotton	0.48	2.62	1.55	1.18	2.90	87.59	0.66	0.75	0.92	0.83	0.51
Corn	0.12	11.69	0.94	18.15	6.06	0.67	40.75	0.61	0.35	7.14	13.53
Coffee	0.15	2.04	0.49	1.26	0.11	0.51	1.78	89.30	0.45	3.61	0.31
Cocoa	0.07	1.79	2.08	3.39	3.27	0.29	0.51	2.18	84.64	0.52	1.27
Canola	0.30	2.09	1.22	13.16	12.22	0.70	6.02	0.65	0.28	56.40	6.95
Soybeans	0.06	5.35	0.35	29.25	4.80	0.08	7.49	0.29	0.06	5.99	46.28
To others	4.54	38.51	8.07	100.73	49.01	7.54	47.08	7.26	4.76	43.60	74.76
From others	4.59	50.53	13.83	62.91	58.98	12.41	59.25	10.70	15.36	43.60	53.72
Net spillover	−0.05	−12.01	−5.76	37.82	−9.97	−4.87	−12.16	−3.44	−10.59	−0.01	21.04
Volatility spillover index:											35.080%
To/From	**Crude oil**	**Wheat**	**Sugar**	**Soybean**	**Soybean oil**	**Cotton**	**Corn**	**Coffee**	**Cocoa**	**Canola**	**Soybeans meal**
Panel B: Post-2006 static spillovers											
Crude oil	60.72	0.87	0.55	3.36	19.58	2.15	4.51	0.65	0.31	6.26	1.04
Wheat	0.07	65.06	3.19	2.83	4.77	7.45	10.22	0.86	0.29	2.36	2.92
Sugar	0.30	4.30	83.83	1.22	4.00	3.46	0.28	0.54	0.24	0.50	1.33
Soybean	0.22	5.33	0.55	28.62	15.27	2.38	9.62	0.32	0.78	14.26	22.64
Soybean oil	4.61	5.66	1.86	16.50	37.73	2.47	3.74	0.26	0.50	20.59	6.10
Cotton	0.21	5.29	3.28	1.98	4.61	76.80	5.60	0.16	0.20	0.47	1.40
Corn	0.21	8.80	1.92	10.97	7.17	7.11	48.28	0.56	0.62	6.08	8.28
Coffee	0.22	1.49	1.90	0.49	0.33	2.93	0.80	88.73	0.85	0.52	1.74
Cocoa	2.85	4.26	2.06	2.22	10.69	6.99	0.91	1.59	60.24	7.68	0.52
Canola	0.76	6.98	0.23	11.15	12.25	3.82	6.10	1.44	0.19	48.36	8.73
Soybeans	0.25	3.11	0.12	24.52	8.33	1.63	8.12	0.30	0.99	7.65	44.96
To others	9.69	46.08	15.65	75.24	87.00	40.39	49.90	6.68	4.97	66.38	54.70
From others	39.28	34.94	16.17	71.38	62.27	23.20	51.72	11.27	39.76	51.64	55.04
Net spillover	−29.59	11.14	−0.51	3.85	24.73	17.19	−1.82	−4.59	−34.79	14.74	−0.35
Volatility spillover index:											41.516%

Notes: This table shows all the possible bivariate relations of directional static volatility spillover between crude oil and the agricultural commodities. The underlying variance decomposition is based on VAR of order 1 (as determined by AIC) and 70-steps-ahead forecasts of error variance decomposition. Each diagonal entry ($S^g_{ii}(H)$) of the table shows the self-caused volatility within the given market. The element "From others" represents the gross directional volatility spillover received by commodity i ($S^g_{i\leftarrow j}(H)$) from all other markets. The element "To others" indicates the gross directional volatility spillover transmitted by commodity i to all other markets ($S^g_{i\rightarrow j}(H)$). The net spillover ($S^g_i(H)$) is the difference between volatility transmitted and volatility received, which is informative of whether the underlying commodity is a net receiver or transmitter of volatility. The average spillover between the commodities, the total volatility index ($S^g(H)$), can be approximated as the ratio of "To others" and the total number of assets.

Furthermore, the degrees of freedom (Student-df) parameters of student-t distribution is strongly significant at 1% threshold level over both subsamples. This suggest that fat tails characterize the distributions of all the return series and potential for tail dependence in the joint distribution. Furthermore, the estimates from diagnostic tests show that Ljung-Box test for residuals and squared residuals do not allow for rejection of null hypothesis of no serial correlation in the underlying series. In addition, the residuals show no remaining ARCH effects, indicating that the marginal distribution model is correctly specified.

5.2. Total spillover index

Table 5 and Table 6 present the total spillover index of returns and volatilities for crude oil and the agricultural commodity futures market, respectively.[7] All results are based on the vector autoregression of order 1 (determined by AIC and Log-likelihood) and generalized variance decomposition of 70-steps-ahead forecast errors.

Before discussing the results of the spillover index, we briefly describe the elements of the index. Application of DY frameworks yield a $N \times N$ matrix[8] of directional spillover ($\theta^g_{ij}(H)$). The diagonal elements ($i = j$) of the spillover index reflects the own-variable spillovers due to self-caused variations within a given market. Whereas, the off-diagonal elements $i \neq j$ measures the spillovers caused by the variations in different markets. Specifically, each entry (i, j) in the spillover index is the estimated contribution of innovations in market j to the FEVD of market i. Based on the matrices of directional spillover, we derive four additional statistics. The gross directional spillover

[7] We thank an anonymous referee for pointing out to include the return spillover in the analysis.

[8] Since there are a total number of 11 assets in our analysis it would produce (11×11) matrix.

to commodity i (termed 'From others', Eq. (8)) is the row sums excluding the main diagonal elements. The gross directional spillover from commodity i (termed 'To others', Eq. (9)) is the column sums excluding the main diagonal elements. The net spillover for commodity i (termed 'Net spillover', Eq. (10)) is the difference between the spillover transmitted to others and spillover received from others. Finally, the total spillover index (termed 'Total spillover index', Eq. (7)) is roughly equals to the total off-diagonal elements sum of spillover index relative to the total sum of the index.

Panel A and B of Table 6 summarize the total static spillover index among the return series of crude oil and agricultural commodities, and decompose the matrix further into receivers and transmitters of return spillovers. In addition, it also provide estimate of net return spillovers, which indicate whether an underlying asset is a net receiver or transmitter of spillover. As shown in Panel A and Panel B, the total return spillover index indicates that an average of 33.90% and 50.43% of the return forecast error variance derives from other assets in the pre-2006 and post-2006 subsample, respectively. With respect to bidirectional net spillover effect among crude oil and agricultural commodity futures market, soybean is the greatest contributor to other underlying commodity futures over both subsamples, contributing 93.26% and 102.12% to other commodity futures while receiving 68.49% and 71.56% over the pre-2006 and post-2006 subsamples, respectively. Among the largest net receivers of spillover are wheat, canola, cotton, and sugar, which in net terms receives an average of 11.08%, 5.31%, 3.95%, and 3.28%, respectively, over the pre-2006 subsample. It is interesting to note that, over the post-2006 subsample, soybean, soybean oil, and corn are primarily net contributors of spillover while the rest of the commodities are net receivers of spillover. Among the largest net receivers are cotton (10.67%), cocoa (9.25%), sugar (8.82%), and crude oil (8.82%) because they transmit less spillover to other commodities than they receive.

Based on the conditional volatility estimates from the marginal distribution model, we estimate the volatility spillover between crude oil and agricultural commodities. Specifically, the conditional volatility from the ARMA(1,0)-EGARCH(1,1) specification is employed in the DY frameworks to estimate spillover between crude oil and agricultural commodities. Panel A and B of Table 6 presents the estimates from total volatility spillover index for the pre- and post-2006 subsample, respectively. These estimates are based on vector autoregressions of order 1 (VAR(1)) and generalized variance decomposition of 70-days-ahead forecast errors. The order of vector autoregressive model is determined based on the lowest values of Akaike information criterion (AIC).

Table 6 summarizes all the possible bivariate relations of directional spillover between the futures markets of crude oil and agricultural commodities, and classifies the transmitters and receivers of conditional volatility spillovers. Furthermore, it also measures whether an underlying asset is net receiver or transmitter. The estimate of pre-2006 subsample indicates that an average of 35.08% of volatility forecast error variance is caused by other markets. The self-caused volatility for crude oil is 95.41%, indicating that a significant proportion of variation in crude oil prices are caused by own-shocks.[9] With respect to bidirectional spillover effect over the pre-2006 subsample, soybean is the greatest contributor and receiver of volatility to and from other markets. On average, soybean transmits 100.73% of volatility spillover to other market, while receiving 62.91% of volatility from others. Whereas, the average transmission from crude oil to agricultural commodities is 4.54% while receiving 4.59% from the agricultural sector. Hence, in net terms, the aggregate spillover between crude oil to agriculture is economically insignificant, −0.05%, over the pre-2006 subsample. This supports the neutrality hypothesis, indicating that the variations in crude oil prices does not contribute to the shifts in agricultural commodity prices over the pre-2006 subsample. Our estimates indicate that the within sector connectedness in agricultural commodities plays a significant role in changing price equilibrium. Among the agricultural commodities, soybean is the largest contributor of volatility to other underlying commodities, contributing 37.82% more volatility to other commodities than received. The second largest net contributor is soybeans meal, which transmits an average of 74.76% and receiving 53.72% volatility, resulting in a net spillover of 21.04%. The rest of the agricultural commodities are net receivers of volatility. Among the largest net receivers are corn, wheat, and cocoa, which in net terms receives an average of 12.16%, 12.01%, and 10.59% because they are transmitting less volatility to other underlying commodities than they are receiving.

The conditional volatility spillover matrix of crude oil and agricultural commodities for the post-2006 subsample is presented in panel B of Table 6. The estimate of total volatility spillover index indicates that 41.52% of the volatility forecast error variance is due to cross-commodity variations. Notably, the self-caused volatility of crude oil significantly reduced from 95.33% (pre-2006) to 60.72% (post-2006). In terms of average directional spillover, soybean oil is the largest contributor of spillover to the futures prices of other underlying commodities (87.00%), followed by soybean (75.24%) and canola (66.38%). Whereas, the average contribution of crude oil to agricultural commodities is 9.69% while it receives 39.28% of volatility from the agricultural sector, indicating it as the average net receiver of volatility (−29.59%). It is interesting to note that agricultural commodities being utilized for biofuel production (soybean oil (19.40%) and corn (4.89%)) are among the largest contributors of spillover to crude oil.[10] In terms of average net spillover among agricultural sector, soybean oil is the largest contributor of volatility (24.73%) and cocoa is largest net receiver (−34.79%).

Overall, the estimates of static spillover analysis of pre-2006 subsample provide evidence of minuscule information transmission between crude oil to agricultural commodities. Furthermore, the volatility caused by spillover in agricultural commodities predominantly originates due to within sector variations. Our analysis of pre-2006 subsample is in-line with the empirical results from Wang et al. (2014) and Liu et al. (2017). However, the analysis of post-2006 subsample indicate that crude oil is a net receiver of volatility from the agricultural sector. The findings of post-2006 subsample are in-line with the empirical findings of Kaltalioglu and Soytas (2011); Awartani et al. (2016); Kang et al. (2017) and Shahzad et al. (2018).

[9] This can be characterized as the demand and supply shocks with the crude oil market, which significantly influence the crude oil prices.

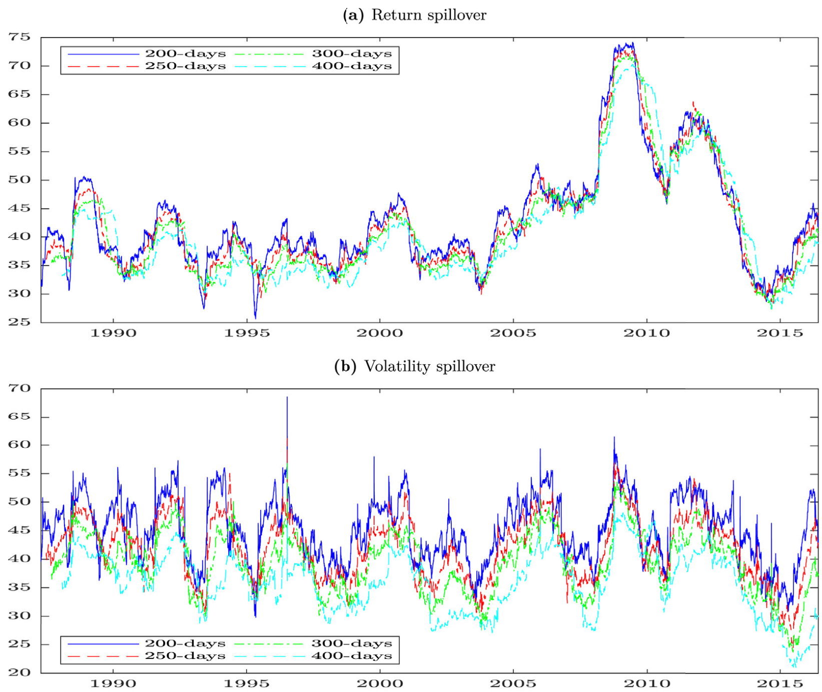
[10] It is noteworthy that one should be careful in interpreting the results from static spillover since they are susceptible to the ad hoc choice of sample and it is hard to make inference based on static estimation. We thank an anonymous referee for pointing this out.

5.3. Temporal spillover analysis

The static total spillover analysis provides an overview of overall connectedness dynamics between the underlying assets and it is well-established that the uncertainty in market can significantly influence the dependence structure over time. More specifically, the estimates of static volatility spillover index might ignore the stylized facts (e.g. aggregational Gaussianity, price and volatility jumps) typically attributed to the financial and commodity markets due to periods of turmoil (e.g. the 2006–2008 food crisis, the global financial crisis of 2007–2009, the European debt crisis of 2009–2012, and the significant decline in crude oil prices 2014). These events occur over the selected timespan and may have influenced the intensity and direction of connectedness between the futures markets of crude oil and agricultural commodities. Consequently, we evaluate the temporal return and volatility spillover index to examine the development of average connectedness in crude oil and agricultural commodities.

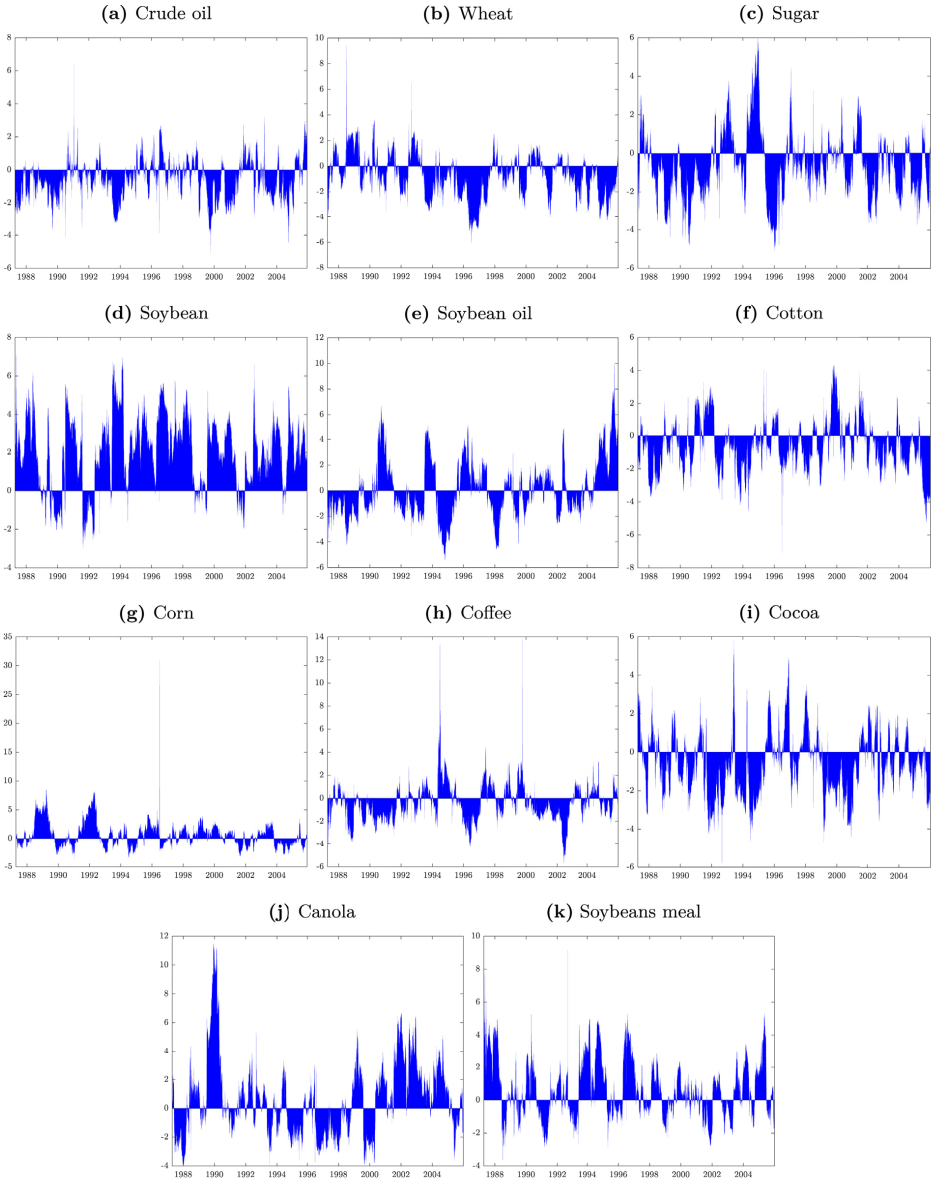
Fig. 2 illustrates the dynamic development of return and conditional volatility spillover index among crude oil and agricultural commodities over the full sample period using a 200-days rolling window sample. In terms of return spillover, we observe the total volatility index primarily fluctuates between 30% and 45% over the period of 1986 to the mid-2005. The spillover index increases slightly during mid-2005 and stabilizes around 50% threshold level until the outbreak of global financial crisis in 2008, which result in a sharp increase in total spillover index over the period of mid-2008 to mid-2009. Later on, the spillover index increase over the period of European debt crisis of 2009–2012. The spillover index gradually decline over the period of 2012 to the mid-2014, which is considered as the period of economic prosperity and development. From the mid-2014, the spillover index exhibits an upward trend, which may be attributed to the decline in crude oil price that may have contributed to a decline in demand for soybean and corn, and eventually leading to increased spillover among crude oil and agricultural commodities.

Panel 2b of Fig. 2 illustrates the development of temporal conditional volatility spillover index using a 200-days rolling window



Notes. The figure portrays the development of temporal total volatility spillover index calculated from the forecast error variance decomposition of 10-step-ahead forecast horizon and different rolling windows samples to provide variations in results due to change in different window sizes.

Fig. 2. Total spillover index. Notes. The figure portrays the development of temporal total volatility spillover index calculated from the forecast error variance decomposition of 10-step-ahead forecast horizon and different rolling windows samples to provide variations in results due to change in different window sizes.



Notes. This figure portrays the development of net volatility spillovers in crude oil and agricultural commodities over the pre-2006 subsample with a 200-days rolling window and 10-step-ahead forecast horizon. Positive (negative) values in each graph indicate that the underlying asset is a net transmitter (receiver) of volatility.

(caption on next page)

Fig. 3. Dynamic net spillover over the pre-2006 subsample. Notes. This figure portrays the development of net volatility spillovers in crude oil and agricultural commodities over the pre-2006 subsample with a 200-days rolling window and 10-step-ahead forecast horizon. Positive (negative) values in each graph indicate that the underlying asset is a net transmitter (receiver) of volatility.

sample. The pre- and post-2006 period exhibits relatively different development in spillover. The movements in pre-2006 period fluctuates around the estimate of average static spillover with simultaneous periods of rise and fall in connectedness structure. Notably, between the period of 1987–1998, the spillover in crude oil and agricultural commodities mainly lies between 40% and 60% range. The index gradually rise in 1998 and remains stable around 50% level till the end of 2001 (the period characterized as the Asian financial crisis and the dot-com bubble). The connectedness measure decreases gradually in 2001 and remain relatively low till the mid of 2004 and increases moderately towards the end of pre-2006 period. For the post-2006 period, the temporal spillover index shows a stable level of connectedness in the underlying commodities varying between 40% and 45% from the last quarter of 2006 to the end of 2007. The spillover index gradually increases in the beginning of 2008 (during the subprime mortgage crisis) and spiked during September 2008 with the onset of global financial crisis. The spillover index persisted till the mid of 2009 while eventually reverting to the pre-crisis level of around 40%. However, the commencement of European debt crisis of 2009–2012 gives rise to the connectedness structure. The spillovers remain persistently high between 2011 and 2013, which may be due to persistence in crude oil prices. Whereas, the index gradually decreases in 2013 and remains persistently low till the first quarter of 2015, which may be interpreted as the period of economic prosperity. Over this period, we observe a downward trend in both return and volatility spillovers, which may be attributed to global economic recovery. It is noteworthy that the financial and economic turmoil intensify the spillovers among the agricultural commodity markets and crude oil. Several studies provide similar findings between oil and stock markets (Awartani et al., 2016; Zhang and Wang, 2014), across stock markets (Diebold and Yılmaz, 2012, 2009), and across crude oil and commodity markets Kang et al. (2017). Towards the end of sample period, the index increases steadily with the decrease in futures prices of crude oil, which might result in lower prices of agricultural commodities, resulting in higher measure of connectedness between the underlying commodities. It is noteworthy that the temporal spillover index provides an overview of development in connectedness structure and therefore it does not indicate that whether the spillover is caused by variations in crude oil prices or changes within the agricultural sector. To evaluate the sensitivity of our findings, we utilize alternative $m-$week rolling windows.[11] The development of spillover indexes appear to have similar patterns for both return and conditional volatility spillovers, indicating that the total spillover index plot is not sensitive to the choice of window size.

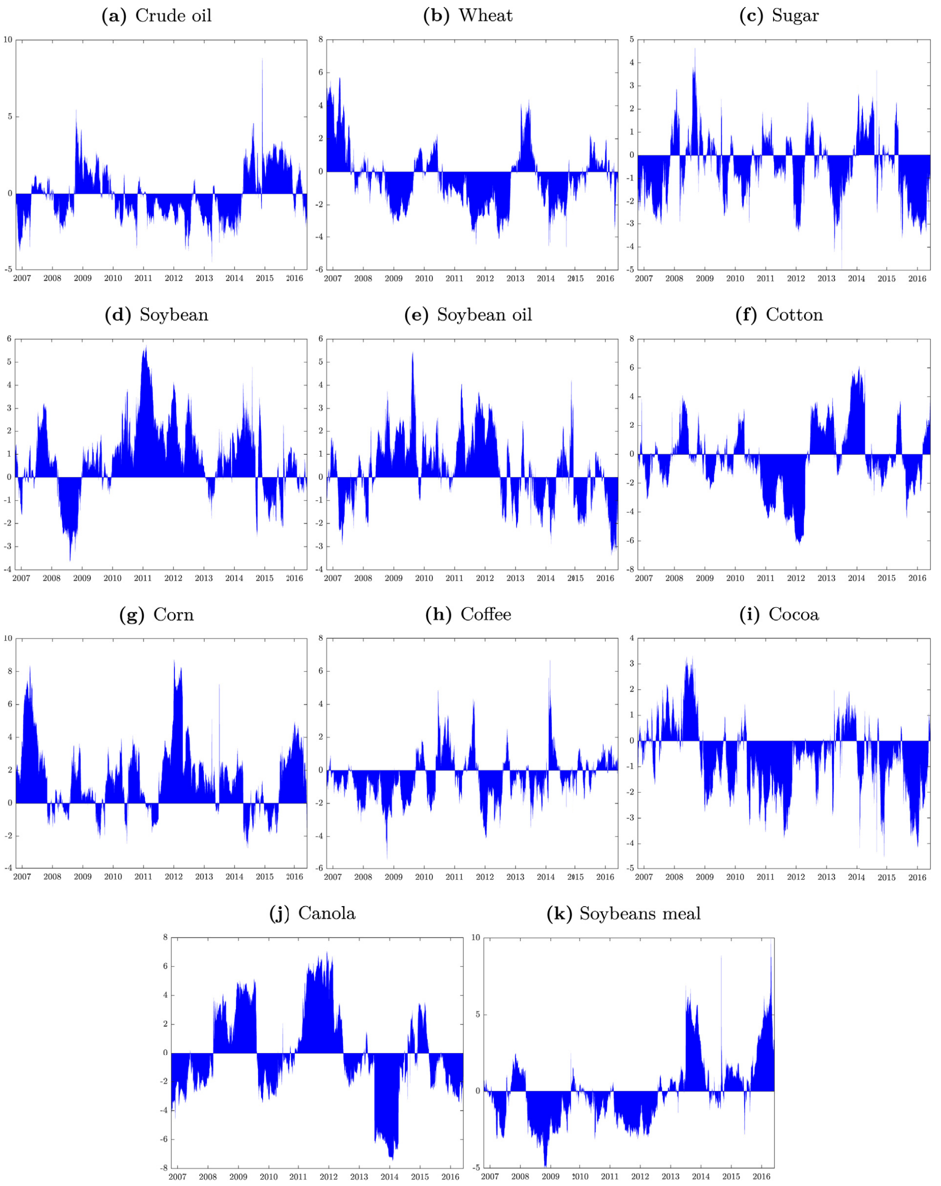
5.4. Net spillovers

The total spillover index provides information about the overall connectedness structure between the underlying commodities, which does not indicate whether an asset is net transmitter or receiver of volatility. Therefore, to examine the role of crude oil in changing equilibrium of agricultural commodities, we estimate net conditional volatility spillover, which provides information about directional volatility spillovers between the underlying assets. Specifically, we estimate two directional spillovers by decomposing the total volatility spillover as: 1) the transmitters of volatility spillovers, termed as 'to others', and the receivers of volatility spillover, termed as 'from others'. We estimate the temporal net conditional volatility spillover by deducting directional 'to others' spillover from directional 'from others' spillovers.[12] The positive and negative estimates indicate whether an underlying asset is net transmitter or net receiver of conditional volatility spillover, respectively.

Figs. 3 and 4 illustrates the development of time-varying net spillover among the underlying commodities. Specifically, the positive and negative values from each asset indicate that the underlying asset is a net transmitter or receiver. Our findings confirm that the conditional volatility spillovers among crude oil and agricultural commodity futures market are asymmetric and bidirectional because each of the underlying commodity exhibit asymmetric magnitude of temporal positive and negative shocks over both subsamples. Panel A shows the temporal net volatility spillover from crude oil to agricultural commodities, which confirms that the conditional volatility spillover in fuel-food nexus is characterized by asymmetric and bidirectional spillover. Predominantly, the net spillover is negative for crude oil over both subsamples, indicating that crude oil is net receiver of volatility in fuel-food nexus. However, occasional positive spikes can be observed in the net connectedness of crude oil over the post-2006 subsample during the GFC 2008 and with the decline in crude oil price in 2008 and again in 2014, suggesting that abrupt variations in oil market can result in increased volatility spillover effect. Whereas, over the period of 2010 to mid-2014, the price of crude oil remained high and persistent, providing avenue for increased biodiesel and biofuel production and thus the spillover to crude oil from the agricultural commodities. These findings are consistent with the results of Pal and Mitra (2017); Silvennoinen and Thorp (2016), as they report higher correlation among the food and oil when the price levels for these assets are high. Soybean, corn, and soybean oil are mainly the net transmitters of volatility, while the remaining agricultural commodities and crude oil are net receivers of volatility. This may be attributed to the high crude oil price that lead to a rapid growth in production of biodiesel and biofuel, which are primarily extracted from soybean and corn, respectively, and are considered as the most suitable substitute of crude oil. Therefore, due to limited planting acreage in a certain period of time, an upsurge in crude oil price might result in an increase in price of soybean and corn, which eventually contributes to increase in prices of

[11] We thank an anonymous referee for pointing this out.

[12] For the sake of brevity, we report only the net directional spillovers as it provides an estimate of both 'to others' and 'from others'. The estimates of 'to others' and 'from others' can be obtained from the authors upon request.



Notes. This figure portrays the development of net volatility spillovers in crude oil and agricultural commodities over the post-2006 subsample with a 200-days rolling window and 10-step-ahead forecast horizon. Positive (negative) values in each graph indicate that the underlying asset is a net transmitter (receiver) of volatility.

(caption on next page)

Fig. 4. Dynamic net spillover over the post-2006 subsample. Notes. This figure portrays the development of net volatility spillovers in crude oil and agricultural commodities over the post-2006 subsample with a 200-days rolling window and 10-step-ahead forecast horizon. Positive (negative) values in each graph indicate that the underlying asset is a net transmitter (receiver) of volatility.

other agricultural commodities. These findings are consistent with the empirical results of Wang et al. (2014). Overall, the net spillovers indicate bidirectional (positive and negative) spillover within agricultural sector intensifies after the recent global financial crisis.

6. Conclusion

This paper examines the return and volatility spillover effects in the futures markets of crude oil and ten major agricultural commodities by employing an ARMA(1,0)–EGARCH(1,1) specification and Diebold and Yılmaz (2009, 2012, 2014, 2015) spillover index. Specifically, we evaluate the static and time-varying return and volatility spillover indexes to examine the direction and intensity of spillovers across the futures markets. We consider the structural variation in data through subsample analysis. We divide the data into two subsamples: from July 1986 to December 2005 (pre-2006 subsample) and from January 2006 to June 2016 (post-2006 subsample).

Our empirical results are as follows. First, our findings of static spillover indicate minuscule information transmission among crude oil and agricultural commodities over the pre-2006 subsample. Whereas, the analysis of post-2006 subsample indicates that crude oil is a net receiver of information from agricultural commodities. Second, we find evidence of bidirectional spillover among the futures markets of crude oil and agricultural commodities, which intensifies during the periods of financial and economic turmoil. These trends are more pronounced, over the post-2006 subsample, due to aftermath of recent financial crisis. Furthermore, our findings indicate that the total spillover declines during period of economic prosperity and development. Last, we find that the abrupt variations in crude oil price can result in increased total spillover index. The spillover index increases with the decrease in futures prices of crude oil, which result in lower demand for soybean and corn to produce biodiesel and biofuel that becomes uneconomical under lower crude oil prices. In other words, due to limited planting acreage in a certain period of time, an upsurge in crude oil price might result in an increase in price of soybean and corn, which eventually contributes to increase in prices of other agricultural commodities.

The findings of this study are of potential interest to various economic agents, for instance, policymakers and regulators, international investors, farmers, and portfolio managers. Understanding the temporal dynamics of volatility spillover among the futures markets of crude oil and agricultural commodities provide these actors with the opportunity to develop optimal risk hedging strategies or to develop and implement appropriate policies that accommodate the variations due to financial and economic turmoil. For instance, investors might be interested in determining the linkage between assets in order to diversify their investment and minimize the risk. Transmission of volatility to agricultural commodities affects farmers in terms of more volatile crop prices and risk management, which can alter their investment and hedging decisions. This might create hindrance in production of crops, which might result in increasingly volatile food prices. The regulatory agencies and policy makers would benefit from this by designing and reformulating the strategies in terms of connectedness of different assets in commodity markets.

The DY frameworks provide estimates of spillover by utilizing information pertaining in the time-domain and thus ignore the information related to the frequency-domain of the data. Whereas, the commodity markets are complex systems with agents having distinctive term objectives and operate at different frequencies and thus the resulting time series pertains information from both time and spectral domain. Therefore, one avenue for future research could be to investigate the time-frequency spillover between crude oil and agricultural commodities that would provide new insight into development of spillovers over various frequencies. The DY approaches are limited to evaluating the overall connectedness and thus ignoring the information in the tails of the distribution. Therefore, another avenue for further research could involve in investigating the causal relationship across various quantiles of the distribution between crude oil and agricultural commodities.

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5 Paper IV: Stock market valuation revealing salmon price information

Stock Market Valuation Revealing Salmon Price Information

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Abstract

This paper investigates the relationship between one of the primary price indices of farmed salmon (the Fish Pool index, FPI) and the stock prices of major publically traded salmon companies. We document that prices of exchange traded salmon stocks reflect the flow of salmon market information earlier than the price index. Forward looking stock prices are predictive of the backward looking price index. Furthermore, the predictive value is greater for the larger companies. The price discovery role of stock prices introduces a potential bias in the salmon futures design utilizing the price index to settle futures contracts as well as reducing hedging efficiency due to lagged reflection of company relevant market information in the price index.

Jel-Codes: O13, C01, C22, Q13, Q02, Q41, Q47

Keywords: Fish pool index, Salmon producers, Cointegration dynamics, return spillovers.

Introduction

Inelastic short run supply and demand exposes farmed salmon production and marketing to considerable price risk (Oglend 2013; Bloznelis 2016; Oglend et al. 2019; Asche et al. 2019; Dahl 2017). Price volatility, reflecting such price risk, has increased over time (Oglend 2013; Bloznelis 2016; Dahl and Yahya 2019), and remains high compared to other commodities and assets (Asche et al. 2019; Dahl and Oglend 2014). Producers hedge this price risk using a combination of bilateral forward contracting (Larsen and Asche 2011; Oglend and Straume 2019a) and futures contracts (Misund and Asche 2016). Previous research on firm level pricing has shown that salmon pricing is competitive and that individual prices are well represented by a price index (Oglend and Straume, 2019 a,b). While efficient risk management can be achieved using market-based hedging measures such as buying and selling standardized futures contract, participation in the salmon futures exchange has generally been low, with low trade volumes in many contracts (Misund and Asche, 2016). Salmon produces appear to prefer forward contracting to futures contracts when dealing with price risk. The market seems to approve of this as there appears to be little discounting of price risk in valuations of salmon companies. Salmon stocks at Oslo Stock Exchange have exhibited a sharp increase in market capitalization. The Seafood Stock Index has appreciated by 38% per year during the last six years (Misund and Nygård 2018).

In this paper, we investigate the relationship between the Fish Pool salmon price index (FPI) and the stock market valuation of the major salmon producers in Norway. Several salmon producers in Norway are listed and traded on organized exchanges, allowing companies access to equity from the public (Asche and Bjorndal 2011; Asche and Sikveland 2015). Furthermore, while individual company transaction prices are private information, the FPI is a publically available measure of the common salmon price in the market. The Fish Pool futures exchange has created the index with the stated aim of providing an unbiased and representative measure of the salmon price. The index functions as the settlement price of salmon futures contracts (there is no physical delivery on the contracts) and consists of a weighted average of salmon prices along the salmon supply chain. While research of salmon and other seafood price volatility is extensive, knowledge about the connection between the publicly available salmon price index and the market value of salmon companies is still lacking.

The empirical analysis in this paper utilizes the cointegration procedure by Johansen (1988, 1991) and Diebold and Yilmaz (2009, 2012, 2014, 2015) to explore the connectedness dynamics and the spillover transmission mechanism between the FPI and the stock prices. First, we utilize the Johansen cointegration approach to evaluate the price linkage among the FPI and stock prices of salmon producers. The Johansen cointegration procedure has been widely utilized in the aquaculture market to examine the price leadership and interdependence structure among different species and markets (see, for example, Asche et al. 2018; Asche and Oglend 2016; Ankamah-Yeboah et al. 2017; Bjørndal and Guillen 2017; Landazuri-Tveteraas et al. 2018, among others). Despite significant literature evaluating the market- and species-level integration structure, examination of firm-level interlinkage structure between major salmon producers and FPI remains uncharted. Secondly, we utilize the Diebold and Yilmaz frameworks to evaluate the directionality and magnitude of connectedness among FPI and salmon producers. The Diebold and Yilmaz frameworks has been primarily utilized in financial and commodity markets to evaluate the spillover dynamics (see, for example, Ferrer et al. 2018; Huang et al. 2016; Yahya et al. 2019, and the references therein). Only recent research has given attention to the interconnected dynamics and volatility spillover in seafood and aquaculture markets (see, for example, Dahl and Jonsson 2018a,b). Despite significant literature on understanding the price and volatility dynamics of salmon, the firm-level impact of spillover has remained unexplored. In this paper, the methods are applied to shed light on how price relevant market information is revealed in company valuations and the price index used to manage price risk in the market. Understanding the magnitude and direction of transmission will enable market participants to make better asset allocation and risk management decisions.

Our results show that the stock prices of the publicly traded companies share a common stochastic trend with the salmon price index over the sample period (April 2011 to December 2018). This has been a period of increasing salmon prices and market values of salmon companies. Results reveal that only the salmon price index adjusts to equilibrium deviations between the price index and the company market values. This result is corroborated by the spillover index estimates using the Diebold and Yılmaz (2009, 2012, 2014, 2015) framework. The price index is a net-receiver of price return shocks in the joint dynamic system of price and company returns. This implies that information on salmon market conditions is revealed in exchange traded company prices *earlier* than in the public price index, making exchange traded stock prices predictive of the price index. Furthermore, the market value of the largest salmon companies are more informative on the future salmon price index. The largest producers are the largest net transmitters of spillovers to the fish pool index and other small- to medium-sized salmon producers. Mowi and Leroy are the largest net contributor of price return spillover to the price index and other salmon producers.

Prices of exchange traded stocks are *forward looking* assessments of future flows of company profits, of which the salmon price is a major determinant. As long as the mapping between salmon price and company profits remains monotonic, changes in expected salmon prices will cause changes to current stock prices. The FPI on the other hand is *backward looking.* It is constructed from recorded bilateral transactions prices along the salmon value chain and is aimed at representing the current supply and demand for salmon. Since the index is only published weekly, and collecting and processing information takes some time, the index will in any given week contain some "dated" market information. In such a context, exchange traded stock prices can add information about current period price as well as future price developments in the salmon market.

Given the competitive nature of the market, the differential predictability of the price index by company size does not reflect the use of market power. Previous research has shown that company transaction prices for larger salmon exporters (such as the companies analyzed in this paper) correlate more strongly with the salmon price index. This is due to the improved "averaging out" of idiosyncratic pricing in larger companies trading with many partners (Oglend and Straume, 2019b). Since the salmon index represents common pricing there will then be a stronger mapping between the index price and the internal salmon price of larger companies, making the market value of larger companies a better signal of the salmon index price. The improved price discovery role of larger firms might also reflect greater trading activity and liquidity in larger companies stocks. That being said, the differential predictive effect by company size might threaten the perceived unbiasedness of the price index used to settle futures contracts, which again might dissuade smaller companies from participating in the futures market. Furthermore, if the futures settlement price reflects outdated market information, the hedging efficiency of the contracts is reduced. This might help explain the lack of interest in the use of salmon futures, as well as the prevalence of bilateral contracting as the main hedging instrument for farmed salmon from Norway. Beyond salmon, our results shows that forward looking at prices of exchange traded seafood assets can provide information on the state and future developments of seafood products.

The remainder of this article is structured as follows. Section 2 and 3 presents the empirical methodology and the dataset, respectively. The empirical results are presented and discussed in section 4. Section 5 concludes.

Methodology

Cointegration framework

To examine whether the underlying time series are cointegrated, we follow the Johansen cointegration procedure Johansen (1988, 1991). The empirical analysis of market integration is based on postulating a linear long-run relationship,

$$lnP_{i,t} = \alpha + \beta P_{j,t} + e_t \tag{1}$$

where P represents prices in market i and j, respectively, and e_t reflects stochastic deviations from the implied long-run relationship. Equation 1 refers to a long-run level relationship. To investigate dynamic adjustments, we utilize a vector autoregressive framework containing prices of both FPI and stock prices. We employ the Johansen's multivariate technique (Johansen 1988, 1991; Johansen and Juselius 1990) to evaluate the cointegration relationship among the prices. The Johansen test relies on a vector autoregressive error correction model (VECM) with vector P_t containing the N price series and the system can then be specified as:

$$\Delta P_t = \sum_{i=1}^{k-1} \Gamma_i \Delta P_{t-i} + \Pi P_{t-k} + \mu + e_t. \tag{2}$$

The Π matrix provides the estimated parameters in the long-term context and it is factorized as: $\Pi = \alpha \,.\, \beta'$ to obtain the full rank. The α and β represents the adjustment parameters and cointegration vectors, respectively.

Static and temporal spillover framework

To examine the spillovers among stock prices and fish pool index (FPI) we use the generalized version of the Diebold and Yılmaz (2012, 2014, 2015) (hereafter: DY) spillover index, proposed originally by Diebold and Yılmaz (2009). The DY framework provide estimates of spillover by utilizing vector autoregressive (VAR) models and decomposition of variance from the VAR framework. The generalized version of DY framework overcomes the shortcomings due to Cholesky factor orthogonalization in Diebold and Yılmaz (2009), which results in order-dependent estimates. Moreover, the generalized version of DY framework provides rolling window estimates, which helps in providing the temporal evolution of spillover effects using spillover plots. Following the work of Diebold and Yılmaz (2009, 2012, 2014, 2015), we briefly present the static and temporal directional spillover frameworks employed in this paper.

Following Koop et al. (1996) and Pesaran and Shin (1998), we carry out the variance decomposition by considering a generalized vector autoregressive (VAR) model. Let the data of N covariance stationary variables be represented by a VAR(p) model of following specification:

$$x_t = \sum_{i=1}^{p} \phi_i x_{t-i} + \varepsilon_t \text{ where } \varepsilon \sim (0, \sigma). \tag{3}$$

Furthermore, let $x_t = \sum_{i=0}^{\infty} A_i \varepsilon_{t-i}$ be the moving average representation of VAR model. Here, the $N \times N$ coefficient matrix is recursively specified, $A_i = \phi_1 A_{i-1} + \phi_2 A_{i-2} + \cdots + \phi_p A_{i-p}$ with $A_i = 0 \; \forall \; i < 0$. The next step comprises of residual variance decomposition obtained from the VAR model. Let the KPPS H-step-ahead generalized forecast error variance decompositions (FEVD) be given as:

$$\theta_{ij}^{g}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} \left(e_i' \Theta_h \sum e_j\right)^2}{\sum_{h=0}^{H-1} (e_i' \Theta_h \sum \Theta_h' e_i)}, \tag{4}$$

where $\theta_{ij}^{g}(H)$ is the generalized form of FEVD, Θ_h is the coefficient matrix multiplying the h −lagged shock vector in the infinite moving average representation of non-orthogonalized VAR, $\sum$ represents the covariance matrix of shock vector in the non-orthogonalized VAR model, σ_{jj} corresponds to the j^{th} diagonal element of covariance matrix, and e_j represents the selection vector with j^{th} element unity and zeros elsewhere. The $N \times N$ spillover index , $\theta_{ij}^{g}(H)$, is estimated by Equation 4, where each element in the matrix represents the contribution of asset j to the forecast error variance of asset i. Each of the diagonal elements of spillover index represents own-variable contribution, whereas, the off-diagonal elements indicates the cross-variable contribution. Since the own- and cross-variable shares of variance contribution do not sum to unity under the generalized decomposition, we normalize each entry of decomposed variance matrix by its row sum as:

$$\widetilde{\theta_{ij}^{g}}(H) = \frac{\theta_{ij}^{g}(H)}{\sum_{j=1}^{N} \theta_{ij}^{g}(H)}, \tag{5}$$

where $\sum_{j=1}^{N} \widetilde{\theta_{ij}^{g}}(H) = 1$ and $\sum_{i,j=1}^{N} \widetilde{\theta_{ij}^{g}}(H) = N$ by construction. The total spillover index (TVI) can be constructed using the contributions of return variations from the KPPS variance decomposition as:

$$s^{g}(H) = \frac{\sum_{\substack{i,j=1 \\ i \neq j}}^{N} \tilde{\theta}_{ij}^{g}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ij}^{g}(H)} \times 100 = \frac{\sum_{\substack{i,j=1 \\ i \neq j}}^{N} \tilde{\theta}_{ij}^{g}(H)}{N} \times 100 \tag{6}$$

The TVI reports the contribution of return spillover shocks across all markets to the total forecast error variance. Likewise, the directional return spillover received by market i from all other markets j, and directional return spillovers transmitted by market i to all other markets j, respectively, as:

$$s^g_{i\leftarrow j}(H) = \frac{\sum_{\substack{j=1 \\ j\neq i}}^N \tilde{\theta}^g_{ij}(H)}{\sum_{i,j=1}^N \tilde{\theta}^g_{ij}(H)} \times 100 = \frac{\sum_{\substack{j=1 \\ j\neq i}}^N \tilde{\theta}^g_{ij}(H)}{N} \times 100, \tag{7}$$

and

$$s^g_{i\rightarrow j}(H) = \frac{\sum_{\substack{j=1 \\ j\neq i}}^N \tilde{\theta}^g_{ji}(H)}{\sum_{i,j=1}^N \tilde{\theta}^g_{ji}(H)} \times 100 = \frac{\sum_{\substack{j=1 \\ j\neq i}}^N \tilde{\theta}^g_{ji}(H)}{N} \times 100. \tag{8}$$

In addition, we estimate the net spillover which is the difference between the shocks "transmitted to" and those "received from" other markets. The net spillover from asset i to all other assets j as:

$$S^g_i(H) = S^g_{i\rightarrow j}(H) - S^g_{i\leftarrow j}(H). \tag{9}$$

The net spillover analysis determines whether an asset is the transmitter or recipient of spillovers. Cointegration analysis and the spillover framework are both utilized to investigate the dynamic relationship between the FPI and stock prices.

Data and descriptive statistics

Our study utilizes weekly data of the fish pool index (FPI) and the seven major salmon producers in Norway. Our data spans from April 2011 to December 2018 with a total 401 weekly observations for each of the underlying series. The stock price data is obtained from Datastream.

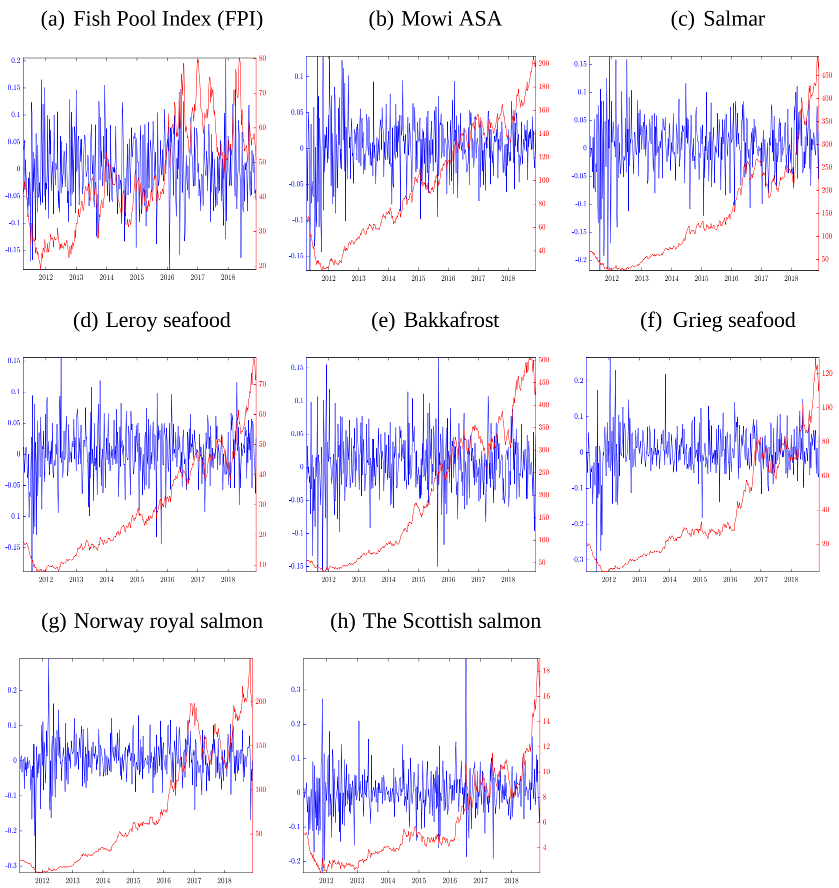
The FPI is constructed by the Fish Pool exchange as a weighted average of different bilateral salmon transactions prices. The weights have changed over time, tending towards fewer sampling points along the supply chain. The primary current sampling point is export prices from Norway. The current index weights 95% into an export price index provided by Nasdaq and 5% into a

Statistics Norway index based on customs declarations in Oslo. There is currently no buyer sampling in the index construction. The stated objective of the price index is to give a correct reflection of the current salmon market price, be possible to re-examine/verify, and remain transparent and neutral to all parties. The index is updated and released weekly. The FPI is the settlement price for the Fish Pool futures contracts.

The selected salmon producers are the following: Mowi ASA[1], Salmar, Leroy seafood group, Bakkafrost, Grieg seafood, Norway royal salmon, and the Scottish salmon.

[1] Mowi is previously known as Marine Harvest.

Figure 1. Development in prices and returns



Notes. The figure provides the development of prices and continuously compounded returns for FPI and the major salmon producers in Norway. All the price series are characterized by an increasingly upward trend post-2012. Furthermore, visual inspection suggest that all of the underlying series are non-stationary in levels and stationary at first difference.

Figure 1 presents the development of prices and continuously compounded returns for FPI and major salmon producers in the sample. The price series of all s producers exhibit an upward trend from mid-2012. The prices of nearly all stocks peaked towards the end of 2018. The FPI price peaked at 80.22 Norwegian Krone during the mid of 2018. The high salmon price can be attributed to strong demand for salmon and relatively stable supply due to regulatory production growth restrictions (Asche et al., 2019).

The continuously compounded return for each series is calculated as the logarithmic difference of two consecutive prices at time t and $t - 1$: $r_{i,t} = ln\left(\frac{P_{i,t}}{P_{i,t-1}}\right)$. Descriptive statistics of our data are presented in Table 1. The average annualized mean return and standard deviation for the FPI is 2.86% and 45.1%, respectively. The annualized mean return for salmon producers ranges from 13.97% (Mowi) to 29.23% (NRS) and the standard deviation varies from 30.7% (Mowi) to 47.0% (TSS). In terms of Sharpe ratio (SR), known as reward-to-risk measure, Bakkafrost provides the highest reward (0.774) relative to risk and TSS provides the lowest SR of 0.287.

Table 1. Descriptive statistics

	FPI	Mowi	Salmar	Leroy	Bakkafrost	Grieg	NRS	TSS
Mean	2.862	13.968	25.679	18.781	27.210	22.557	29.230	15.509
SD	0.451	0.307	0.369	0.311	0.326	0.443	0.409	0.470
SR	0.019	0.390	0.641	0.540	0.774	0.464	0.667	0.287
Max	0.205	0.128	0.164	0.156	0.166	0.266	0.291	0.391
Min	-0.186	-0.170	-0.218	-0.189	-0.158	-0.333	-0.319	-0.233
Skew	0.070	-0.398	-0.620	-0.434	-0.198	-0.373	-0.409	0.442
Kurt	3.223	4.413	5.372	4.620	4.472	7.513	7.470	7.210
JB STAT	1.151	43.850*	119.442*	56.308*	38.705*	348.684*	344.161*	308.432*
Q Stat	23.352*	23.882*	34.403*	28.083*	27.453*	27.514*	27.427*	25.093*
Q Stat1	18.719*	302.137*	195.706*	70.562*	55.819*	78.611*	52.031*	29.143*
ARCH	14.244*	119.547*	83.018*	62.070*	49.829*	57.855*	37.587*	25.044*
Panel A								
ADF	-0.536	2.283	3.363	2.640	1.693	2.226	1.147	1.729
PP	-0.485	2.186	3.507	2.660	1.684	2.209	1.208	1.653
ADF	-16.478*	-13.903*	-15.107*	-14.252*	-15.151*	-13.962*	-12.896*	-15.653*
PP	-19.821*	-21.292*	-21.683*	-21.475*	-22.516*	-20.421*	-20.375*	-23.575*

Notes. Annualized figures of mean and standard deviation are presented. SR represents the Sharpe ratio and J–B provides the t-statistics from the Jarque-Bera test of normality. Q(15) and Q2(15) represents the Ljung-Box test-statistics for serial autocorrelation with 15 lags of returns and squared returns. ARCH(15) provides the test-statistics of Engle (1982) test with 15 lags for conditional heteroscedasticity. The notation $*$, $**$, and $***$ indicates the rejection of null-hypothesis of normality, no autocorrelation, and conditional homoscedasticity at the 1%, 5%, and 10% threshold level.

The distribution of returns for nearly all assets exhibits negative skewness with exception of FPI and TSS, which are positively skewed. Furthermore, the values of kurtosis are above 3 for all assets. These findings indicate that returns are predominantly negatively skewed and exhibit leptokurtic distributions. The t-statistics from a formal Jarque-Bera test strongly rejects the null-hypothesis of normality for all the assets and affirms the non-Gaussian distribution. The test-statistics from Ljung-Box portmanteau test with 15 lags of returns and squared returns are significant rejecting the null-hypothesis of independence. The ARCH test Engle (1982) with 15 lags are significant at 1% threshold level thus rejecting the null-hypothesis of homoscedasticity.

Panel A and B of Table 1 provide estimates of Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) unit root tests on prices and returns for all the assets. Both the ADF and PP tests fail to reject the null-hypothesis of unit root, but first differences support stationarity.

Empirical Results

We first examine the cointegration relation among the FPI and the salmon producers. We then employ the static and temporal spillovers to evaluate the dynamics of connectedness among the assets.

Cointegration analysis

The output from the bivariate cointegration analysis is presented in Table 2. The first four columns present test statistics and p-values for the Maximum Eigenvalue and Trace test of the null-hypothesis of zero and one cointegrating rank, respectively. The next two columns report test statistics for the null that the respective series do not adjust to deviations from long-run equilibrium. The final column reports the obtained long-run relationship parameter β for the respective salmon producer.

Both cointegration tests reject the null of no cointegrating vectors in the relationships between the FPI and the salmon producers at the 5% significance level, except for the Scottish Salmon that produce higher p-values and ultimately does not reject the null-hypothesis. The tests do not reject the null of one cointegration vector at the 5% significance level. Therefore, all underlying price series are cointegrated and follow the same stochastic trend over the sample period.

The speed of adjustment parameter (α) for company stock prices fail to reject the null-hypothesis of no-adjustment, or long-run weak exogeneity.[2] However, the null-hypothesis for the FPI is rejected in all cases. As such, the FPI is long-run endogenous, adjusting to deviations from the long-run relationship between salmon stock prices and the price index. For instance, an increase in company valuation relative to the current price index predicts an increase in the next week price index. The long-run relationship parameter suggests a positive relationship between the stock market value of salmon companies and the FPI at the 1% significance level.

[2] With exception of The Scottish salmon, which rejects the null-hypothesis complete price transmission. Whereas, the test-statistics for that of Norway Royal salmon is marginally insignificant.

Table 2. Bivariate Johansen cointegration tests

Fish Pool Index	Cointegrating vectors = 0		Cointegrating vectors = 1		Speed of adjustment (α)		Long-run relationship
	Max Eigen	Trace	Max Eigen	Trace	FPI	Producers	
Mowi	22.485***	22.487***	0.001	0.001	-0.094***	-0.008	0.545***
	(0.003)	(0.004)	(0.973)	(0.973)	(0.000)	(0.571)	(0.000)
Salmar	15.771***	16.041***	0.27	0.27	-0.077***	0.013	0.368***
	(0.029)	(0.041)	(0.722)	(0.722)	(0.000)	(0.405)	(0.000)
Leroy	18.039***	18.143***	0.104	0.104	-0.085***	0.001	0.501***
	(0.012)	(0.020)	(0.785)	(0.785)	(0.000)	(0.921)	(0.000)
Bakkafrost	19.124***	19.271***	0.147	0.147	-0.079***	-0.015	0.35***
	(0.008)	(0.013)	(0.769)	(0.769)	(0.000)	(0.240)	(0.000)
Grieg	16.172***	16.191***	0.019	0.019	-0.074***	0.0283	0.33***
	(0.025)	(0.039)	(0.890)	(0.890)	(0.000)	(0.157)	(0.000)
NRS	20.015***	20.04***	0.024	0.024	-0.081***	0.037*	0.287***
	(0.006)	(0.010)	(0.876)	(0.876)	(0.000)	(0.051)	(0.000)
TSS	12.298	12.864	0.567	0.567	-0.035**	0.042**	0.499***
	(0.100)	(0.120)	(0.609)	(0.609)	(0.034)	(0.015)	(0.000)

Notes. This table presents the estimates of bivariate Johansen cointegration between Fish Pool Index (FPI) and each of the salmon producers. ***, **, and ** represent the significance at 1%, 5%, and 10% threshold level, respectively. p−values are presented in parenthesis. We assume the presence of intercept in the cointegrating vector and there are linear deterministic trends in the levels of underlying data series.

Total spillover index

Table 3 present the total spillover index of returns among the FPI and major salmon producers. Based on the lowest values of Akaike-Information-Criterion (AIC) and highest values of Loglikelihood (LogL), the vector autoregression (VAR) of order 1 is determined to better capture the return dynamics. Therefore, the static spillovers are based on VAR(1) and 15-weeks-ahead forecasts error variance decomposition.

Before discussing the outcomes of spillover index, we briefly describe the elements of the index. Application of DY frameworks yields a $N \times N$ matrix of directional connectedness $\left(\theta_{ij}^{g}(H)\right)$. The off-diagonal entries, $i \neq j$, represents the spillovers caused due to variations in other markets. The diagonal entries, $i = j$, represents the self-caused variations within a market. Each entry (i, j) of the spillover index corresponds to the estimated contribution of innovation in market j to the FEVD of market i. Based on the spillover index, we estimate four additional statistics: “From others” (Eq. 7), “To others” (Eq. 8), “Net spillovers” (Eq. 9), and “Volatility spillover index” (Eq. 4).

The return spillover index among the underlying series is presented in Table 3, which is decomposed further into transmitters and receivers of spillover. Furthermore, it also provides estimate of net spillover, which is estimated as the difference between information transmitted and information received. The total return spillover index indicates that an average of 52.56% of return forecast error variance derives from other assets in the sample. With respect to bidirectional net return spillover, the three largest salmon producers are the main transmitters of information to the FPI and other salmon producers, contributing 14.99%, 13.41%, and 10.77% to the returns of the other assets, respectively. Among the largest net receivers are FPI, TSS, and NRS, which in net terms receive an average of 30.66%, 9.71%, and 3.34% spillover from other assets in the sample. These estimations of spillovers are based on static full sample analysis.

Table 3. Static spillover index

	FPI	Mowi	Salmar	Leroy	Bakkafrost	Grieg	NRS	TSS
FPI	66.947	5.376	5.616	7.571	4.112	5.076	2.939	2.363
Mowi	0.009	38.285	13.623	15.024	7.435	13.424	7.318	4.881
Salmar	0.238	13.764	39.256	17.067	11.240	8.483	6.323	3.629
Leroy	0.024	15.300	16.739	38.285	9.187	9.551	6.664	4.251
Bakkafrost	0.758	9.032	13.311	11.193	46.688	6.491	7.355	5.172
Grieg	0.034	15.052	8.945	10.685	5.945	41.567	11.922	5.852
NRS	0.292	9.697	7.772	8.489	7.679	13.660	48.398	4.015
TSS	1.041	6.905	5.510	6.675	5.662	8.342	5.741	60.125
To others	2.395	75.126	71.515	76.704	51.258	65.027	48.260	30.163
From others	33.053	61.715	60.744	61.715	53.312	58.433	51.602	39.875
Net spillover	-30.657	13.411	10.771	14.990	-2.053	6.594	-3.342	-9.712
Volatility spillover index:								52.556

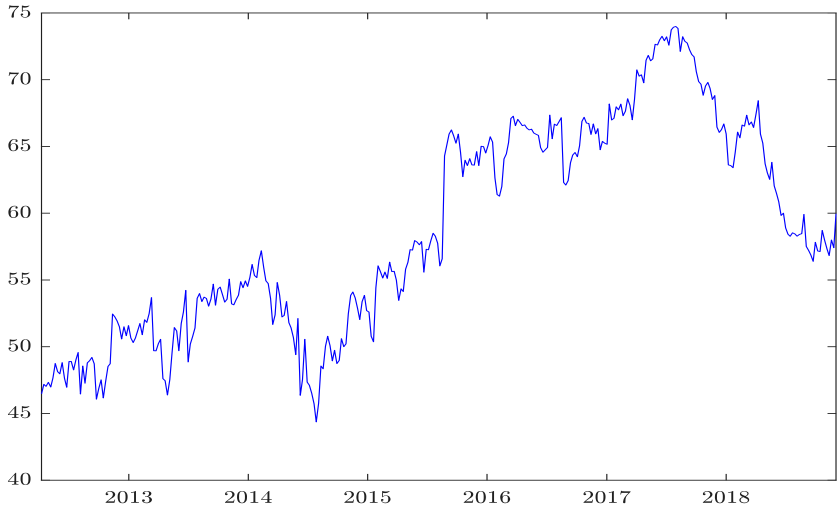
Notes. This table presents all the possible bivariate relations of directional spillover between FPI and the salmon producers.

Temporal spillover analysis

The total spillover index provides an overview of the time variation in connectedness among the assets. It is well documented in the literature that the temporal uncertainty can significantly influence the connectedness structure. Satic spillover estimates might ignore stylized facts (e.g. price and volatility jumps, aggregational Gaussianity, and volatility clustering), which may be due to systematic (Chile's algae blooms in 2016) or idiosyncratic (production inefficiencies) events. Such events influence the intensity and direction of connectedness between FPI and salmon producers.

Figure 2 present the time-varying development of return connectedness over the sample period based on 52-week rolling window and 10-step-ahead forecast horizons. We observe an upward trend in total connectedness over the period from 2012 to mid-2017, while it gradually declines to below 60% level during 2018. The general increase in connectedenss implies a greater importrance of common information on pricing among salmon companies and a tighter connection to the FPI. Sea lice infestation in Norway and algae blooms in Chile have contributed to stagnating production while demand form salmon has remained strong, contributing to rising prices. It is noteworthy that while the static total return spillover index is 53%, the time-varying spillover fluctuates from 45% to 75%.

Figure 2. Total spillover index



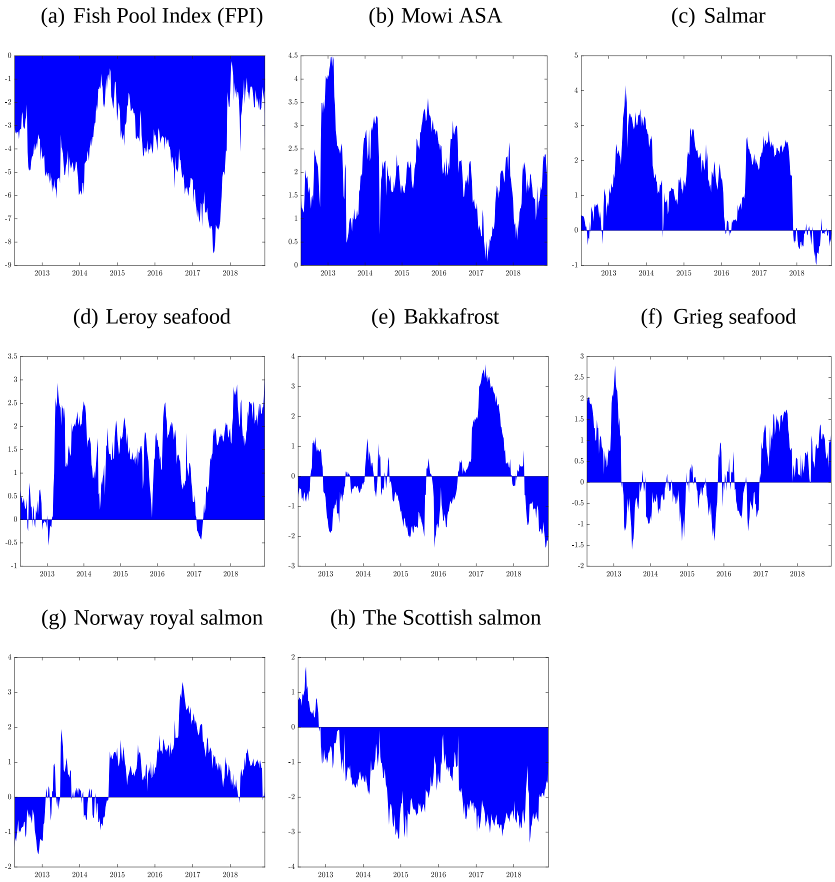
Notes. The figure provides the temporal development of total return spillover index estimated from the forecast error variance decomposition of 52-week rolling window and 10-step ahead forecast horizon.

Net spillovers

The time-varying total spillover index provides an estimate of the overall development of connectedness among the FPI and the salmon company stock prices. However, it hides information on whether the spillover is caused primarily by the FPI or the returns of salmon producers. To examine whether an underlying asset is a net transmitter or receiver of shocks, we estimate net return spillovers.[3]

[3] For the sake of brevity, we only report the net directional return spillovers as it provides an estimate of both 'to others' and 'from others'. The estimates of 'to others' and 'from others' are available from authors upon request.

Figure 3. Dynamic return spillover



Notes. The figure provides the development of net return spillovers among FPI and major salmon producers with a 52-weeks rolling window and 10-step-ahead forecast horizon. Positive (negative) values in each graph indicate that the underlying asset is net transmitter (receiver) of information.

Figure 3 illustrates the temporal development of net return spillover for each of the asset in the sample. The net spillover is estimated as the difference between information transmitted and information received (Eq. 9). The positive or negative values of each asset indicate that the underlying asset is a net transmitter or receiver of shocks, respectively. The FPI is consistently a net receiver of information as it receives more than it transmits to stock prices. Similar to total spillover index, the net spillover to FPI declines during 2014 due to relatively stable demand and supply. The net spillover to FPI gradually increases and peaks in the mid-2017.

The largest salmon producers are the primary sources of information spillover to the FPI and smaller producers. These findings are in-line with the results of the cointegration analysis.

Concluding Remarks

This paper investigates the cointegration and return spillover dynamics among the fish pool index and stock prices of major salmon producers over the period between April 2011 and December 2018. To the best of our knowledge, this is the first empirical paper to study market integration and spillover dynamics using firm-level stock price data from major salmon producers and the FPI.

The empirical results show that the FPI and all stock prices of major salmon producers are cointegrated and share a common stochastic trend over the sample period. Furthermore, we find that stock prices provide predictive information on the FPI. Stock prices contain information on the markets assessment of future salmon prices. The FPI on the other hand is constructed from actual bilateral salmon transaction prices along the salmon supply chain. As salmon is a consumption price, the index reflect current supply and demand conditions. As such, our results reveal how asset prices reflecting forward looking assessments of the market for the underlying seafood product can provide information on the dynamics of seafood product when the product itself to a lesser degree reflects forward looking market conditions.

Our findings also show that spillovers are asymmetrical and bidirectional in the case of small- to medium-sized firms. The FPI and small- to medium-size salmon firms are primarily the net receivers of spillovers from the largest salmon companies. Since the larger companies appear to provide better predictive information on future index prices, this might threaten the perceived unbiasedness of the price index used to settle futures contracts. Indeed, most salmon producers appear to favor bilateral contracting to deal with price risk, and participation in the futures exchange has been relatively weak. Furthermore, if the futures settlement price reflects outdated market information, i.e. lagged transaction prices, the hedging efficiency of the contracts will be lower.

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