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Economic policy uncertainty and grain prices volatility

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ABSTRACT. *This paper applies TVP-VAR-based connectedness approach proposed by Antonakakis and Gabauer (2017) to identify and analysis the relationship between EPU and grain prices in seven countries over the period 2003:01-2019:02. The results of estimation suggest total connectedness index in the seven countries are time-varying and presented a significant spike during the Great Depression. Furthermore, any variables can be the net transmitter or net recipient of the spillover shock depending on the time period and grain trade situation. These results are important for policy makers, as well as, investors interested in the grain trade market.*

KEYWORDS: *Economic policy uncertainty; Grain prices; Dynamic spillover; TVP-VAR model; Connectedness decomposition*

1. Introduction

The notion of “Food is the first thing for people “is the most and essential idea in Chinese Civilization Life. In recent years, the anti-globalization trends has led to the emergence of trade protectionism which has exacerbated the global economic uncertainty and grain prices volatility. So in this paper, we addresses an important question, that is, the relationship between grain prices and the economic uncertainty index. To achieve that, we apply the TVP-VAR-based connectedness proposed by Antonakakis and Gabauer (2017).

First of all, we need to figure out the development of economic policy uncertainty. Since the 2008 Global Financial Crisis, uncertainties related to the economy and government policies have been highly valued by the academia and policymakers and have been “rediscovered” in theory (Antonakakis and Gabauer, 2018). Therefore, it is an important basic work to measure the macroscopic uncertainty effectively. Constructing appropriate macroscopic uncertainty indicators will enhance a central bank’s transparency and promote central bank strives to meet its goals (Reifschneider and Tulip, 2018). Simultaneously, a series of uncertainty measures have emerged (see, f or example, Bloom (2009), Bekaert et al (2013), Bechmann et al (2013), Jurado et al (2015). This is an important line of research, Alexopoulos and Cohen (2009) took the lead to build an economic uncertainty index

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based on the data of *New York Times*. After that, Baker et al. (2013) developed the economic uncertainty policy index (EPU), and their innovative approach relies in large part on automated text-search process of 10 large US newspapers. Based on this method, Baker also established EPU index for other countries such as the United Kingdom, China, Brazil and Canada and so on, which provides a good source of data for scholars to study economic policy uncertainty (Bali et al. 2017).

What factors have caused the volatility of agricultural market prices? The problem is important because policies to stabilize agricultural markets must consider the sources of volatility in the industry (Lapp, 1990).The literature on causes of price volatility in agricultural markets is large. On the one hand, Baffes and Haniotis (2016) suggest that the most influential volatility factors are stock levels, oil price and exchange rate movements. Tadesse et al. (2014) explore empirical evidence on the quantitative importance of supply, demand and market shocks for international food price changes. Brummer et al. (2016) examine the effect of oil price, exchange rates and weather shocks as exogenous determinants. There are some scholars focus on the theory of competitive storage. Cafiero et al. (2011) got conclusion of stock data are effective indicators of price vulnerability. Gil (2012) suggest that storage contribute to price fluctuations. On the other hand, numerous studies investigate the effects of imports and exports on grain price volatility ((Martin and Anderson 2011; Anderson 2012; Anderson and Nelgen 2012; Gouel 2013, 2016; Ivanic and Martin 2014; Rude and An 2015; Pieters and Swinnen 2016; Santeramo and Lamonaca 2019) and conclude that trade policies intended to reduce exports increase domestic and global price volatility.

In addition to the above factors, price volatility is also related to economic policies closely such as monetary policy and trade policy. At least from 1974, Schuh raised that interest has continuous effects of monetary policy on agricultural markets. After that, more and more studies have pay attention to the impact of macroeconomic policies on agriculture (e.g., Chambers and Robert, 1982; Dorfman and Lastrapes, 1996; Awokuse, 2005). Most recent studies have focused on the extent and direction of the impact of monetary policy on agricultural prices. Kown and Koo (2009) suggest that the unexpected movements of the exchange rate and interest rate are the main macroeconomic shocks to cause agricultural fluctuation. Furthermore, Martin and Anderson (2011) raised that the agricultural trade policies which is aiming at stabilizing price fluctuations may amplify price volatility. Moreover, macroeconomic policies can make an influence on the agricultural sector through domestic channels (Saghaian et al., 2002) and international channels (Orden, 2002).

From the above literature, we can find that economic policy is an important driving factor affecting price fluctuations in agricultural markets. In order to examine these spillover effects between grain price volatility and economic uncertainty index, first we need to figure out their relationship. Four of the most important grain products in the world are corn, rice, wheat and soybean, which are important source of raw materials (Correa and Oliveira, 2014). In other words, these four major grain are closely related to the economic activities. Fabio and Santeramo (2019) distinguish the drivers of grain price volatility in market based drivers and

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external shocks. The shocks generated by demand or supply and the arbitrage by spatial and temporal via trade are market based drivers (Santeramo et al.2018). Examples of external shocks may be the trend in oil prices, exchange rates and the influence of policy intervention (Tadesse et al.2014). As it is understood, previous research has established that the economic policy uncertainty affect grain price by external shocks via trade, exchange rates or policy intervention and so on.

Against this backdrop, we revisit the relationship between the grain price volatility and the EPU index, and add to the literature along the following dimensions:

(a) This is the first study to undertake a longitudinal analysis of the relationship between the grain price and the economic policy uncertainty of seven countries: the United States, Brazil, China, Canada, Russia, India and Australia. There are two reasons for choosing the seven countries: on the one hand, the grain market is not a perfectly competitive market because it is characterized by a high concentration of production, trade, and consumption in few countries (Fabio and Emilia, 2019). That means some tiny changes in domestic economic markets may generate great impacts on international grain price. Therefore, we concentrate on the world's top ten grain exporters and importers and finally select seven representative countries above based on the availability on EPU index (Baker et al., 2013). On the other hand, the agricultural products are very important to economies of several countries, where these output value account for a large percent of the GNP (Gross National Product). Research in this area has shown that agricultural activities are the backbone of many economic systems. For example, assets of agricultural commodities account for 7.3% of the GNP in Brazil (Correa et al, 2015). Australia is also a large agricultural country, with agricultural assets accounting for 12% of GDP.

(b) To the best of our knowledge, this is the first attempt to analyze the relationship between economic uncertainty and grain price volatility, using a TVP-VAR-based connectedness approach, which is full-fledged time-varying parameter vector autoregression (TVP-VAR) suggested by Antonakakis and Gabauer (2017). This approach is based on the methodology of Diebold and Yilmaz(2012) considerably, and it has the following innovations:(1) There is no need to arbitrarily set the rolling window size; (2)There is no loss of observations;(3) It is not outlier sensitive.

Based on the aforementioned analysis, we argue that conditional on a relationship that exists between grain prices and the economic policy uncertainty index, the following hypotheses can be formulated:

Hypothesis 1: Spillover effects from economic policy uncertainty to grain prices exist. Specifically, policy uncertainty has a direct effect on demand and supply for grain, which further affect import and export for grain and thus its international price.

Hypothesis 2: Spillover effects from grain prices to economic policy uncertainty also exist. In particular, we postulate that negative influence of grain prices on economic activity exists difference between four kinds of grain and put extra

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pressure on policy decision making, which finally leads to increased economic policy uncertainty.

Hypothesis 3: Spillover effects between grain prices and economic policy uncertainty are time-varying and exist regional variation. We put forward the argument that dynamic spillover effect can be explained by different economic- and grain-related events that take place at different time periods.

In this regard, the main contribution of this paper to the existing literature as (i) it is the first the estimate time -varying spillover effects between grain prices and economic policy uncertainty, (ii) it investigates the effects of different countries' economic policy uncertainty on international grain prices and (iii) it adds to the limited number of studies pertaining to Baker et al. (2013) economic policy uncertainty index.

The reminder of the paper is organized as follows. Section 2 details the methodology used in the study. Section 3 describes the data. Section 4 presents and discusses the empirical results while Section 5 summarizes the findings and draws some conclusions for future research.

2. Methodology

2.1 TVP-VAR

In order to explore the relationship between grain prices and economic policy uncertainty in a time-varying fashion, we use the TVP-VAR methodology of Antonakakis and Gabauer (2017). This method extends the originally proposed connectedness approach of Diebold and Yilmaz (2009, 2012), by allowing the variances to vary via a stochastic volatility Kalman Filter estimation with forgetting factors used in Koop and Korobilis (2014). By doing so, it overcomes the shortcoming of the often arbitrarily chosen rolling-window size, which could lead to very unstable or flattened parameters. In particular, the TVP-VAR model can be written as follows,

$$\square_{\square} = \square_{\square}\square_{\square-1} + \square_{\square} \qquad \square_{\square}|\square_{\square-1} \sim \square(0, \square_{\square}) \qquad (1)$$

$$\square\square\square(\square_{\square}) = \square\square\square(\square_{\square-1}) + \square_{\square} \qquad \square_{\square}|\square_{\square-1} \sim \square(0, \square_{\square}) \qquad (2)$$

where $\square_{\square}$ is an $N\times 1$ dimensional vectors, $\square_{\square-1}$ represents an $\square_{\square} \times 1$lagged dimensional vectors, $\square_{\square}$ is an $\square \times \square_{\square}$ dimensional time-varying coefficient matrix and $\square_{\square}$ is an $N\times 1$ dimensional error disturbance vector with an $\square \times \square$ time-varing variance-covariance matrix, $\square_{\square}$. $\square_{\square}$ depend on $\square_{\square-1}$ and on an $\square \times \square_{\square}$ dimensional error matrix with an $\square_{\square} \times \square_{\square}$ variance-covariance matrix.

In order to calculate the generalized impulse response functions (GIRF) and generalized forecast error variance decomposition (GFEVD) (Koop et al., 1996; Pesaran and Shin,1998), we convert the its vector moving average (VMA) representation:

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$\square_{\square} = \square_{\square}\square_{\square-1} + \square_{\square}$ (1)

$\square_{\square} = \square_{\square}\square_{\square}$ (1)

$\square_{0,\square} = \square$ (1)

$\square_{\square,\square} = \square_{1,\square}\square_{\square-1,\square} + \square_{2,\square}\square_{\square-2,\square} + \cdots + \square_{\square,\square}\square_{\square-\square,\square}$ (1)

Where $\square_{\square} = [\square_{1,\square},\cdots,\square_{\square,\square}]', \square_{\square} = [\square_{1,\square},\cdots,\square_{\square,\square}]'$ .So $\square_{\square,\square}$ and $\square_{\square,\square}$ are $\square \times \square$ dimensional matrix.

The GIRFs represent the responses of all variables following a shock in variable $\square$. Since we do not have a structural model, we compute the differences between a J-step-ahead forecast where once variable $\square$ is shocked and once where variable $\square$is not shocked. The difference can be accounted to the shock in variable $\square$, which can be calculated by

$\square\square\square\square_{\square}(\square,\square_{\square,\square},\square_{\square-1}) = \square(\square_{\square+\square}|\square_{\square,\square} = \square_{\square,\square},\square_{\square-1}) - \square(\square_{\square+\square}|\square_{\square-1})$ (5)

$\square^{\square}_{\square,\square}(\square) = \frac{\square_{\square,\square}\square_{\square}\square_{\square}\square_{\square,\square}}{\sqrt{\square_{\square\square,\square}}}\frac{\square_{\square,\square}}{\sqrt{\square_{\square\square,\square}}} \quad \square_{\square,\square} = \sqrt{\square_{\square\square,\square}}$ (6)

$\square^{\square}_{\square,\square}(\square) = \frac{\square_{\square,\square}\square_{\square}\square_{\square,\square}}{\sqrt{\square_{\square\square,\square}}}$ (7)

Where the variable $\square$ and $\square$ represents the forecast horizon, $\square_{\square,\square}$ the selection vector with one on the $\square$th position and zero otherwise, and $\square_{\square-1}$ the information set until $\square - 1$. Afterwards, we compute the GFEVD that can be explained as the variance share one variable has on others. Mathematically, this is calculated as follows

$\tilde{\square}^{\square}_{\square\square,\square}(\square) = \frac{\sum_{\square=1}^{\square-1}\square^{2,\square}_{\square\square,\square}}{\sum_{\square=1}^{\square}\sum_{\square=1}^{\square-1}\square^{2,\square}_{\square\square,\square}}$ (8)

With $\sum_{\square=1}^{\square}\tilde{\square}^{\square}_{\square\square,\square}(\square) = 1$ and $\sum_{\square,\square=1}^{\square}\tilde{\square}^{\square}_{\square\square,\square}(\square) = \square$. Using he GFEVD, we construct the total connectedness index(TCI) by

$\square^{\square}_{\square}(\square) = \frac{\sum_{\square,\square=1,\square\neq\square}^{\square}\tilde{\square}^{\square}_{\square\square,\square}(\square)}{\sum_{\square,\square=1}^{\square}\tilde{\square}^{\square}_{\square\square,\square}(\square)} * 100$ (9)

$= \frac{\sum_{\square,\square=1,\square\neq\square}^{\square}\tilde{\square}^{\square}_{\square\square,\square}(\square)}{\square} * 100$ (10)

This connectedness approach shows how a shock in one variable spill over to other variables. First, we look at the case where variable $\square$ transmits its shock to all other variables $\square$, called total directional connectedness to others and defined as

$\square^{\square}_{\square\rightarrow\square,t}(\square) = \frac{\sum_{\square=1,\square\neq\square}^{\square}\tilde{\square}^{\square}_{\square\square,\square}(\square)}{\sum_{\square=1}^{\square}\tilde{\square}^{\square}_{\square\square,\square}(\square)} * 100$ (11)

Second, we compute the directional connectedness variable $\square$ receives it from variables $\square$, called total directional connectedness from others and defined as

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$$\square^{\square}_{\square\leftarrow\square,t}(\square) = \frac{\sum^{\square}_{\square=1,\square\neq\square}\tilde{\square}^{\square}_{\square\square,\square}(\square)}{\sum^{\square}_{\square,\square=1}\tilde{\square}^{\square}_{\square\square,\square}(\square)} * 100 \qquad (12)$$

Finally, we subtract *total directional connectedness to others* from *total directional connectedness from others* to obtain the influence of variable $\square$ on the whole variables' network.

$$\square^{\square}_{\square,\square} = \square^{\square}_{\square\rightarrow\square,t}(\square) - \square^{\square}_{\square\leftarrow\square,t}(\square) \qquad (13)$$

The value of $\square^{\square}_{\square,\square}$ illustrates if variable $\square$ is driving the network ($\square^{\square}_{\square,\square}$>0) or driven by the network ($\square^{\square}_{\square,\square}$<0). Finally, we examine the bidirectional relationship by computing the net pairwise directional connectedness (NPDC),

$$\square\square\square\square_{\square\square}(\square) = \frac{\tilde{\square}^{\square}_{\square\square,\square}(\square) - \tilde{\square}^{\square}_{\square\square,\square}(\square)}{\square} * 100 \qquad (14)$$

2.2 Connectedness decomposition

Since we are analyzing the spillovers between seven countries, we are interested in how much of those spillovers is transmitted from one country to another. The breakdown of $\square$ countries can be explained as follows:

$$\varphi(J) = \left[\tilde{\square}^{\square}\right]_{\square\square} = \begin{bmatrix} \square_{11} & \square_{12} & \cdots & \square_{1\square} \\ \square_{21} & \square_{22} & & \square_{2\square} \\ \vdots & & \ddots & \vdots \\ \square_{\square 1} & \square_{\square 2} & \cdots & \square_{\square\square} \end{bmatrix}$$

where $\square_{\square\square}$ includes the internal spillovers of country $\square$ and $\square_{\square\square}$ represents the spillovers of country $\square$ to country $\square$. In a next step, to compute the internal and external spillovers we set $\mathrm{diag}(\square_{\square\square}) = 0$ and compute:

$$\square\square_{\square\square} = \sum_{\square=1}^{\square} \square_{\square\square,\square\square}$$

$$\square\square\square\square_{\square\square} = \sum_{\square=1}^{\square} \square_{\square\square,\square\square}$$

$$\square\square\square_{\square\square} = \square\square_{\square\square} - \square\square\square\square_{\square\square}$$

Where $\square\square_{\square\square}$ is the *total country-specific connectedness to others*, $\square\square\square\square_{\square\square}$ is the *total country-specific connectedness from others*, $\square\square\square_{\square\square}$ is the *net total country-specific connectedness*.

3. Data

In this study we use monthly data from January 2003 to February 2019 of the economic policy uncertainty indices for: the United States, Brazil, China, Canada, Russia, India and Australia. The series come from Baker et al. (2013), whereas the

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data for the EPU index have been retrieved from the website http://www.policyuncertainty.com. It is worth noting that the choice of countries, as well as, the sample period are directed by the availability of data provided by Baker et al.(2013). Despite the fact that our study could be limited to countries such as the United States, Brazil, Canada, China and India, this is motivated by our conviction that these countries represent a sizeable portion of the global agricultural economy due to the high concentration of grain market (Fabio and Emilia,2019).

In addition, monthly data for the same period have been collected for corn prices, rice prices, soybean prices and wheat prices, which are used for the estimation of grain prices. Data for the four grain prices have been extracted from the International Monetary Fund. As we all know, grain prices are different from other commodities' price because of the seasonality effect. In order to eliminate the effect, we use the X-12-ARIMA seasonal adjustment program which is an enhanced version of the X-11 Variant of the Census. Table 1 reports the source and description of the grain prices.

Table 1 Description of grain prices

series	description	sample	frequency	unit	source
Corn	U.S. No.2 Yellow, FOB Gulf of Mexico, U.S. price	2003m1-2019m2	Month	USD/t	International Monetary Fund
Rice	5 percent broken milled white rice, Thailand nominal price quote	2003m1-2019m2	Month	USD/t	
Soybean	U.S. soybeans, Chicago Soybean futures contract (first contract forward) No. 2 yellow and par	2003m1-2019m2	Month	USD/t	
Wheat	No.1 Hard Red Winter, ordinary protein, Kansas City	2003m1-2019m2	Month	USD/t	

Table 2 represents the descriptive statistics of all variables. To generate stationary time series, we first apply the Z-score method to standardize all data. Then, the first-difference estimator approach is applied to adjust the nonstationary sequence according to the ADF unit root test-statistics. Finally, as evident in Table 2, all variables are stationary, showing that there is no cointegrating relationship between the underlying series. It is worth noting that India and Brazil exhibit the lowest and highest mean values respectively. With regard to skewness and kurtosis, we observe that China EPU, India EPU, soybean prices and wheat prices are skewed to the left, all series are leptokurtic distribution which displays greater kurtosis than a mesokurtic distribution. Furthermore, none of the series is normally distributed, as indicated by the skewness and kurtosis.

Table 2: Summary Statistics

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	Mean	Variance	Skewness	Kurtosis	ADF	Obs
Brazil.epu	0.291	1.153	1.917	5.515	-4.017***	182
Canada.epu	0.236	1.169	0.781	0.088	-3.722***	182
US.epu	0.156	1.075	0.930	0.670	-7.221***	182
China.epu	0.028	0.312	-0.253	1.722	-10.479***	182
India.epu	-0.001	0.567	-0.238	3.890	-9.582***	182
Austrilia.epu	0.053	1.121	1.389	1.930	-6.842***	182
Eussia.epu	0.169	0.93	1.003	0.448	-3.460***	182
Corn	0.005	0.035	0.911	8.284	-8.986***	182
Rice	0.007	0.059	4.457	45.920	-10.651***	182
Soybean	0.005	0.034	-0.166	2.455	-8.710***	182
wheat	0.001	0.068	-0.010	4.570	-16.463***	182

*Note: ADF denotes Augmented Dickey Fuller test with 10%, 5% and 1% critical values respectively. *, ** and *** indicate significance at 10%, 5% and 1% respectively.*

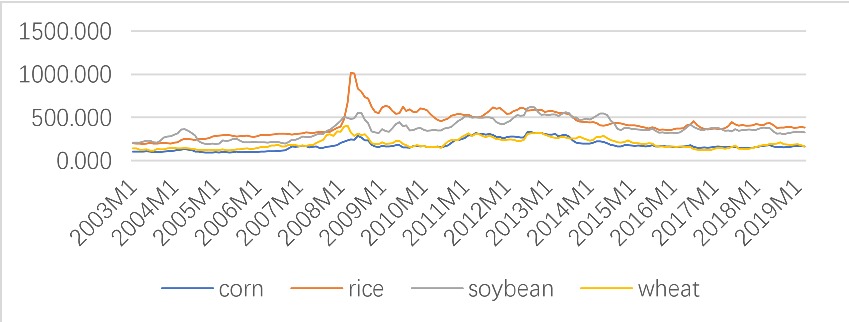

Figure 1 Grain prices

Figure 1 exhibits the evolution of international grain prices for corn, rice, soybean and wheat during the sample period. As shown in Figure 1, international grain prices have been increasing in a comparatively stable way until the spikes experienced during 2007-2008 and the following spikes noticed during 2010-2011. There is a large number of studies (e.g.,Serra,T.,2011) have shown that the price of crude oil and the demand for bio-energy are the main causes of international grain prices fluctuations, and there is a positive correlation between energy prices and food prices (Nazlioglu,S. 2012,Ciaian,P., 2010). Moreover, the figure displays a large extent of comovement between these four grain prices during the sample period, with an obvious similarity between the prices of corn and wheat.

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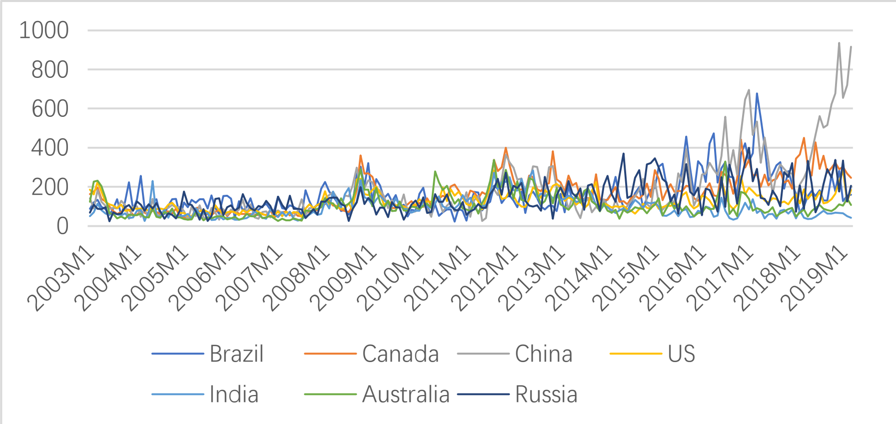

Figure 2 Economic Policy Uncertainty indices

As is illustrated in figure 2, we can find that China's EPU index shows a significant fluctuation from 2018, which is largely caused by trade friction between the United States and China. In addition, all economic policy uncertainty indices exist some common peaks. For instance, we notice an common increase in all countries of the economic policy uncertainty index during the Great Recession (2007-2009) and the European Debt crisis (2011), indicating the obvious increase of economic uncertainty during turbulent or recessionary economic periods. Finally, the effects of the Great Recession (2007-2009) can also be observed on grain prices changes, which significantly declined in 2009.

4. Empirical Results

As we observe from Fig.1, the dynamic total connectedness index (DTCI) of the system has an obvious time-varying tendency. There are four spikes can be observed around 2004, 2008, 2011 and 2018, justifying the choice of a time-varying approach. The first significant spike is observed in 2004 when the rise of grain prices was triggered by the increase of international crude oil prices or maybe the war in Afghanistan and Iraq . In addition, the spike may be related to the interest rate hike in the U.S., China and Australia because of the inflation. As is known to all, the world economy experienced a great recession during 2008-2009, which aggravated economic uncertainty and commodity price volatility. Thus, the second spike is easy to understand. Furthermore, it is possibly associated with the European debt crisis with the later reaching peak in 2011. Finally, the world has suffered trade wars, stock market crash and the fluctuating oil prices which has attracted the last spike in this figure. Overall, according to these spikes, we can draw a conclusion that the DTCI of the system grow rapidly after being subjected to external shocks.

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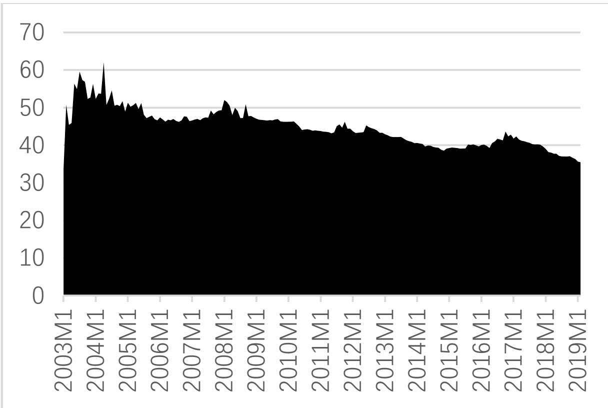

Figure 3 Dynamic total connectedness index

Figure 4 visualizes the main transmission mechanism of this network. The relationship between variables and the system can be observed from the positive and negative values of Net total directional connectedness(net). Specifically, note that positive values correspond to net transmitters of shocks, while negative values correspond to net receivers. It can't be ignored that rice prices and corn prices are driven by the system basically, while soybean prices and wheat prices has gradually converted to net transmitter from 2013.

First of all, we turn to the net total directional connectedness of EPU indices in the seven countries. Prominent among the results illustrated in Fig.4 is the fact that Canada EPU and the US EPU are, for the most, a net transmitter of shocks. These two countries net total directional connectedness of EPU indices show some interesting information, there are four distinct fluctuation can be observed around 2004, 2008, 2011 and 2018 which is same with the dynamic total connectedness index. Overall, the net total directional connectedness of the US.EPU and CAN.EPU has shown a downward trend. As can be seen from the figure 5 and figure 6, the main reason for downward is that the influence from others is decreasing. In other words, the impact of the United States and Canada on other elements in system is gradually increasing. About Australia, it is a net transmitter in the last ten years.

With regard to the Brazil EPU, it's obvious that Brazil has been driven by the system over the period from 2006 to February 2019, which is similar to Russia. China is more passive than the above three countries, by contrast, is a net receiver on the whole, which can be explained as the fact that China is a net importer of corn, rice, soybean and wheat. That means basically it is totally affected by changes in international grain prices. Last but not least, net total directional connectedness of India EPU presents a special trend, it turned into a net transmitter since 2017 due to the success of India's second agricultural "green revolution".

Fig.5 and Fig.6 report the total directional connectedness FROM and TO others. In Figure 5, we can find the total directional connectedness from the US EPU, which

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has a similar average value and trend with Canada and Australia. In addition, it is obvious that the total directional connectedness from China is basically same with India, with the lower average value. Turning to the effect from grain prices, we notice that for corn, soybean and wheat prices, in the sample period, fluctuate within a range around 5, which are high than rice prices. However, in order to provide a more in-depth analysis of the results, we proceed with reporting the total directional connectedness to others. Interestingly, the shock from the system to the US is still very significant, so we infer that the US EPU is a proactive transmitter to others as well as a receiver from others. By contrast, we notice that the average value of shocks from others to China and India are small again. Thus, we maintain that the degree of agricultural and economic development is one of the key factor to determine whether it is the net recipients of shocks.

In order to gain a clearer perception of the situation, we proceed with our analysis by presenting net pairwise directional connectedness between economic uncertainty and grain prices volatility respectively. This information is presented in Figure 7. Each country is related to the price of four kinds of grain. By doing so, we are able to trace the contribution of each type of grain price shock and produce a more credible interpretation of the results.

Results showed in Figured 7 confirm our anticipation that spillover effects between grain prices and economic policy uncertainty are time-varying and exist regional variation. More specifically, we notice that countries mainly export these four kinds of grain have a greater impact on the system than those countries which import them. Furthermore, we observe that the magnitude of net pairwise directional connectedness (NPDC) is considerably smaller compared to Figure 5 and Figure 6. In order to gain a wider understanding of these NPDC, we proceed to country-specific results.

First of all, according to the FAO , the US is the world’s top grain-exporter, and all four major products are exported in large quantities. In 2016, for example, the US is the world’s largest exporter of corn and soybeans, the second largest exporter of wheat and the fifth largest exporter of rice, which means the US has a more proactive influence on the fluctuation of food prices. As evident in Figure 7, the NPDC behavior for the US resembles the previous connectedness, although with some minor differences. Notably, an obvious peak in NPDC effect between grain prices and the US EPU is observed for the first few years of the sample period, but it gradually declined in the following years. From the above analysis, we know that the shocks from the US and to the US are both higher and performed with basically same value during the latter years of the sample period, so it is easy to understand why the subsequent values are almost zero.

Turning to Canada, according to FAO, it is the third largest exporter of wheat and the fifth largest exporter for soybeans in 2016. The evidence illustrated in Figure 7 suggests that the value and trend of shocks about Canada are basically same with the US, which can be also explained as the fact that the Canada EPU is a proactive transmitter to others as well as a receiver from others. However, Canada does not have an advantage in corn and rice production, whether for climate reasons or

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dietary habits. Thus, the influence to these two kinds of grain prices by Canada's shock is mainly driven by the system.

We further our analysis with Brazil, which ranks third, eighth and second in terms of export quantity of corn, rice and soybeans according to FAO. In particular, soybeans play an more and more important role in Brazilian agricultural trade, which the production output also ranks second in the world and increase steadily . As can be seen in Figure 7, the NPDC average value about Brazil and soybeans appear on the negative lower area of the panel, which indicates that soybeans prices have a shock on Brazil EPU after 2011. As for the other three types of grain prices, they are largely net recipients of Brazil EPU.

Interestingly enough, China have undergone significant structural changes of agricultural production and exports since market reforms started in 1978, allowing the country to be self-sufficient in the main crops (Vasilii Erokhin and Tianming Gao, 2018). However, China it is also a major grain importer for soybeans, corn and wheat, especially the soybeans import accounts for almost 60 percent of global imports. And Wailes et al. (1998) pointed out that after 20 years of reforms the growth rates for China's agricultural trade were still slower than for total trade, and that the share of agricultural trade in total trade had declined. These phenomena shows that China is a passive recipient of the international grain prices, which can be observed in Figure5, 6, 7 clearly. Turning to India, the evidence illustrated in Figure 7 shows that all types of shocks are important to India and the negative value in the panel can be credited with the fact that grain prices mainly remains a net transmitter of spillover effects throughout the period. The situation of India is similar with China, which can be explained as the fact that the major grain importing countries of developing countries such as India and China are at a disadvantage in the world grain market, as well as, are passive recipients of international grain prices.

According to Figure 7 about Australia, it is obvious that Australia is a net transmitter to all types of grain. According to Mick Keogh (2013), Australian grain growers are at a disadvantage relative to the situation they would face under a lower $AUD exchange rate, moreover, the agricultural industry has been and remains the most volatile sector of the Australian economy over the past four decades. It is understandable that agricultural activities in Australia are vulnerable to shocks by the economy environment, in fact, the point may be also apply to the rest of countries.

Finally, as evident in figure 5, 6 and 7,the NPDC spillover behavior for the Russia resembles the previous cases like the US and Canada, although with some minor difference that Russia's shock is more moderate. According to FAO(2016), Russia is the largest exporter of wheat in the world, meanwhile, large quantities of soybeans and maize have also been exported to other countries. From this information, we can infer that Russia is a proactive net transmitter to grain prices during the sample period, which is confirmed by the figures. However, it became even more evident in the background of Western sanctions, when grain prices become more sensitive to the economic policy uncertainty and is one of the main

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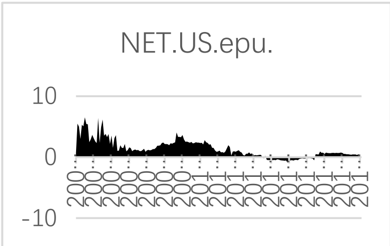
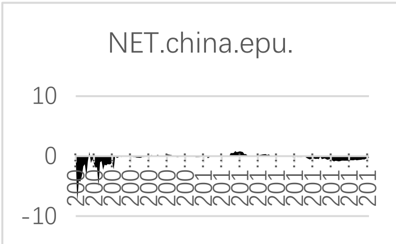
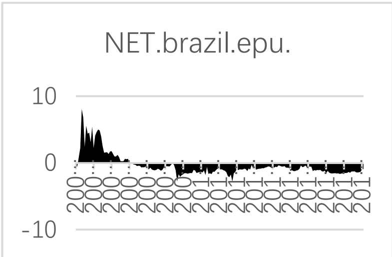
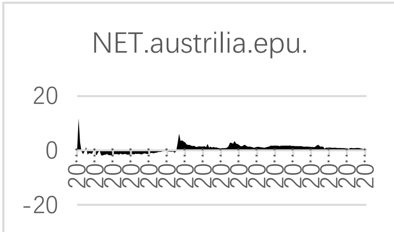
factors to against political and economic pressure (Moiseev et al.,2018).

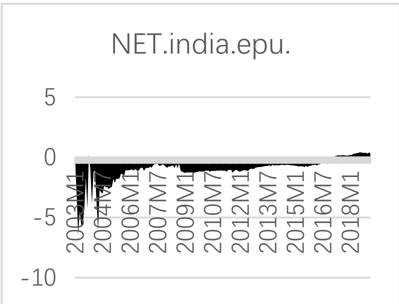
In retrospect, we find that there is no one single net transmitter of EPU spillover shocks, but all variables assume this character at different time periods. This is suggestive of the fact that there is no consistent relationship between grain prices and economic policy uncertainty indices and this relationship varies with the type of grain prices.

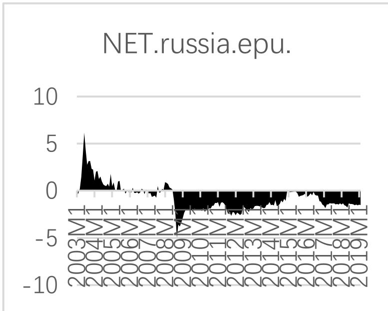


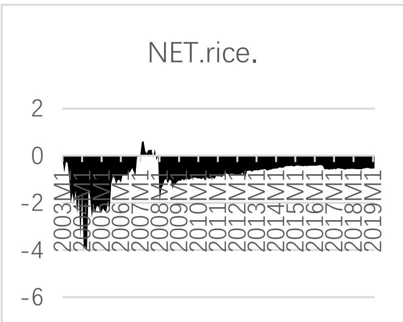


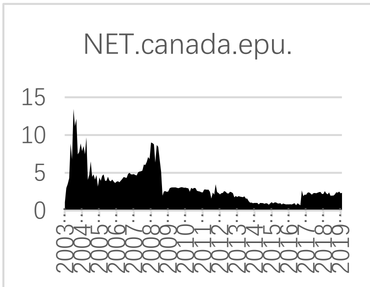












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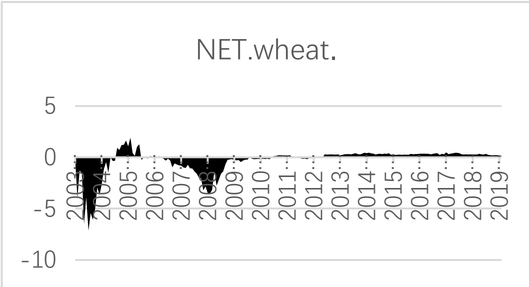

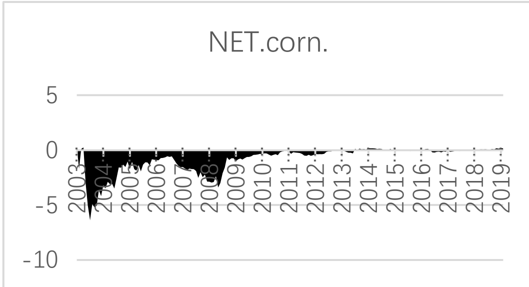

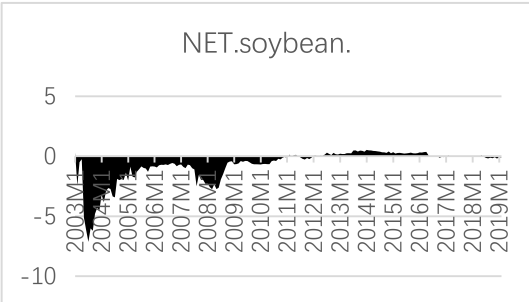

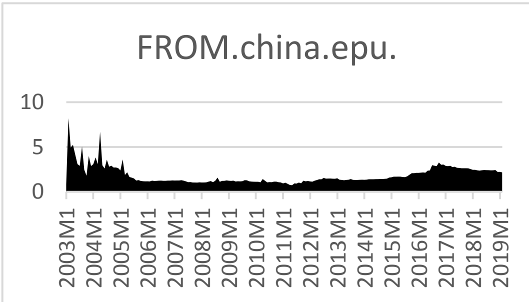

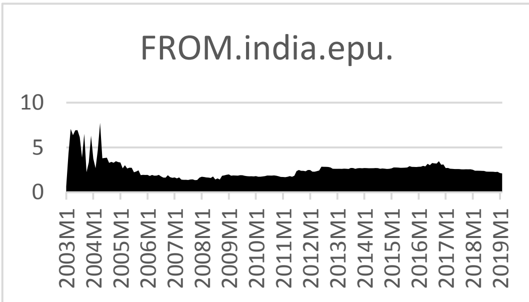

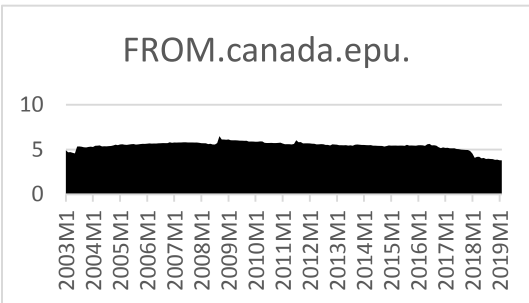

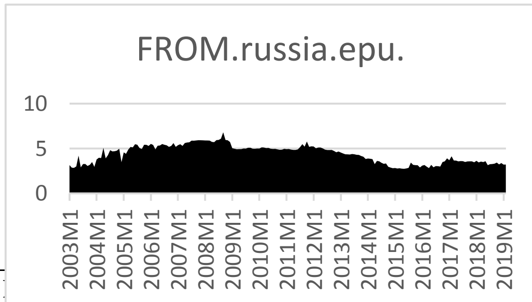

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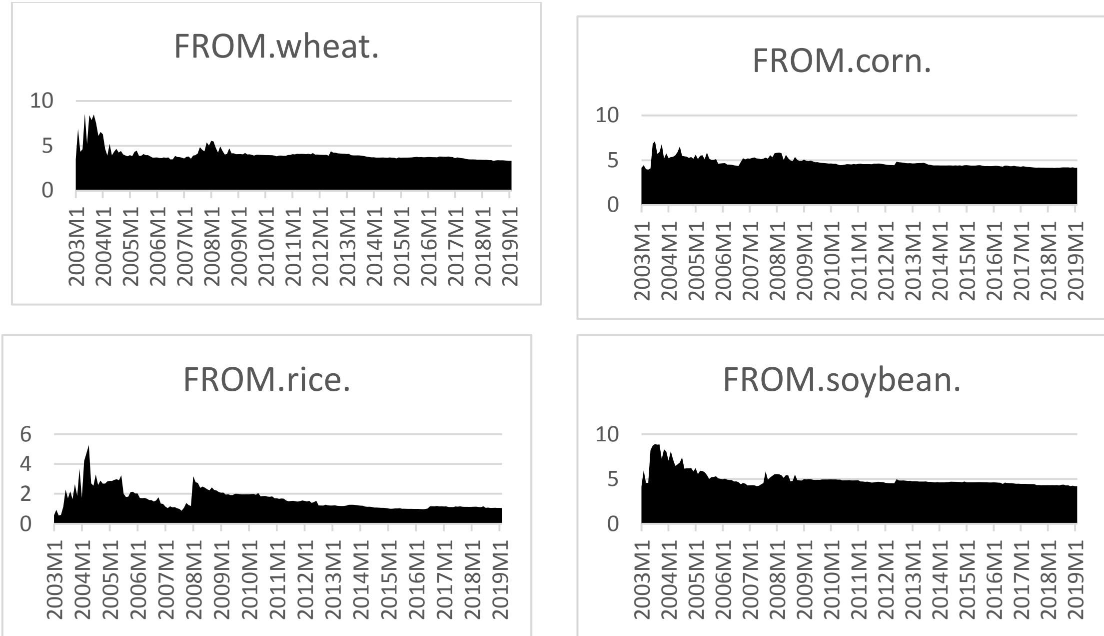
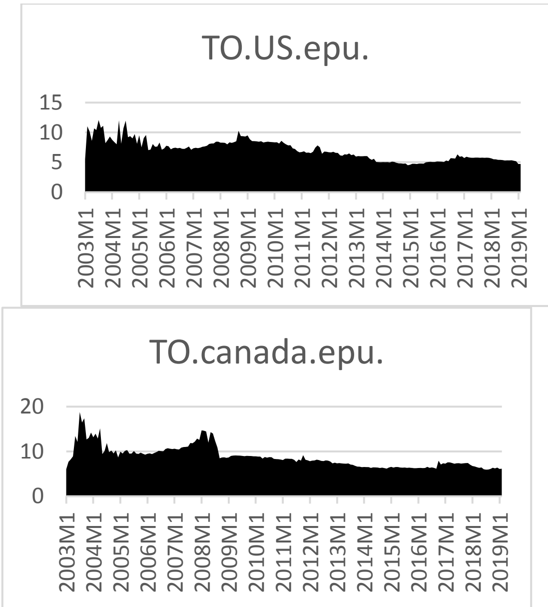


Fig.5. Total directional connectedness FROM others



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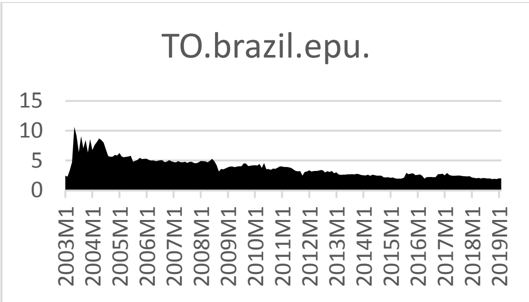

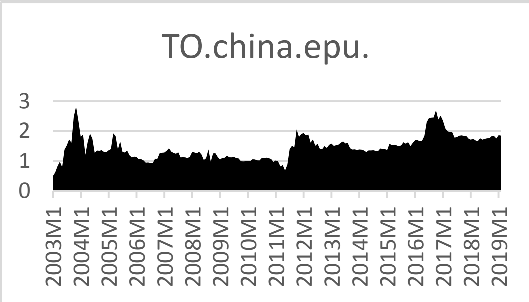

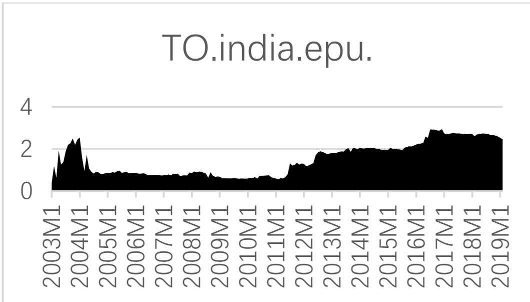

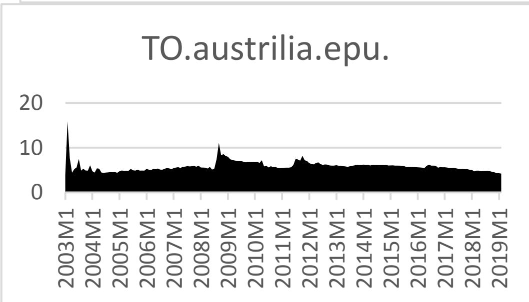

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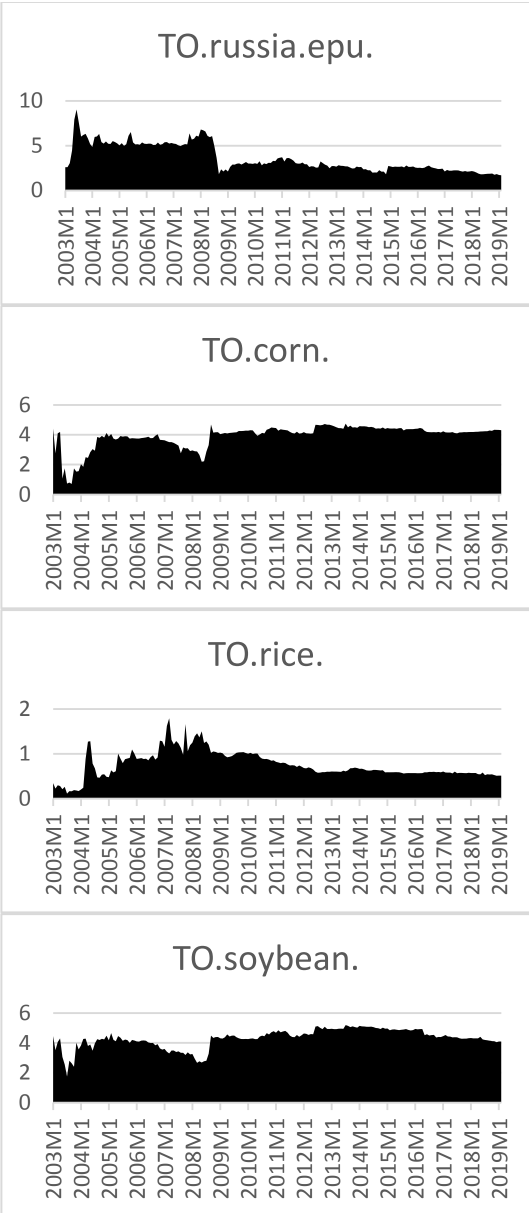

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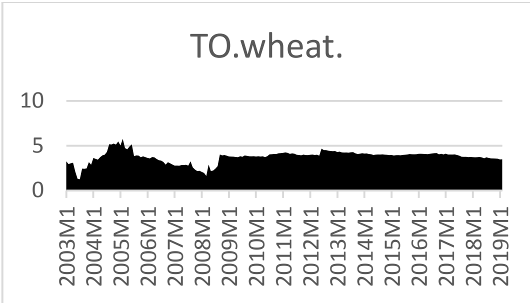
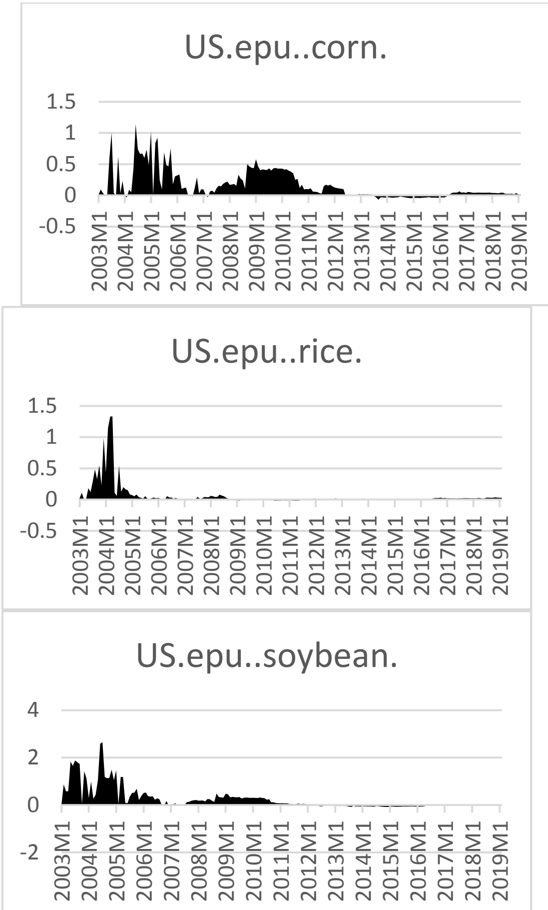


Fig.6. Total directional connectedness TO others



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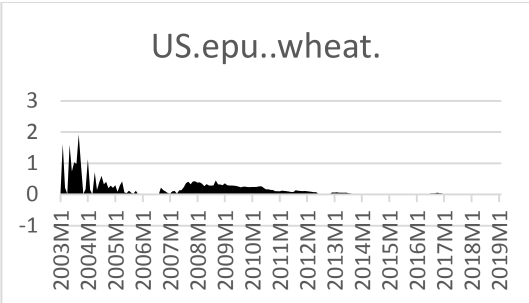

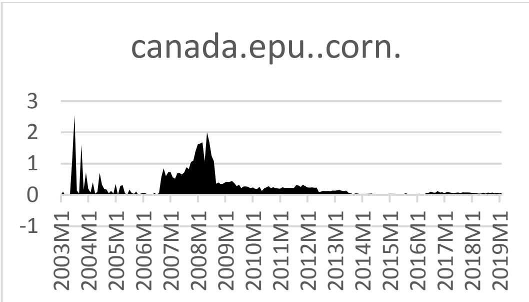

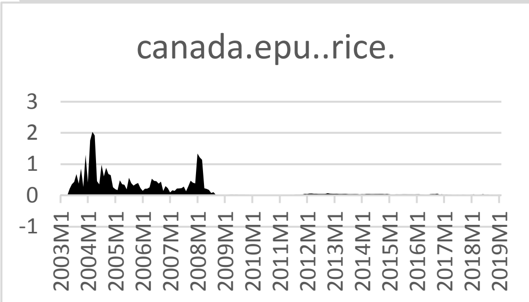

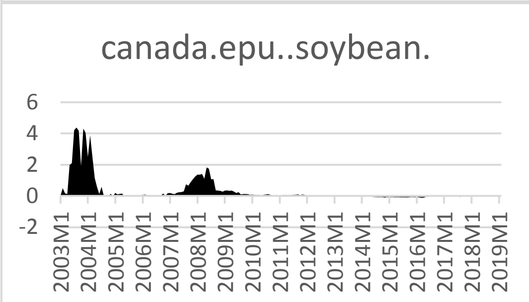

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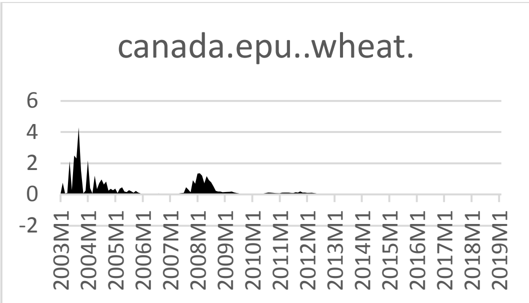

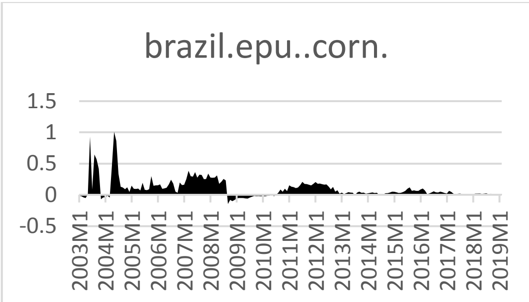

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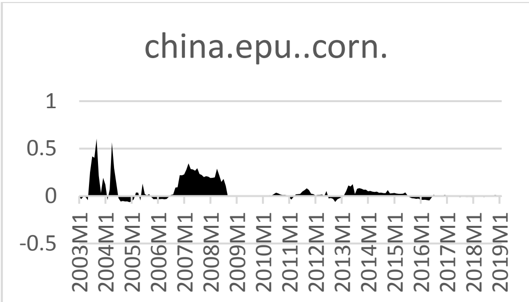

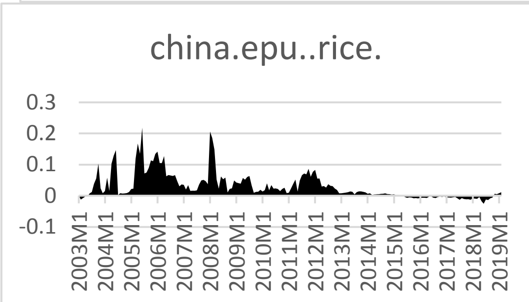

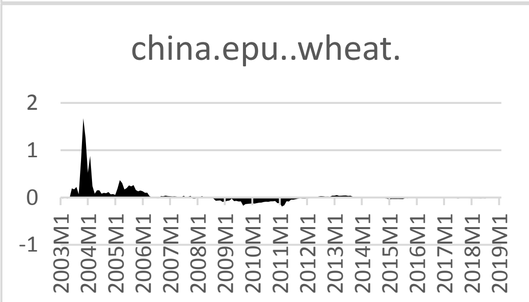

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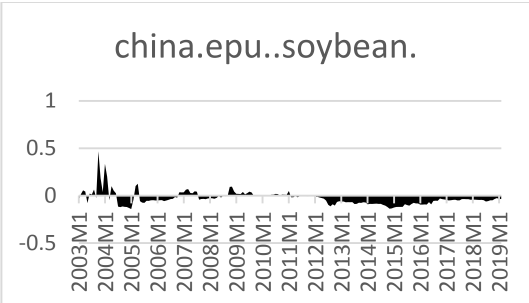

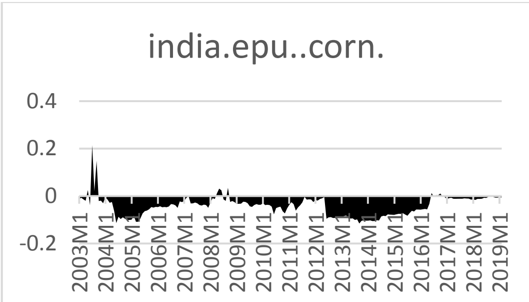

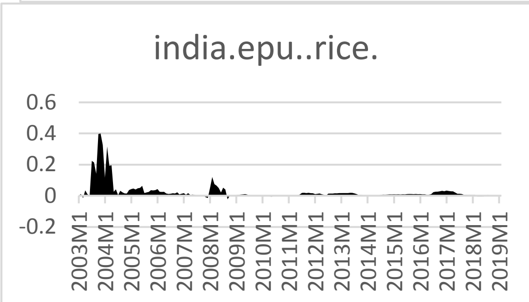

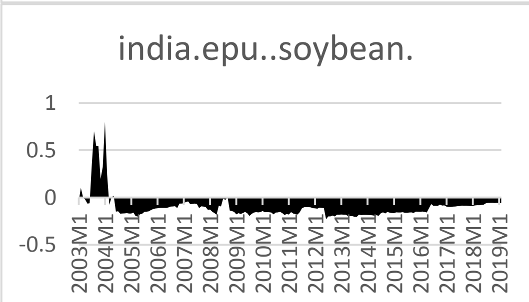

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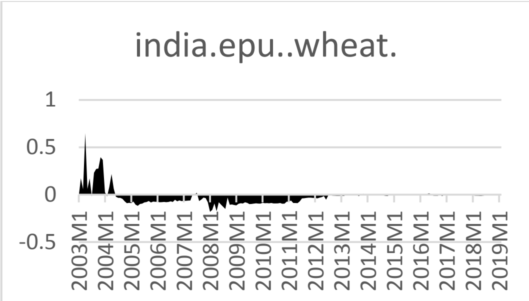

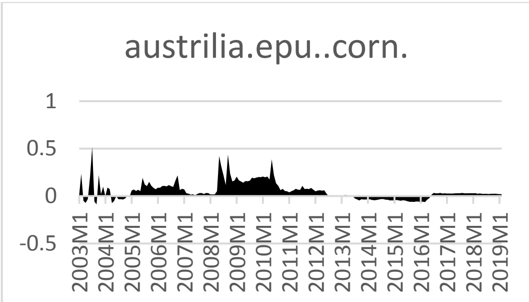

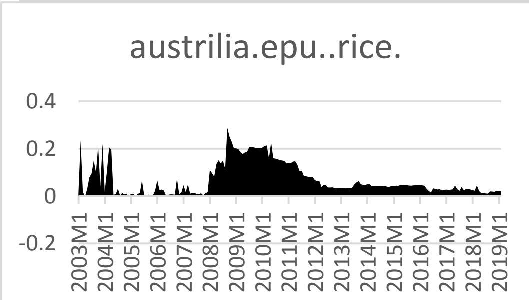

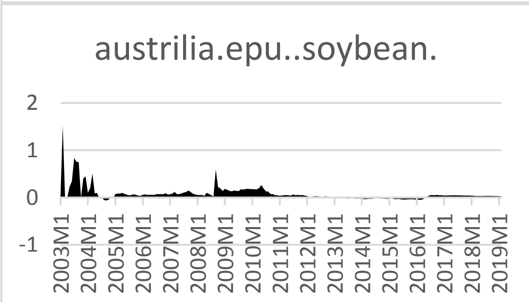

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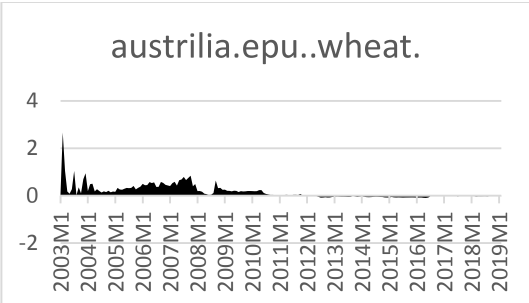

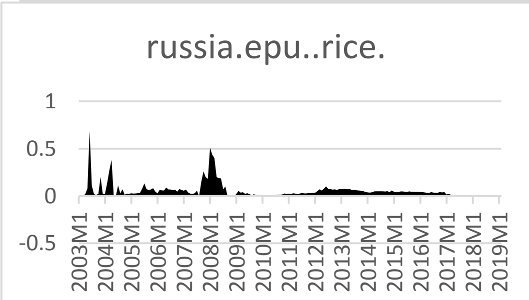

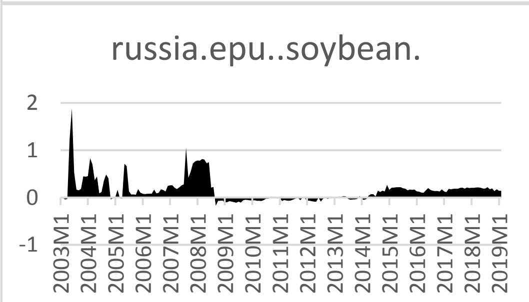

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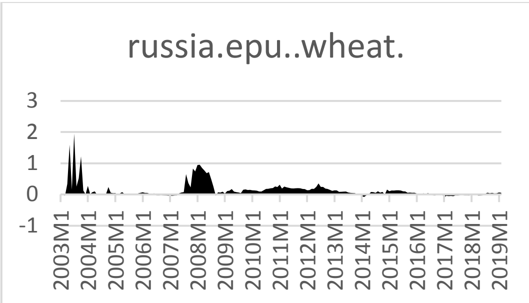

Fig.7. net pairwise directional connectedness

Conclusion

This paper examines the relationship between grain prices and economic policy uncertainty, using monthly data on international grain prices and the economic policy uncertainty index built by Baker et al. (2013), over the period 2003:01-2019:02. We apply TVP-VAR-based connectedness approach proposed by Antonakakis and Gabauer (2017) and disaggregate the connectedness into five types: Total, Net, To, From and NPDC. Sample countries include the US, Canada, Brazil, China, India, Australia and Russia.

From the above analysis, we can find that, as far as the whole network is concerned, total connectedness index (TCL) in the seven countries are time-varying and presented a significant spike during the Great Recession. From the perspective of spillover intensity and spillover direction, the predominant transmitter of this network is the US, Canada and Australia. Furthermore, any variables can be the net transmitter or net receiver of the shock, which depends on the time period, as well as, the situation of grain trade. Specifically, world grain exports are concentrated in few countries with abundant land resources and developed agricultural productivity, while grain imports are scattered in most countries of the world. Thus the imbalance of the import and export of grain trade brings about the realistic problem that the developing countries which mainly import grain are at a disadvantage and become a passive recipient of world grain prices. Moreover, we can divide spillover effect into three levels: the EPU of the US, Canada and Australia are proactive transmitters to the grain prices, while Russia and Brazil are relatively moderate transmitters to the specific grain; in addition, India and China are passive recipients of grain prices with similar situation.

These findings of this research have significant implications for the understanding of the dynamic spillovers of economic policy uncertainty and grain prices and they also lay the groundwork for future research into exploring the dynamic spillovers of categorical policy. Finally, future research could also examine spillover effects between grain prices and particular categorical policy of the Baker et al. EPU index, such as the monetary policy uncertainty and trade policy uncertainty. This approach would help identify the component which is more closely

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related to grain prices and thus deepen our understanding in this area.

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