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Mehmet Balcilar , Festus Victor Bekun

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Spillover Dynamics Across Price Inflation and Selected Agricultural Commodity Prices

Mehmet Balcilar^{a,b,c}, Festus Victor Bekun^{a,*}

^a Eastern Mediterranean University, Famagusta, North Cyprus, via Mersin 10, Turkey

^b Montpellier Business School, Montpellier, France

^c University of Pretoria, Pretoria, South Africa

Abstract

This article contributes to the existing empirical literature by examining the spillovers across price inflation and agricultural commodity prices in the case of Nigeria. To achieve this objective, we employ the Diebold and Yilmaz (2012) spillover index. Subsequently, we examine the directional spillover, total spillover, and net spillover indexes. Further analysis to capture cyclical and secular movements were addressed with 40 months of subsamples via the rolling window analysis. Our empirical results, based on the monthly frequency data from January 2006 to July 2016 show that the total spillover effect was about 75%. This suggests a high interconnectedness of the selected agricultural commodity prices and inflation. Our study further reveal that inflation, sorghum, soybeans, and wheat were net receivers while cocoa, barley, groundnut, maize, rice were net givers. We find a negative net spillover for price inflation, implying a net positive spillover from commodity prices to price inflation. These outcomes have inherent policy implications for the government administrators, farmers, investors and all stakeholders.

Keywords: Agricultural commodity prices; inflation; VAR model; forecast error variance; price spillover; Nigeria.

JEL classification: C32, Q02, Q43

* Corresponding author.

1. Introduction

Agricultural commodity prices in recent times have been experiencing an upward trend in record time (see Loening *et al.* 2009), since the 2006-2008 global food crisis. The spillover effect of the global food price surge in 2006-2008 has left most economies with the high inflation rate, large trade deficits and general poor macroeconomic environment especially in the developing economies. The explanation to this phenomenon is worthy of investigation so as to provide academicians, stakeholders and policymakers ample background as well as open opportunities for investors (Balcilar *et al.* 2014). The quest to underpin the rationale behind agricultural commodity price surge has been explored by several agricultural economists and interested researchers. Abbott *et al.* (2008) posited that the key drivers of hike in agricultural commodity prices are found in the huge synergy that exists among macroeconomic indicators. These indicators include oil prices, interest rate, exchange rate, unemployment, as well as the gap between agricultural productivity and increasing demand for food. In addition to the drivers of the increased agricultural commodity prices are policy decisions by decision/policy makers, which go a long way to mold the destiny of an economy. However, the hike in oil price stands out among these factors. It is seen as the paramount driving force for high agricultural prices (see FAO, 2008; Mitchell, 2008 and OECD, 2008).

Furthermore, there exists a burgeoning literature that explored the causal explanation of the global food price crisis (see Herndon, 2008; Rosegrant, 2008; Trostle, 2008). These studies have attributed the explanation to exchange rate volatility. For example, Trostle (2008) attributed the increase in agricultural food price to the weakness of the U.S dollar, which translates into a more competitive export market and thus spurs foreign demand for commodity prices volatility.

Additionally, climate change is also expected to lower yield and increase variability in many production processes as are reflected in high food prices (Irz *et al.* 2012).

Previous empirical studies on the food-price inflation dynamics of an agricultural commodity like Baek and Koo (2010) and Lambert and Miljkovic (2010) for the case of United States especially have a common feature of examining the theme via graphical, descriptive and simulation approaches. In addition, to the best knowledge of the authors only the studies of Baek and Koo (2010), and Lambert and Miljkovic (2010) only examined the theme with cointegrated vector autoregressive model.

Thus, the motivation for this study is to fill the identified gap by examining the food price inflation spillover nexus for the case of Nigeria, which is known to be plagued by the high inflation rate. Until now, little is known regarding the casual explanation(s) to the theme for Sub Saharan Africa (SSA) especially Nigeria. Thus, to the best of the authors' knowledge, this study is novel for a few reasons. Firstly, the study contributes empirically to the food-inflation spillover nexus for a large array of major import agricultural commodity prices. Simply put that, our study seeks to investigate to what extent inflation spillover is explained by the selected agricultural commodity prices for the studied area. Secondly, our study contributes to the scanty empirical literature on the theme by leveraging on recently developed generalized forecast error variance decomposition methodology of Diebold and Yilmaz (hereafter DY) to examine the level of interdependencies among variables under consideration. Thirdly, we examined the rolling window analysis in order to explore both cyclical and secular movements to capture episodes that may be responsible for the magnitude of spillover for the selected agricultural commodity prices. The modified version of the DY approach in measuring spillovers has become popular in

the empirics given that the technique itself is recent. Few studies have employed the technique (See Louzis, 2012; Ducan and Kabundi, 2013; Nishimura *et al.*, 2015).

Thus, based on the above highlights, the current study examines the dynamic spillover of price inflation across different cash crops in Nigeria over recent time series dataset. The justification for this investigation is timely and informative to stakeholders in the agricultural business and policymakers after the 2006-2008 global food crisis. Empirical evidence shows high interdependencies among the selected agricultural commodity prices and price inflation. Thus, suggesting significant correlation among the variables. Further analysis reveals that a negative net spillover for price inflation. Indicating a net positive spillover for the selected commodity prices to inflation. In addition, cocoa, barley, groundnut, maize, rice were observed as net givers of spillover effect. Thus, the attention of stakeholder and government administrators should be focus on net givers rather than net receivers like Sorghum, Soybeans, and wheat.

The layout of this study is structured as follows: Section 2 focuses on agricultural commodity prices and inflation: the peculiarity of Nigeria. Section 3 presents data and methodology while next Section 4 detail on results and discussions. Section 5 presents the rolling window analysis while concluding remarks and policy implications are reported in Section 6.

2. Agricultural commodity price inflation dynamics: The peculiarity of Nigeria

Nigeria is a country in the African continent, located in the western region of the continent, specifically in the Sub-Saharan Africa (SSA) bordering around Benin republic, Niger and Cameroon With a population of over 170 million, Nigeria has the highest population in Africa. Nigeria is reputed for being the largest economy with the economy relying heavily on crude oil production as her source of foreign exchange earnings. The Nigeria economy is known to be an

agrarian state with huge arable land for agricultural cultivation and production. Most of the crops produced such as cocoa, coffee, rubber tea, cotton, palm oil, corn, rice, sorghum, millet, cassava among others have export potential and value. Statistics have shown that despite the latent potential of Nigeria agricultural sector with large arable land and abundant natural resources, there has been a noticeable diminishing contribution of the sector to national prosperity. The empirical study of Alene *et al.* (2005) revealed that back in the 1960's the agricultural sector accounted for over 65-70% of total export. This statistics have declined in recent times to 40% in the 1970's, and has trickled down to less than 20% in the 1990's and much more in recent times. A further threat in the peak of world food price hike experienced from 2006-2008. The aftermath is seen in general increase in agricultural commodity food market. The Nigerian economy over the years since the 1970s has witnessed high and volatile inflation. This inflation has spillover to the commodity market and the agricultural commodity market is not an exception, this was seen in the global 2006-2008 food crises and the effect has a great toll on the Nigerian food market severally with an obvious significant hike in agricultural commodities prices. The high inflation episodes experienced in the country is mainly driven by structural changes and macroeconomic indicators further plausible explanation include wage rise.

The selected agricultural crops for this study namely (groundnut, soybeans, sorghum, barley, maize, cocoa, rice, wheat) form the major crops in Nigeria. These crops are also known as cash crops given their inherent characteristics such as being a major staple food; they are the most produced and consumed in all parts of Nigeria. They also serve as a source of daily nutrition need giving their availability and affordability. In addition, these crops are the most traded agricultural commodities both domestically and internationally. Hence, they constitute the bulk of the commodity exports of Nigeria in the international market for grains. As noted by Akpan

and Udoh (2009), the selected crops (rice, maize, millet, and sorghum) constitute a large fraction of staple food in Nigeria. This claim is further buttressed given that in the early 1980's precisely 1985 and 1995, cereals crops constitute almost 50% of Nigeria's total food supply in terms of grain equivalent. To this extent, the need to investigate their price movements and spillover effect in regards to an inflation-prone country like Nigeria is crucial with the recent novel methodology of Diebold and Yilmaz (2012) spillover index. The knowledge about the pattern and magnitude of the spillovers among the selected crops will inform agricultural business portfolio managers for diversification of crop selection bundles

3. Methodology

As earlier stated, our study leverages on the methodology of Diebold and Yilmaz to quantify the spillover between inflation and the selected agricultural commodity prices under review. The DY approach is unique given its less computational requirements, which helps in characterizing various episodes and events. The DY index is structured in a vector autoregressive (VAR) model and variance decomposition framework. The DY index is dated to 2009, as advanced by Diebold and Yilmaz (2009). However, the 2009 version of the DY index had the variance decomposition that is sensitive to the ordering of the variables as achieved by Cholesky factorization. The aforementioned procedure was flawed; in order to ameliorate the setback mentioned DY (2012) is an improvement on DY (2009) version with generalized VAR framework, which offers variance decomposition that is invariant to the ordering of variables after that of Koop *et al.* (1996) and Pesaran and Shin (1998)

Thus, this section provides the econometrics procedure for the current study to measure the spillovers from inflation to the selected major import prices of agricultural commodity prices. Our study empirically follows the recently developed Diebold-Yilmaz (2012) methodology,

which is an improvement on the DY (2009). The DY (2012) approach is structured under (VAR) model framework, which is known to be invariant to variance decomposition ordering (Koop *et al.*, 1996). The DY index reports four different spillovers indices namely; net spillovers, net pairwise spillovers, total spillovers and directional spillovers. DY methodology is based on a covariance stationary VAR:

$$y_t = \Phi_0 + \sum_{i=1}^n \Phi_i y_{t-i} + \varepsilon_t \#(1)$$

where $y_t = (y_{1t}, y_{2t}, \dots, y_{nt})'$ is a vector of covariance stationary series Φ_i , $i = 0, 1, 2, \dots, p$, denotes $(n \times n)$ matrix of parameters ε_t is a $(n \times 1)$ vector of zero mean errors required to be independent and identically (*iid*) distributed with covariance matrix Σ , $\varepsilon_t \sim iid(0, \Sigma)$. The moving average (MA) representation of the VAR in equation (1) is given as:

$$y_t = \mu + \sum_{i=0}^{\infty} \Psi_i \varepsilon_{t-i} \#(2)$$

where Ψ_i are $(n \times n)$ matrices recursively obtained from the equation $\Psi_i = \sum_{j=1}^i \Psi_{i-j} \Phi_j$, $i = 1, 2, \dots$, μ is a $(n \times 1)$ vector of intercepts, and $A_0 = I_n$, where I_n is an identity matrix with dimension n . The spillover index is derived from equation (2) that forms the variance decomposition. Prior to the presentation of the diverse indices, the following pertinent notices are crucial:

- (a) Own variance shares are described as the fractions of the H -steps-ahead error variance in forecasting y_{it} that are attributed to shocks for y_{it} , $i = 1, 2, \dots, n$.
- (b) Cross variance spillovers are described as a share of the H -step-ahead error variance forecasting y_{it} that are accrue to y_{jt} , $j = 1, 2, \dots, n$, shock to such that $i \neq j$.

(c) Base on the Koop *et al.* (1996) generalized VAR framework, H -step-ahead forecast error variance decomposition represented by $\theta_{ij}^g(H)$ is obtained by

$$\theta_{ij}^g(H) = \frac{\sigma_{jj}^{-1} \sum_{h=1}^{H-1} (e_i' \Psi_h \Sigma e_j)^2}{\sum_{h=1}^{H-1} (e_i' \Psi_h \Sigma \Psi_h' e_i)^2} \#(3)$$

where σ_{jj} depicts the standard error of ε_t for j -th equation and e_i is the selection vector, with one as the i -th element and zeros otherwise.

(d) Given that the sum of the contribution to the variance of the forecast error is not equal to one, which implies that $\sum_{j=1}^n \theta_{ij}^g(H) \neq 1$; Diebold-Yilmaz (2012) approach normalizes each entry of the variance decomposition matrix. The normalized H -step-ahead forecast error variance decomposition by Koop *et al.* (1996) is given by

$$\tilde{\theta}_{ij}^g(H) = \frac{\theta_{ij}^g(H)}{\sum_{j=1}^n \theta_{ij}^g(H)} \#(4)$$

where $\sum_{j=1}^n \tilde{\theta}_{ij}^g(H) = 1$ and $\sum_{i,j=1}^n \tilde{\theta}_{ij}^g(H) = n$ by the construction.

Thus, given these prelude, the total spillover index is deduced as

$$S^g(H) = \frac{\sum_{i,j=1, i \neq j}^n \tilde{\theta}_{ij}^g(H)}{\sum_{i,j=1}^n \tilde{\theta}_{ij}^g(H)} = \frac{\sum_{i,j=1, i \neq j}^n \tilde{\theta}_{ij}^g(H)}{N} \#(5)$$

Equation (5) captures the total spillovers index. For our case, total spillover across 8 selected agricultural commodity prices and the consumer price inflation. The DY (2012) technique offers the opportunity to explore the flow of direction of spillover across inflation and the selected agricultural commodity prices under review. The directional spillover are of two divide namely “to” directional spillover and “from” directional spillover. The “to” directional spillover measure whether spillovers transmitted by all other variables to the considered variable. While “from”

directional spillover accounts for spillovers received by one variable from all others variables. In this study case, we consider directional spillover received from inflation to the agricultural commodities is investigated and *vice versa*.

The “to” directional spillover is computed as

$$S_{\cdot i}^g(H) = \frac{\sum_{j=1, j \neq i}^n \tilde{\theta}_{ij}^g(H)}{\sum_{i,j=1}^n \tilde{\theta}_{ij}^g(H)} = \frac{\sum_{j=1, j \neq i}^n \tilde{\theta}_{ij}^g(H)}{N} \#(6)$$

While the directional spillover “from” is represented as and computed by the index given as:

$$S_{i \cdot}^g(H) = \frac{\sum_{j=1, j \neq i}^n \tilde{\theta}_{ji}^g(H)}{\sum_{i,j=1}^n \tilde{\theta}_{ij}^g(H)} = \frac{\sum_{j=1, j \neq i}^n \tilde{\theta}_{ji}^g(H)}{N} \#(7)$$

Thus, net spillover can be computed as the difference between the “to” and “from” directional spillover indices. It is described as:

$$S_i^g(H) = S_{\cdot i}^g(H) - S_{i \cdot}^g(H) \#(8)$$

Our study considers a first order 9-variable VAR with 10-step-ahead forecast. Adequate diagnostic analyses are offered to affirm robustness of our estimation to avoid spurious analysis.

4. Data and empirical results

This section proceeds with preliminary analysis on the selected agricultural commodity enlisted in Table 1. To ascertain their statistical properties, our study advantage on monthly frequency data set from 2006M1 to 2016M7, which was retrieved from the African Development Bank (ADB) database.

The summary statistics of the interest variables and correlation analysis are reported in Table 2. Noteworthy here is that all variables investigated are seasonally adjusted via census X-13

additive outlier approach. Summary statistics given in Panel A of Table 2 show that all variable has an average between 5.2 and 6.2 with all series negatively skewed with the exception of maize. Thus, indicating non-normality across the variables, that is affirmed by the heavy tail exhibited by the series as reported by kurtosis. Jarque Bera (JB) probability corroborates the non-normality distribution across the mean values of the variables being considered for our study for the period considered. The JB probability is rejected for cocoa, groundnut, soybean and barley crops while for JB probability could not be rejected for the case of maize, sorghum, rice, and CPI. Panel B of Table 2 renders the correlation relationship between the pairs of variables. Observed is a positive significant relationship is imminent. For example, the positive significant relationship is observed between cocoa and coffee, a similar trend is seen among barley and soybean.

4.1 Spillover analysis

This section focuses on the analysis of DY results. Using VAR(1) model chosen by the Schwarz Bayesian information criterion (SBIC) as the optimal and most parsimonious one, we perform the spillover analysis for a 10-step ($H = 10$) forecast error variance decomposition following the majority of the previous studies (Salisu *et al.*, 2018; Louzis, 2012; Diebold and Yilmaz, 2009; Diebold and Yilmaz, 2012). The Table 3 below presents the lag selection criterion and this is necessary to choose the most parsimonious and appropriate model. This is essential in our study in order not to estimate misleading regressions and analysis.

The DY methodology is divided into two main sub-groups namely; (i) Spillover analysis and (ii) rolling window analysis. The spillover analysis renders a single scalar that are fixed values for the various indices over the considered period based on the full sample estimates. Thus, it help to capture aggregate spillovers over the interest period. On the other hand, the rolling window

analysis becomes handy where unprecedented events or episodes are observed. The rolling window helps to account for a deeper and intuitive dynamics. Both divides of the DY index complement each other where the rolling window stretches beyond the scalar values to unveil the cyclical and secular movement of spillovers from a particular period to another.

The spillover estimation as reported in Table 4 are computed for the entire sample period based on VAR(1) for 9 variables with 10-step-ahead forecast error. The table has both “contribution to others” derived from the sum of the off-diagonal column and in same fashion “contribution from others” which is the sum of off-diagonal of row. Both aforementioned directional spillovers could either be “directional spillovers to others” and “directional spillover from other” represents the contribution from others all available in Table 4. Therefore, each value on the Table 4 with the exclusion of the main diagonal value captures individual agricultural commodity prices spillover and inflation to the forecast error variance of the other commodity prices under consideration. Similarly, in the same fashion, each value in each row, with the exception of the main diagonal values helps to captures the amount of contribution of others agricultural commodity price spillover and inflation to the forecast error variance over the period under review.

There exist similarity between the spillover table and the input-output table as they share common features to show among investigated variables impact of shock and identify absorber and transmitter of shock among interest variables. Also, the spillover table also displays net spillover, which is computed by the difference between contributions from others, and contribute to others or *vice versa* (see equation 8 in the methodology section). Noteworthy here is that a positive value depicts that the commodity in our study case the various agricultural commodity prices and inflation has a greater influence on another commodity than it receives from them;

thus makes the commodity less vulnerable to external shock. On the other hand, a negative magnitude implies that the commodity is a net receiver that is more vulnerable, that is responsive to external shock from other commodities and inflation. The total spillover index is a lump sum value computed by the aggregate of contributions to others as a percentage of the sum of contribution including own shock. Thus, the total spillover offers the various directional spillover numbers into a single index number in percentage terms.

The Table 4 displays spillover calculations for the selected agricultural commodity prices under review and inflation for the full sample period.

The empirical results show that the total spillover index is 75.1% indicating a high level of interconnectedness among the investigated commodities prices and inflation. In other words, well two thirds of the total forecast error variances across all investigated agricultural commodity can be attributed to a spillover effect. That is, overwhelming, over 75% of total variance forecast error during the investigated period is explained by shocks across the variance errors while idiosyncratic shocks accounts for 24.9% in our estimation.

The examination of the individual directional spillovers measures from other (row) excluding main diagonal shows that rice recorded the highest dedicated contribution to forecasting error variance of price inflation among the investigated commodities with 22.7% seconded by maize with about 22.2%. That is, shocks on rice are more likely to spill over to the other commodities as well as the general price inflation. Thus, shocks to rice exhibit more likely to affect the pattern of another commodity in the investigated area with 158.1% of the contribution to others and net spillover of 77.9%. Insightful in our results is that rice possesses the greater impact on the forecast error variance (column) with 10.9% distantly followed by cocoa and soybeans with 3.2% and 1.1% respectively. A similar analysis holds for the other commodity prices. On the

whole contribution from others records significantly high values amidst all commodity and inflation buttressing the high connectedness already established with wheat ranking highest followed by soybean, inflation and groundnut are least in this order. In other words, shocks to other commodity account for greater forecast percentage of the forecast error variance of wheat, soybean, rice, soybean, cocoa, and CPI than their own shocks while forecast error variance of groundnut and barley are considerably explained by their own shock. Thus, suggestively wheat are more vulnerable to shocks relatively to others variables investigated in the current study. These findings further give credence to the role cereal crops plays in the study area and global food commodity market. Finally, on the spillover table is the net spillovers section on the tail bottom of Table 4. The net spillover shows that 4 of the investigated variables are net receivers (CPI and sorghum, soybean and wheat) while the remainder is a net giver. Thus, for the policy decision by government administrators are encouraged to pay more attention to major actors in the markets that are net givers, as shocks to such market will be transmitted to others. We find that price inflation is net spillover receiver, that is a 38.5% net spillover from the 8 commodities to CPI inflation, implying a commodity inflation pass-through to price inflation.

5. Rolling sample analysis

A glimpse on the “average” spillover effects over the full sample period is rendered by spillover analysis. Diebold and Yilmaz (2009, 2012, 2014) expressed that the full sample spillover measures cannot explicitly reflect important secular and cyclical movement in spillovers. On these premise of the aforementioned bottlenecks, we offer a rolling window framework that allows for time-varying spillover indices, using a 40-month subsample in order to circumvent the earlier shortcomings of the spillover index, it is pertinent the rolling window analysis also help to holistically capture some episodes and events over the interest period under consideration. First,

it is a matter of importance to check the way and pattern with which inflation spilled over to the agricultural commodities involved and how spillovers from the agricultural commodities affected inflation. Figure 2 reveals the presence of strong interdependence between inflation and other agricultural commodities. However, it is obvious that directional spillovers from inflation depict more several high episodes than directional spillovers to inflation. This being evident even from the spillover table as inflation exerts great influence on the agricultural commodities.

Further analysis from Figure 3 affords us to investigate the net transmitters and receivers and their input to total spillovers via the net directional spillover. Our study identifies groundnut, rice, and inflation net spillovers as net receivers as they showed negative patterns between 2007 and 2016. On the other hand, soybean and maize were identified as net transmitters while wheat, cocoa sorghum, and barley exhibited mixed patterns. Interestingly, during the electioneering process in 2011, wheat was considered net receiver coincidentally, sorghum, barley, and cocoa were net spillover transmitter. It is worthy of mention that all investigated agricultural commodities exhibited significant spillovers after 2006-2008 food crises as well as global financial crunch period.

We proceed to plot the total spillover index as presented in Figure 4, the total spillovers start with about 89% and maintained such level before hitting around 85% as a result of the global meltdown crisis at that time. Immediately after 2008, the spillovers fluctuated between 80% and 85%. In 2009, there were high indications that oil and gas could no longer sustain the economy even as the petroleum subsidies became almost equal to the capital budget, hence, strong indications were made to deregulate the sector as well diversify the economy by giving special attention to the agricultural sector. This stern demand made the total spillovers hit a high of about 88% at that time. According to the National Bureau of Statistics, 2011 witnessed a high

fluctuation of inflation and even this is evidenced in the agricultural commodities that saw the total spillovers fall to less than 80% as well as going as high as 90% in the very year. This being also an effect caused by the 2011 presidential elections. Around February 2012, the total spillovers fell to a dip of 75%, this being a resultant effect of the protest against the unanticipated shock that arose from the removal of petroleum subsidy that occurred on January 1, 2012, a day dedicated for new year celebrations. The total spillovers relatively maintained stability around 80% before hitting another low of about 71% around March 2015, this being an obvious effect of the Nigeria presidential election at that time. The 2016 recession also saw a level of spillovers to the tune of 75%.

6. Conclusion

We investigated the degree of interconnectedness between inflation and selected agricultural commodity prices in the face of the inflation-prone economy. Empirical analysis are based on newly developed forecast error variance decomposition framework of Diebold-Yilmaz (2012). The DY methodology offers the all-requisite spillovers indexes. In addition to the reported single fixed spillover index, the rolling window analysis is added to affirm the robustness and reliability of all estimations as well as it helps to capture secular and cyclical movement such as striking events and episodes for more engaging arguments.

Empirical results for our study span through 2006M1 to 2016M7 on a monthly frequency. The empirical analysis shows that the total spillover reveals an overwhelming high interdependency with 75% of the selected agricultural commodity prices and inflation over the investigated period considered is explained by spillover effects.

Our study further reveal that inflation, sorghum, soybeans, and wheat are net receivers while cocoa, barley, groundnut, maize, rice are net givers. These outcomes have inherent policy implication(s) for both end users and major actors in the agricultural commodity market for the case of Nigeria. Regarding the commodities that are net receivers, it implies that the spillover shock from those commodities are absorbed and not transmitted to the other commodities while the net givers are those that transmit spillover shocks when received. By and large, focus for policy makers and government administrators in the agricultural domain is to gear concerted efforts to net givers as acclaimed by Diebold-Yilmaz (2009,2012) “*It is better to give than to receive*”.

As a way for further direction for other researchers, we propose that this study could be extended by exploring the agricultural commodity market spillover and other determinants like climate change and even oil price.

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Table 1: Data description

Variables	Description
Cocoa	(cents/kg)
Groundnut	\$/mt
Soybeans	\$/mt
Barley	cents/kg
Maize	\$/mt
Sorghum	\$/mt
Rice	\$/mt
Wheat	\$/mt
CPI (Inflation)	Index

Table 2: Summary statistics and Correlation Coefficient estimates

<i>Panel A: Descriptive statistics</i>									
	CO	GN	SB	BA	MA	SO	RI	WH	CPI
Mean	5.551	7.190	6.100	5.137	5.278	5.245	6.123	5.436	4.752
Median	5.594	7.214	6.120	5.170	5.183	5.276	6.132	5.449	4.773
Maximum	5.878	7.920	6.501	5.575	5.816	5.781	6.765	6.052	5.319
Minimum	5.010	5.329	5.542	4.618	4.619	4.558	5.656	4.943	4.211
Std. Dev.	0.225	0.484	0.239	0.252	0.295	0.267	0.247	0.244	0.315
Skewness	-0.837	-2.081	-0.683	-0.324	0.035	-0.270	-0.071	-0.003	-0.077
Kurtosis	2.786	9.031	2.830	2.131	2.413	2.526	2.506	2.196	1.732
Jarque-Bera	15.065	284.138	10.034	6.209	1.846	2.738	1.395	3.418	8.639
Probability	0.001	0.000	0.007	0.045	0.397	0.254	0.498	0.181	0.013
Sum	705.016	913.126	774.733	652.394	670.291	666.126	777.623	690.383	603.512
Sum Sq. Dev.	6.404	29.534	7.191	8.033	10.979	8.986	7.681	7.515	12.489
Observations	127	127	127	127	127	127	127	127	127
<i>Panel B: Correlation coefficient estimates</i>									
	CO	GN	SB	BA	MA	SO	RI	WH	CPI
CO	1								
<i>T-stat</i>	----								
<i>P-value</i>	----								
<i>No.Obs</i>	127								
GN	0.150	1							
<i>T-stat</i>	1.701	----							
<i>P-value</i>	0.091	----							
<i>No.Obs</i>	127	127							
SB	0.512	0.337	1						
<i>T-stat</i>	6.664	4.007	-----						
<i>P-value</i>	0.000	0.000	-----						
<i>No.Obs</i>	127	127	127						

BA	0.218	0.244	0.668	1					
<i>T-stat</i>	2.502	2.814	10.048	-----					
<i>P-value</i>	0.014	0.006	0.000	-----					
<i>No.Obs</i>	127	127	127	127					
MA	0.309	0.233	0.874	0.798	1				
<i>T-stat</i>	3.639	2.678	20.090	14.828	-----				
<i>P-value</i>	0.000	0.008	0.000	0.000	-----				
<i>No.Obs</i>	127	127	127	127	127				
SO	0.398	0.176	0.790	0.792	0.894	1			
<i>T-stat</i>	4.853	1.998	14.415	14.494	22.327	-----			
<i>P-value</i>	0.000	0.048	0.000	0.000	0.000	-----			
<i>No.Obs</i>	127	127	127	127	127	127			
RI	0.450	0.236	0.744	0.452	0.689	0.539	1		
<i>T-stat</i>	5.632	2.714	12.465	5.669	10.615	7.152	-----		
<i>P-value</i>	0.000	0.008	0.000	0.000	0.000	0.000	-----		
<i>No.Obs</i>	127	127	127	127	127	127	127		
WH	0.252	0.356	0.853	0.749	0.822	0.763	0.461	1	
<i>T-stat</i>	2.907	4.263	18.265	12.651	16.167	13.212	5.800	-----	
<i>P-value</i>	0.004	0.000	0.000	0.000	0.000	0.000	0.000	-----	
<i>No.Obs</i>	127	127	127	127	127	127	127	127	
CPI	0.651	0.011	0.393	0.340	0.342	0.499	0.163	0.224	1
<i>T-stat</i>	9.591	0.124	4.784	4.049	4.063	6.429	1.853	2.569	-----
<i>P-value</i>	0.000	0.902	0.000	0.000	0.000	0.000	0.066	0.011	-----
<i>No.Obs.</i>	127	127	127	127	127	127	127	127	127

Note: All above mentioned series were log transformed as well as seasonally adjusted with the exception of CPI with census X-13 with additive outlier option type. WH, SB, SO, RI, MA, BA, GA, and CO denote wheat, soybean, sorghum, rice, maize, barley, groundnut, and cocoa, respectively.

Table 3: Lag selection criterion

Lag	Log L	LR	FPE	AIC	SC	HQ
0	399.9509	NA	1.13e-14	-6.570603	-6.360417	-6.485253
1	1664.351	2316.295	2.62e-23*	-26.45967	-24.35781*	-25.60617*
2	1725.735	103.1676	3.72e-23	-26.13000	-22.13647	-24.50836
3	1780.613	83.93005	6.10e-23	-25.69097	-19.80577	-23.30117
4	1844.075	87.46122	9.15e-23	-25.39622	-17.61935	-22.23828
5	1911.276	82.44795	1.40e-22	-25.16430	-15.49576	-21.23821
6	2005.404	101.2466	1.51e-22	-25.38494	-13.82472	-20.69070
7	2122.521	108.2593	1.30e-22	-25.99194	-12.54005	-20.52956
8	2259.367	105.7974*	1.00e-22	-26.93054*	-11.58698	-20.70001

Note: LR represent sequential modified LR statistic, Log L is the log likelihood, FPE is the Final Prediction Error, AIC is the Akaike Information Criterion, SIC is the Schwarz Information Criterion and HQ is the Hannan-Quinn Information Criterion, respectively, while * depict the optimum lag selected.

Table 4: Spillover measures for agricultural commodity prices and inflation

Variables	CPI	CO	BA	GN	MA	RI	SO	SB	WH	From Others
CPI	19.2	3.3	20.6	4.7	21.2	22.7	1.0	3.9	3.4	80.8
CO	1.1	39.0	5.6	16.8	12.3	4.7	4.3	10.1	6.0	61.0
BA	4.2	9.1	32.3	10.9	1.1	20.5	8.0	11.5	2.4	67.7
GN	6.6	9.8	5.1	46.3	8.1	8.1	8.9	3.6	3.7	53.7
MA	3.6	14.2	8.1	3.8	25.1	28.6	1.4	3.4	11.8	74.9
RI	10.9	8.1	21.6	7.4	18.3	19.8	4.3	5.0	4.7	80.2
SO	4.8	7.5	6.3	19.8	9.9	30.7	11.1	2.1	7.8	88.9
SB	3.2	18.6	7.2	3.0	7.4	15.3	10.9	23.0	11.3	77.0
WH	7.9	9.1	12.4	6.6	12.0	27.5	6.1	10.2	8.2	91.8
Contribution to others	42.3	79.8	86.9	73.1	90.3	158.1	44.9	49.7	51.1	676.2
Contribution including own	61.5	118.7	119.2	119.4	115.4	177.8	56.0	72.7	59.3	Total spill over index (75.1%)
Net Spillover	-38.5	18.8	19.2	19.4	15.4	77.9	-44.0	-27.3	-40.7	

Figure 1: Time series plot of variables under consideration

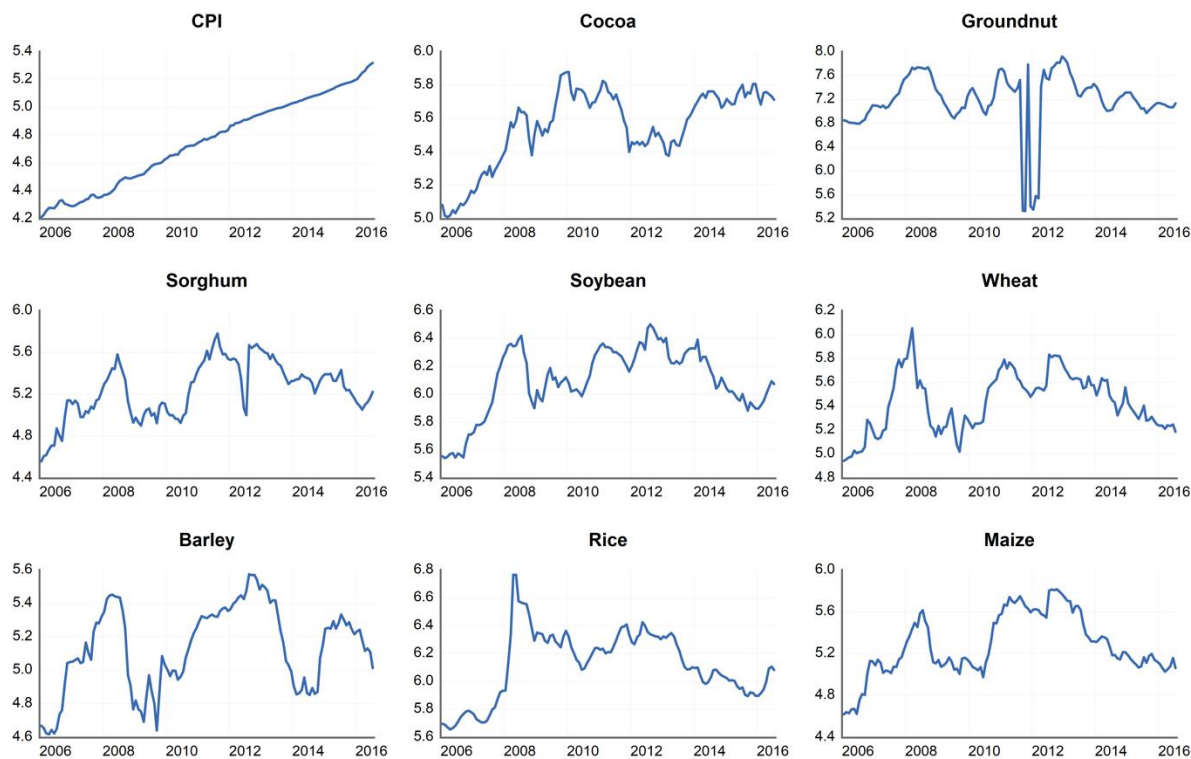


Figure 2: Rolling estimates of direct spillover from and to CPI

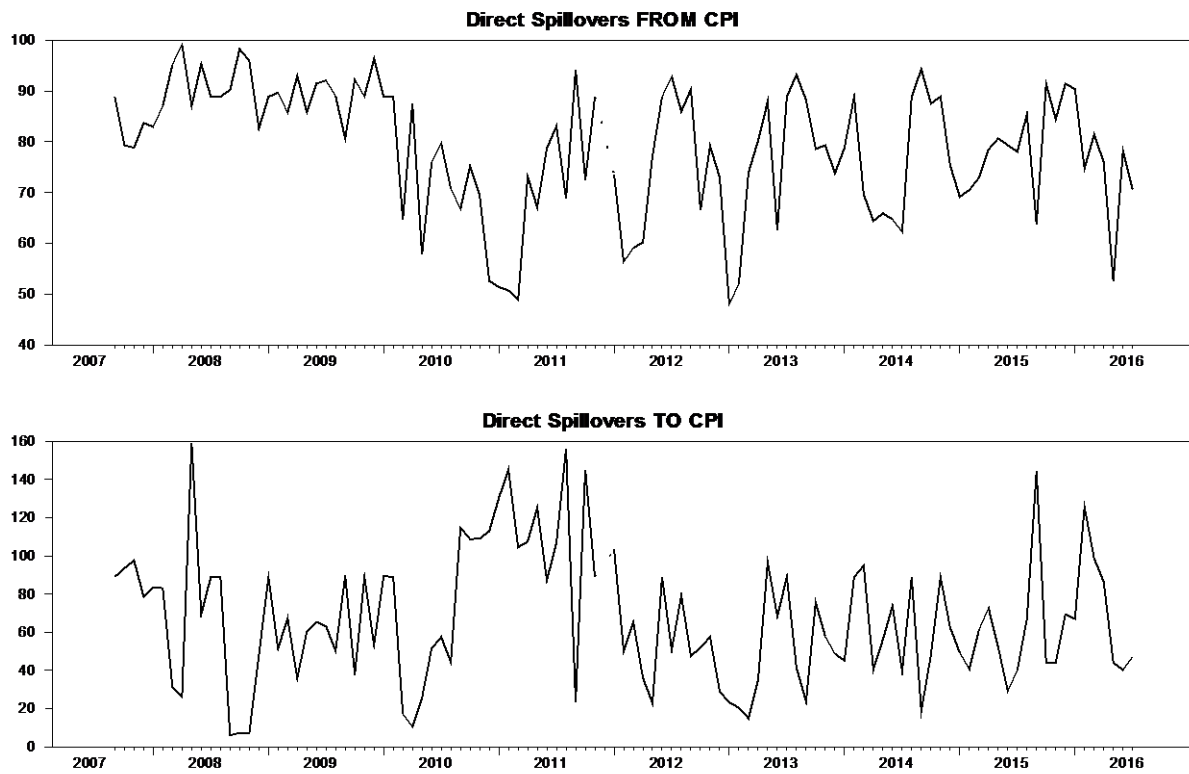
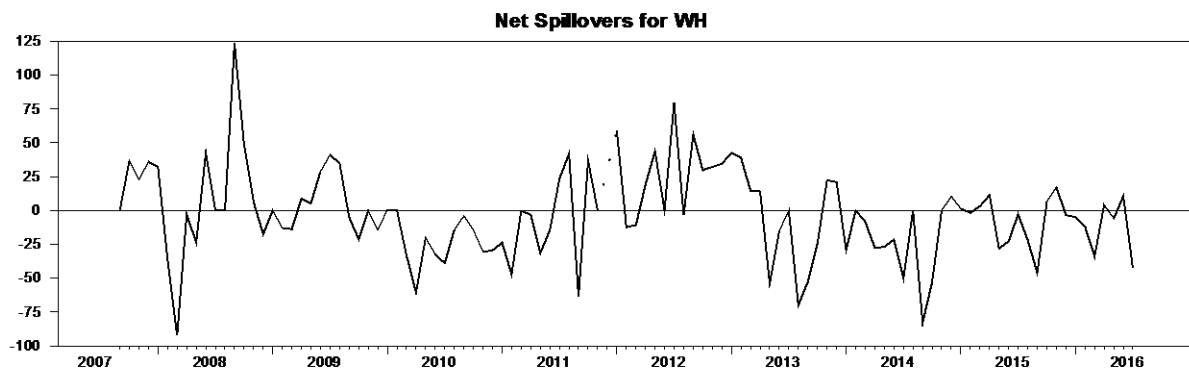
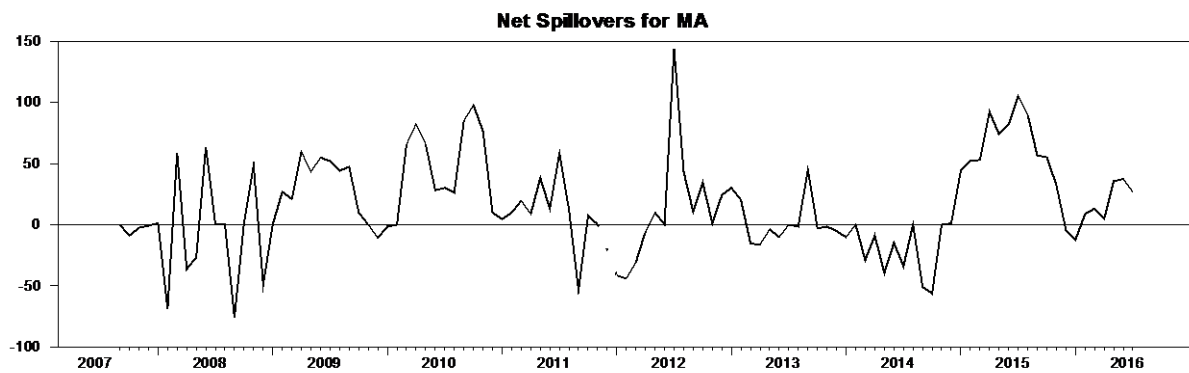
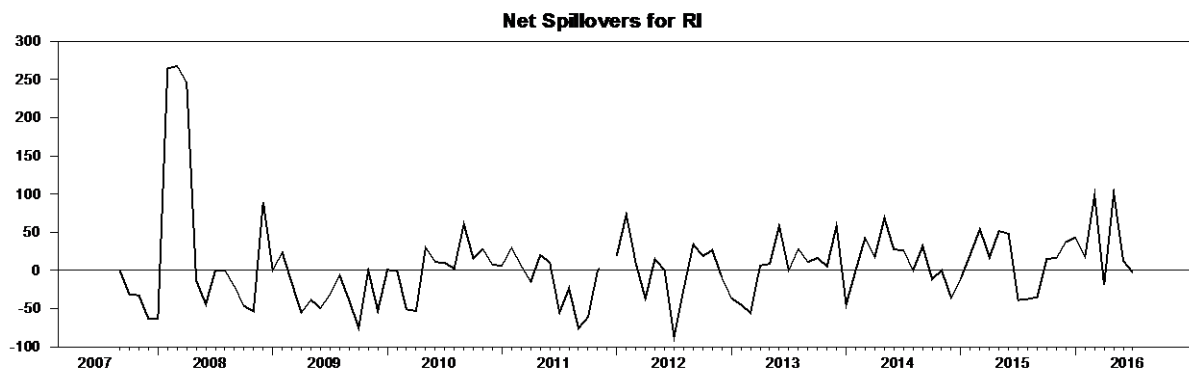
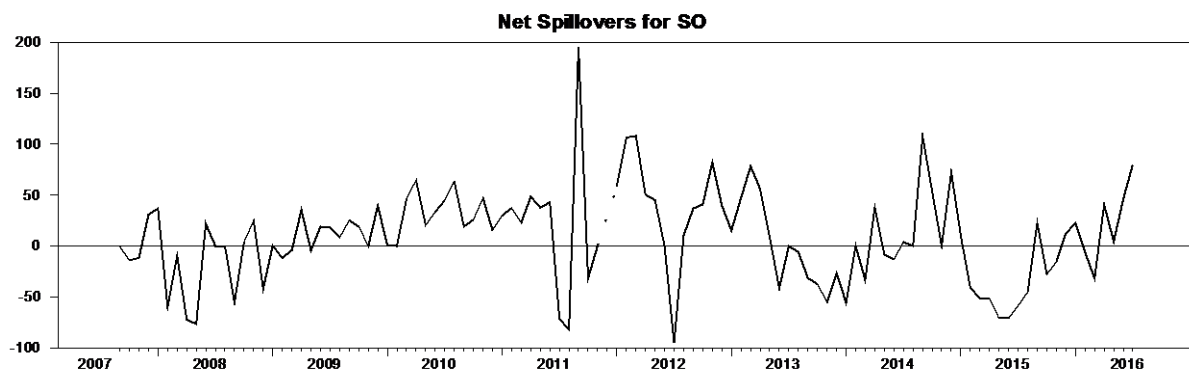
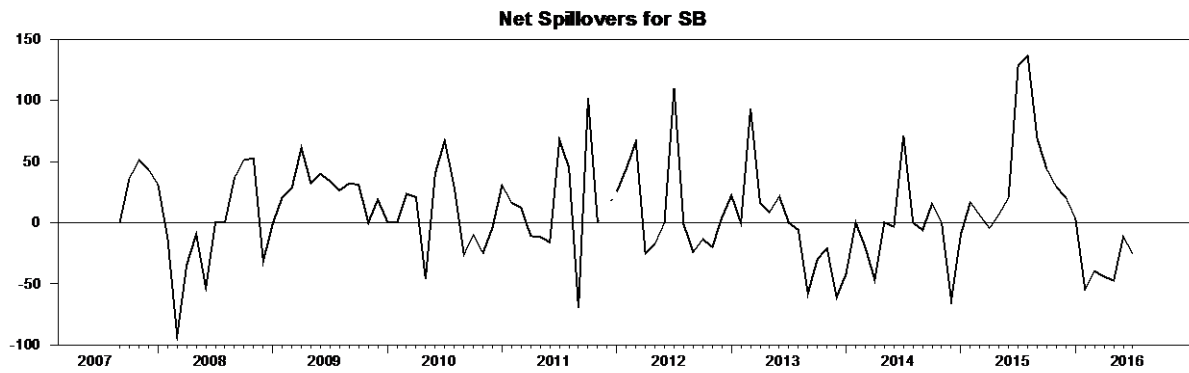


Figure 3: Rolling net spillover estimates for commodities





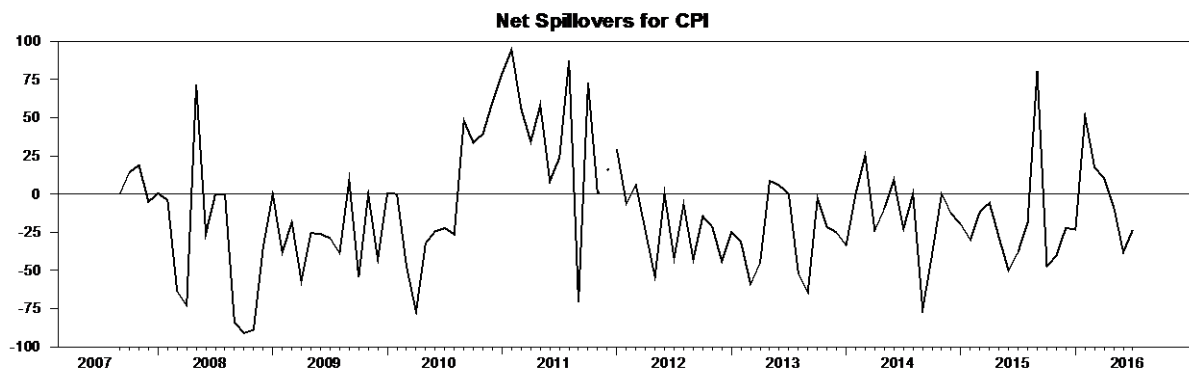
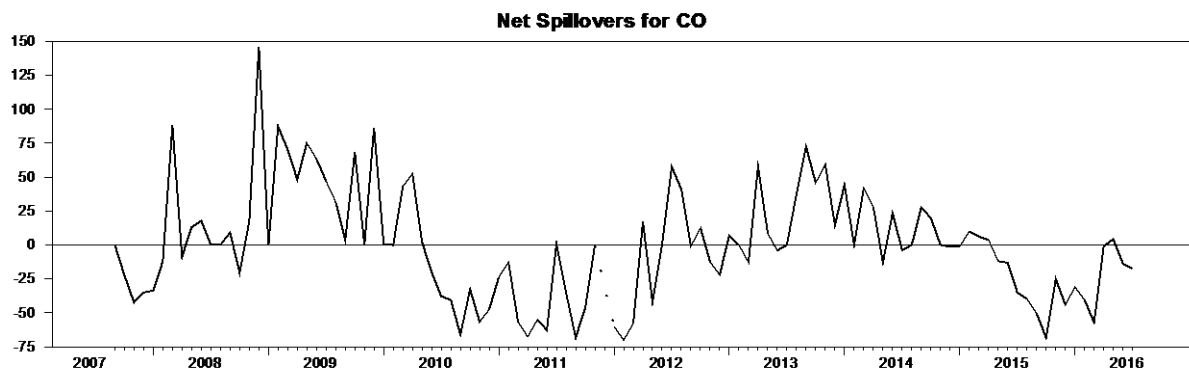
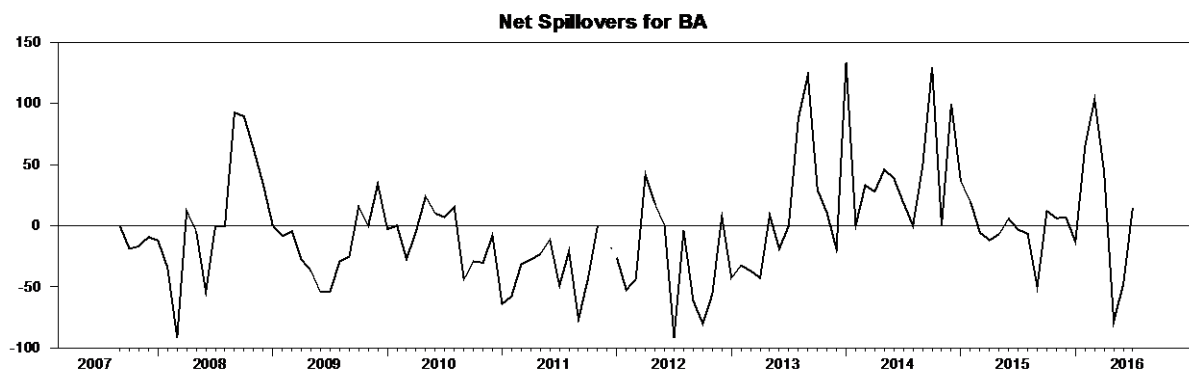
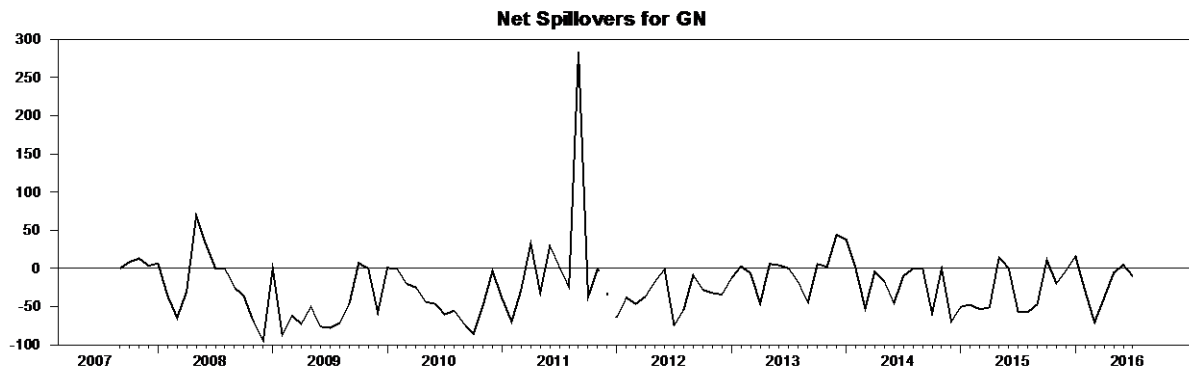


Figure 4: Rolling total spillover estimates

