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NETWORK MOTIF OF INTERBANK PAYMENT AS EARLY WARNING SIGNAL OF LIQUIDITY CRISIS*:*

DIRECTED RANDOM GRAPH AND DIRECTED CONFIGURATION MODEL APPROACHES

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Abstract

The widespread impact of the global financial crisis has increased the focus of global attention on the transmission of spread risk through interbank connectivity on payment system networks. In its development, changes in interbank connectivity patterns within the network can be identified as early warning signals of future crises. This study aims to identify network motives of large value interbank payment transactions (RTGS) and interbank retail payment transactions (national clearing system) to become early warning signals on financial liquidity conditions. The relationship pattern is estimated using Directed Random Graph (DRG) and Directed Configuration Model (DCM) models. The results indicate that interbank reciprocal network motive, through the RTGS system, has a relationship with the liquidity condition of the financial system so that it can be used as an early warning system. In addition, estimates, using the DCM approach, are better at explaining interbank network relationships compared to the DRG model.

Keywords : Network motif; interbank payment; RTGS; clearing; liquidity crisis; directed configuration model; directed random graph

JEL Classification :

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I. INTRODUCTION

The widespread impact of the global[3] the financial crisis is due to the connectedness between actors on the financial markets. Some studies suggest that the impact of the crisis can be transmitted through interbank connectedness within complex financial system networks (OECD, 2012; European Central Bank, 2012; Jo, 2012; Chang, *et al.,* 2014). This valuable lesson on crisis impact spreading has increased the focus of world attention on interbank connectivity patterns in a network over the last decade.

The connectedness between banks in a network is dynamic and can change when shocks occur in the economy. Several studies have described the relations between liquidity in the financial system and the connectivity topology between actors within the network of payment transactions. Soramaki, *et al.* (2006) found that interbank connectivity patterns, in meeting their daily liquidity, change when there is a disruption to a number of financial systems and infrastructure in America[4]. Using the same approach, Becher, *et al.*, (2008) and Schmitz and Puhr (2009) demonstrated that the operational disruption in one of the payment system actors can influence the interbank connectedness pattern. In this context, the magnitude of the pressure in the financial system affects the interbank connectivity pattern in the payment system.

The interbank connectedness pattern, in its development, began to be used in estimating the occurrence of pressures on the financial system in the future (early warning signal). Squartini (2013) developed an interbank motif model to find changes in motifs as an early warning system both before and during the crisis in the Netherlands. The model was then replicated by Kawada (2016) who found a change in the motifs of the relations between the three banks (triadic motif). Both studies used high-value payments data (RTGS[5]) as the source of all payment transactions. On the other hand, the retail payment transactions (clearing[6]), as the beginning of transactions conducted by the public, have the ability to predict interbank connectedness so as to enrich the estimated liquidity in the payment system.

In contrast to previous studies, the present study intends to compare the motif connectedness between two banks (dyadic motif) in RTGS transactions with clearing transactions as early warning signals. Using a null model consisting of Directed Random Graph (DRG) and Directed Configuration Model (DCM), this study found that the reciprocal interbank connectedness motif in the RTGS transactions is related to the financial system liquidity condition. Meanwhile, interbank connectedness motif in the clearing transactions can be a leading signal to RTGS transactions.

The results of the present study will be presented in five chapters. The first chapter explains, in general, the background and purpose of the study. The second and third chapters describe the conceptual framework related to the use of interbank interconnection variables in the payment system as an early warning indicator and the research methodology. The fourth chapter describes the results of modeling the interconnection pattern of interbank as an early warning indicator. Finally, the fifth chapter summarizes the

[3] International Monetary Fund (IMF) The International Monetary Fund (IMF) stated that the mentioned crisis was the worst financial crisis that has happened in the world since the tragedy of the great depression.(Claessens and Kose, 2013).

[4] The World Trade Center attack on September 11, 2001, destroyed most of the facilities and financial infrastructure in the US. The incident triggered a debt crisis in the United States that reached USD17T or 93% of the Gross Domestic Product of the United States(https://www.thebalance.com/how-the-9-11-attacks-still-affect-the-economy-today-3305536 accessed December 13, 2017).

[5] High-value payment transactions are usually performed between banks through the Real Time Gross Settlement (RTGS) system.

[6] Retail transactions are carried out by customers through credit transfer using the clearing system.

results of the research and the policy implications.

II. THE CONCEPTUAL FRAMEWORK AND THEORETICAL BASIS

2.1. The conceptual framework

The increased awareness of the crisis is marked by the growing research that raised the topic of crisis occurrence indicators. The topic of the crisis was first discussed by Krugmans (1979) with a focus on the balance of payments crisis. According to Krugmans (1979), the decrease in international reserves indicates the occurrence of exchange rate speculation that could lead to a crisis. The monetary crisis that hit several Asian countries, in 1997, gradually shifted the focus of the world attention from the topic of the balance of payments crisis. A study that discusses the monetary crisis in Asia and is often used as a reference by various studies on early warning indicator is a study conducted Kaminsky, et al., (1998). According to Kaminsky, et al., (1998), some economic variables can become leading indicator[7] of the crisis. Kaminsky, et al., (1998) found that the leading indicators have the ability to predict the occurrence of monetary crisis within the next 24 months. The study conducted in the following years is generally still discussing the crisis occurrence indicators based on variables in the monetary field.

The global financial crisis (2008-2009), that was triggered by subprime mortgage problems and affected the deterioration of the world economy, began to attract attention with regard to the feedback loop between the financial sector and the real sector. Some literature began to use the macroprudential approach in discussing the leading indicators of the crisis. According to Babecky (2012), the indicator of the ratio, between the lending to the private sector and Gross Domestic Product (GDP), is able to signal the crisis within the next four years. In line with this study, Drehmann (2013) explained that the ratio of loan to Gross Domestic Product (GDP) is a strong indicator to predict the occurrence of the banking crisis and can be used as an approach to improve macroprudential resilience. Unlike previous research, Shin (2013) found that a total indicator of bank liabilities as an intermediary institution is better in showing the sign of crisis than loan ratio variable to Gross Domestic Product (GDP) and asset price on the financial market. These macroprudential approaches were then developed by various authorities and stakeholders to prevent systemic risks in the financial sector.

Based on studies of early warning indicator of the crisis, the empirical analysis using variables related to the payment system is still relatively limited. Some studies that utilize payment system variables use network theory approach to find early warning signal of crisis. Using the null model, Squartini (2013) and Kawada (2016) estimated the motifs of actor connectedness within the payment system network. The empirical analysis is done by comparing the real value of the topological quantity of interest property obtained from the original data to the expected values obtained from the Directed Random Graph (DRG), the Directed Configuration Model (DCM), and the Reciprocated Configuration Model (RCM). The interbank connectedness motif is analyzed, based on the z-scores from the triadic motifs, to compare the crisis and pre-crisis phases. The results of the study indicate an anomalous cycle that was found in the connectedness motifs between the three banks (triadic motifs) and identified as a pre-crisis phase that can signal the occurrence of a crisis within the next three years.

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[7] The monetary crisis can be estimated based on indicators such as export value, exchange rate deviation, broad money ratio to gross international reserves, output level and equity of prices (Kaminsky, 1998).

In the modern economy, every agent interconnects with others in a complex network of financial systems. According to Squartini, *et al.,* (2013), inter-agency economic connectedness in the financial system are dynamic. The patterns of connectedness can be altered, either due to endogenous factors such as internal management mismatches that impact on other institutions, or exogenous factors due to the pressures in the economy transmitted through interconnected financial linkages (May, *et al.,* 2008; Haldane and May, 2011). Following the global financial crisis that occurred in 2008-2009, linkages among financial institutions were identified as a source of systemic spread risk (Jo, 2012). The mentioned condition raises awareness of the stakeholders to begin analyzing the resilience of the financial system based on connectedness patterns within the network.

2.2. Literature Study

To analyze interbank connectedness pattern in the network is actually not independent of the network/graph theory that comes from the branch of science algebra. Based on the graph theory, the analysis of a network can be done by categorizing patterns of relationships that occur between individuals in the network. One of the most widely used methods for analyzing relationship patterns within a network is the degree of heterogeneity approach (Soramaki, *et al.,* 2006; Becher, *et al.,* 2008; Schmitz and Puhr, 2009). Using the RTGS data in the United States, Soramaki, *et al.,* (2006) suggested that national crises may lead to changes in the payment system network topology as evidenced by reduced points, links, and connectivity. Meanwhile, the average path length of the inter-points has increased. The method is also adopted for RTGS data in the UK (Becher, *et al.,* 2008) and Austria (Schmitz dan Puhr, 2009) to see the impact of the operational shock on network characteristics in the payment system.

In addition to using the degree of heterogeneity approach, several studies also used a core-periphery model to analyze interindividual relationships within the network. Craig dan von Peter (2014) conducted a study to understand the "too-connected-to-fail" macroprudential concept using interbank transactions data on Dutch financial markets. The results of the study showed that the network structure on Dutch financial markets spread around the core banks. In the network, there is a bank that acts as a mediator between core banks and periphery banks. The core-periphery model was also applied in various studies on the network, among others, a study performed by Leij, *et al.,* (2016) to describe the banking networks in the Netherlands and Baek, *et al.,* (2014) to monitor the intraday liquidity of BOK-Wire+[8] using network indicators.

In network theory analysis, finding the degree of heterogeneity is an approach used to determine the disintegration of the network in the event of pressure. The approach is able to show the interconnection structure differences between banks before and after the shock, by measuring the distance of the connectedness within different time periods. Meanwhile, the approach with the core-periphery model is used to determine the structure of the connectedness by classifying the group of banks acting as core/center or periphery. For the stakeholders, this core banks group will be the focus of intensive monitoring. On the other hand, both approaches have limitations i.e. they cannot be used as monitoring tools to identify potential future crises.

Studies conducted by Squartini (2013) and Kawada (2016) used the same model and transaction data types. The empirical analysis is done by using the null model, consisting of DRG, DCM, and RCM, and using the type of interbank exposure transaction included in the category of transaction data of high-value payment system. Based on these two studies, the

[8] BOK-Wire + is an RTGS system in Korea (Baek, *et al.,* 2014)

estimation using the Reciprocal Configuration Model (RCM) approach is better at explaining the relationship motifs among the three banks in the network, compared to others such as the null model, DRG, and DCM. In addition, the motif relationship between the three banks (triadic motif) in the network payment system is able to show early warning signal of the occurrence of the crisis. The difference between them lies only in the scope of the data used. Squartini (2013) used data on interbank exposure on the German money market, while Kadawa (2013) used transaction settlement data on BOJ-Net, a real-time gross settlement (RTGS) system in Japan.

In contrast to previous studies, this study used more diverse data types. In addition to using the RTGS transaction data, the present study also explored the use of clearing transaction data. The interbank relationship motif that was estimated was the relationship motif between the two banks (dyadic motif). Therefore, this study adopted a null model from Squartini (2013) to compare the crisis and pre-crisis phases, consisting of the DRG and DCM models. The RCM was not used as the model is used to estimate the z-scores of triadic motifs.

II. METHODOLOGY

3.1. Data

The data used in this study were the data of high-value payment transactions and retail transactions (clearing) of Bank Indonesia (BI) during the period of 2005-2016 (observed on a monthly basis). The data came from both the RTGS system and the National Clearing System of Bank Indonesia. In addition, this study also used the Financial System Stability Index (ISSK) data as a proxy for the pressures that occurred related to the liquidity of the payment system in Indonesia. The data was obtained from Bank Indonesia.

3.2. Local Constraint (Null Model)

In this study, the null model used consisted of Directed Random Graph (DRG) and Directed Configuration Model (DCM). The model was used to measure the differences between the link of the model estimation results and the link of the transaction data network used (z-score). Model estimates generate z-scores to see early warning signals of crisis.

There was a local constraint in the DRG model which was the total number of links, $L = \sum_i \sum_{j \neq i} a_{ij}$, of a network. It means, in the context of the payment system, the number of interbank payment relationships in a system. The Hamiltonian DRG was formulated as follows:

$$H(A, \vec{\theta}) = \theta L$$

and opportunities for networks are generally formulated as follows:

$$P(A|\vec{\theta}) = \prod_i \prod_{j(\neq i)} p^{a_{ij}} (1-p)^{1-a_{ij}} = p^L (1-p)^{N(N-1)-L}$$

where $p = \frac{x}{1+x}$ with $x \equiv e^{-0}$. Parameter x can be changed to x^* that maximizes likelihood A*. in this case,

$$\langle L\rangle = \sum_i \sum_{j(\neq i)} \frac{x^*}{1+x^*} = L^* \quad (13)$$

After an unknown variable with numerical analysis, the expected value of the adjacency matrix entry becomes $a_{ij} = p^* = \frac{x^*}{1+x^*}$. By completing equation (13), then the P parameter formula i.e.:

$$p^* = \frac{L^*}{N(N-1)}$$

which is a link density.

Furthermore, the DCM model has two-degree sequences for the local constraint i.e. out-degree sequence, $k_i^{out} = \sum_{j(\neq i)} a_{ij}$, which is the number of out-going links and in-degree sequence, $k_i^{in} = \sum_{j(\neq i)} a_{ij}$, which is the number of in-going links. The DCM is obtained if in- and out-degree are entered as constraints in vector $\vec{C}$. The Hamiltonian DCM is formulated as follows:

$$H(A,\vec{\theta}) = \sum_{i=1}^{N} (\alpha_i k_i^{out} + \beta_i k_i^{in})$$

and the opportunity coefficients for network A generally become:

$$P(A|\vec{\theta}) = \prod_i \prod_{j(\neq i)} p_{ij}{}^{a_{ij}} \left(1-p_{ij}\right)^{1-a_{ij}}$$

where $p_{ij} = \frac{x_i y_j}{1+x_i y_j}$ with $x_i \equiv e^{-\alpha_i}$ dan $y_i \equiv e^{-\beta_i}$. Parameters $\{x_i\}$ and $\{y_j\}$ can be replaced with values $\{x_i{}^*\}$ and $\{y_i{}^*\}$ which maximize likelihood A*. In the following case,

$$\begin{cases} \langle k_i^{out}\rangle = \sum_{j(\neq i)} \frac{x_i{}^* y_j{}^*}{1 + x_i{}^* y_j{}^*} \\ \langle k_i^{in}\rangle = \sum_{j(\neq i)} \frac{x_j{}^* y_i{}^*}{1 + x_j{}^* y_i{}^*} \end{cases}$$

After all of the parameters have known values, the expected value of the adjacency matrix entry becomes:

$$\langle a_{ij}{}^*\rangle = p_{ij}{}^* = \frac{x_i{}^* y_j{}^*}{1+x_i{}^* y_j{}^*}\ .$$

3.3. Dyadic motif

The network structure of the interbank exposure transaction used in this study was analyzed based on the dyadic motifs i.e. the motifs formed from the relationship between two nodes in the directed network. Dyadic motifs consist of single link[9], reciprocated link[10], and null link[11] which can be seen in Figure 3.1.

[9] In a payment system network, the single link is a transfer relation from Bank A to Bank B.
[10] Reciprocated link is a transfer relation from Bank A to Bank B, and contrariwise.
[11] Null link is the absence of transfer relation from Bank A to Bank B and vice versa.

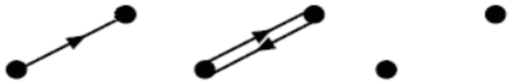


Figure 3.1. Dyadic Motifs that represent All Possible topological configurations of two nodes connected to a Directed network

The number of occurrences of a particular motif was denoted by N_m and $m = L^{\rightarrow}, L^{\leftarrow}, L^{\leftrightarrow}$, Formula N_m for the dyadic motif i.e.:

$$N_{L^{\rightarrow}} = \sum\nolimits_{j(\neq i)} a_{ij}(1 - a_{ji})\,, N_{L^{\leftarrow}} = \sum\nolimits_{j(\neq i)} a_{ji}(1 - a_{ij})\,, N_{L^{\leftrightarrow}} = \sum\nolimits_{j(\neq i)} a_{ij}a_{ji}$$

The original value information, the expected value, and the N_m variant can be used to compare the observed value and the expected value, known as z-scores, i.e.:

$$z_m \equiv \frac{N_m(A^*) - \langle N_m \rangle^*}{\sigma^*[N_m]}$$

where $\sigma^*[N_m] \equiv \sqrt{\langle {N_m}^2 \rangle^* - (\langle N_m \rangle^*)^2}$ is the standard deviation of the null model. If the z-scores value = 0, it means that the value of the observation is exactly the same as the expected value. If the z-scores is higher, both positive and negative, it indicates the existence of an overpassed or under-estimated empiric motif. The value of z-scores is considered as a 'fingerprint topology' which will be a benchmark to see how the 'fingerprint' is moving in every phase before the crisis, during the crisis, and after the crisis, as an early-warning signal prior to the crisis.

3.4 Cross−Correlation Function

To further explore the patterns of interbank payment transaction movement, the cross-correlation (CCF) is used to determine whether a series includes lagging or leading indicator. The main objective of the CCF is to determine the dynamic linear relationship in stationary time series data so that the relationship between payment transaction (RTGS and clearing) and can be determined.

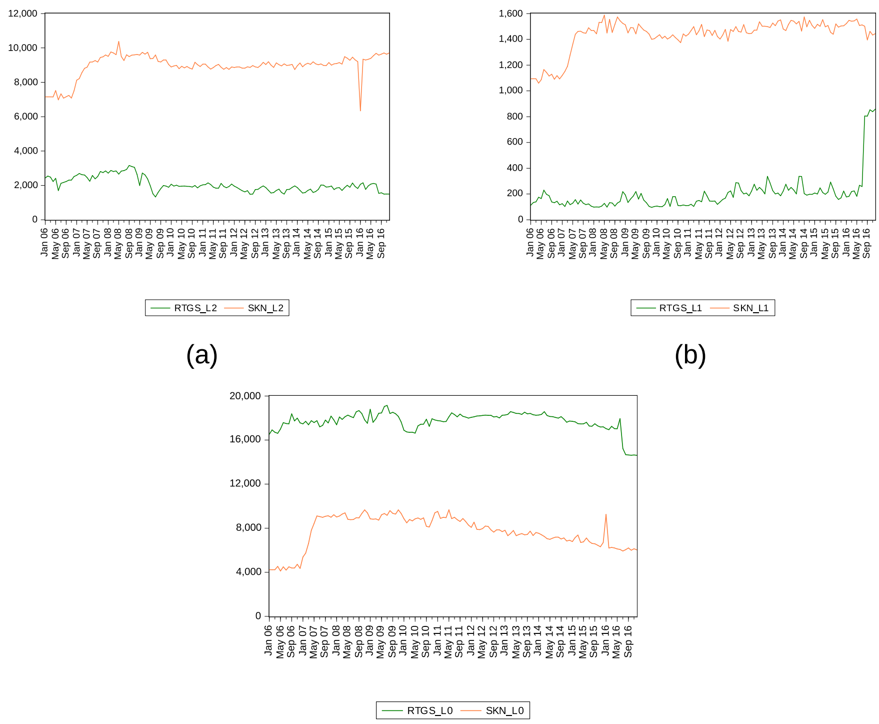
IV. RESULTS OF THE RESEARCH

4.1 Descriptive Analysis

The present study only analyzed three dyadic motifs based on Squartini (2013). The number of links of the motif is presented in Figure 4.1. Based on the results of motif calculations on transactions, there were average results for reciprocated, single, and null links that were 2025, 426, and 17,465, respectively. In the RTGS transactions, null link motifs were more dominant compared to the other motifs. The number of null links was suspected, since, in the RTGS transactions, a transactional relationship occurs as a result of the need for liquidity or placement funds. Thus, interbank transactions in the RTGS do not occur daily. In addition, the concentration in interbank relations indicates a selective process in every interbank transaction within the RTGS, resulting in many null links in the RTGS transaction.

Conversely, reciprocated link motifs were more dominant compared to other motifs in the clearing transactions. In the clearing transactions, the average links were 8,871 for the reciprocated links, 1,502 for single links, and 7,580 for null links. This can happen as the interbank transactions through the clearing are random, and the transactions are initiated by the customers. In this case, the bank only functions to continue the client's order so that the interbank transaction relationship can occur randomly with various banks in accordance with the customer orders.

Based on Figure 4.1, it can be seen that the number of degrees (reciprocated and single link) occurring in the clearing transaction is much greater than that of the RTGS transaction (in general). In contrast, null links in high-value transactions (RTGS) are higher than those of the clearing transactions.



(c)

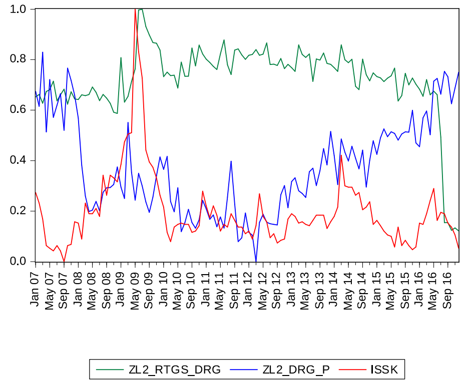
Figure 4.1. Series (a) Reciprocated, (b) Single, and (c) Null Links within the period of 2006-2016.

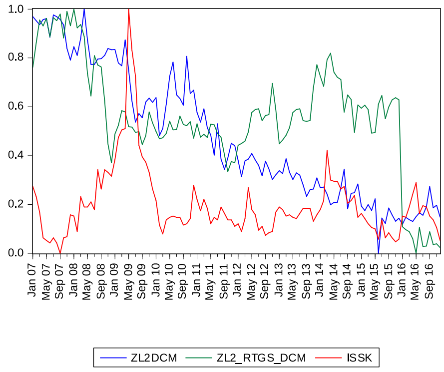
4.2. Early Warning Signal Model

The transaction pattern, between two banks in the payment system network, was estimated through the DRG and DCM models based on three relationship motifs i.e. reciprocated link, single link, and null link. Figure 4.2. shows the z-score results of the DRG and DCM models.

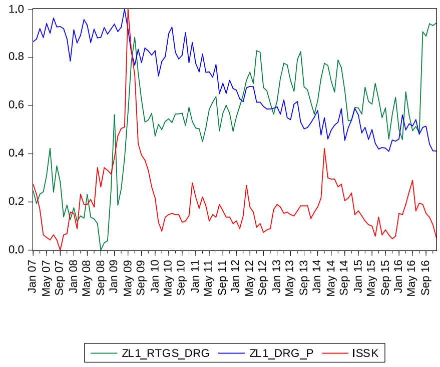
DRG	DCM

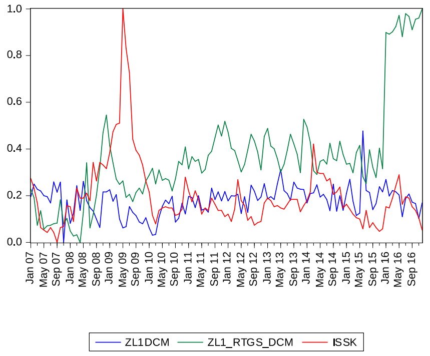
Reciprocated Link



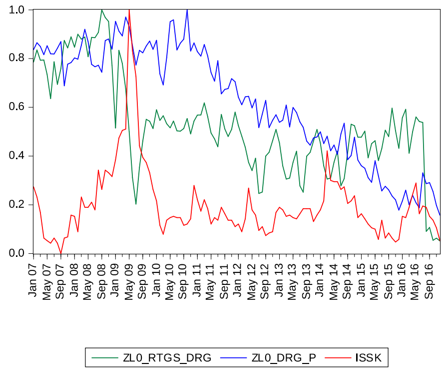


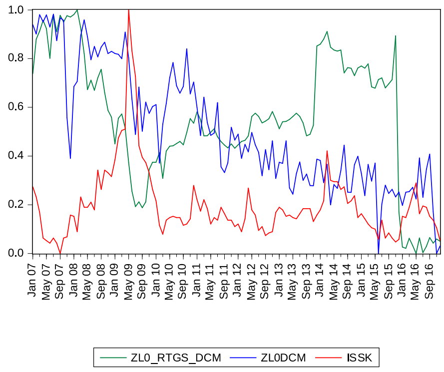
Single Link





Null Link





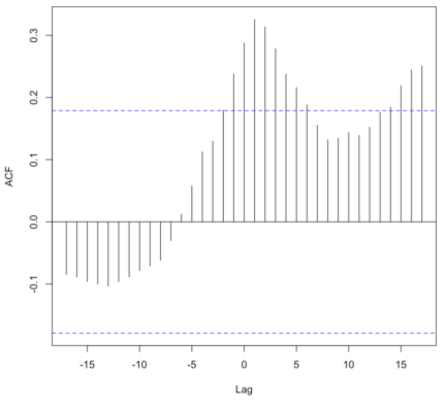
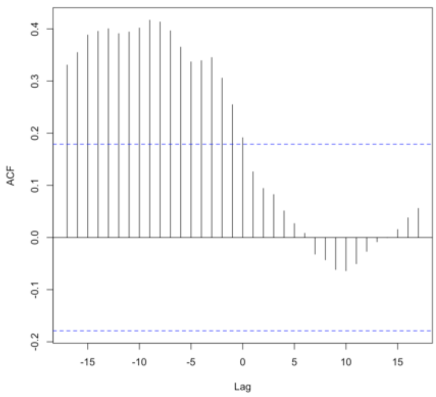
Description: Z-score series of the RTGS (green), Z-score of the clearing (blue) and ISSK (red).

Figure 4.2. Z-score results normalization of the DRG and DCM at various link motifs.

Based on the z-score results, the best model is the model that produces the smallest z-score (the smallest deviation). In the RTGS transaction, the average z-scores in the DRG model were 176.71 for the reciprocal link, 51.55 for the single link, and 22.4 for the null link. Meanwhile, the average z-scores of RTGS transaction in the DCM were 33.81 for the reciprocated link; 53,163 for the single link, and 15.47 for the null links. Based on the RTGS transaction z-score results from both models, the DCM produced smaller z-scores compared to the DRG.

Likewise, in clearing transactions, the DCM z-score results were smaller than those of the DRG. For the DCM model, the z-scores generated for the reciprocated, single, and null links were 13.06, 63.87; and 20.77, respectively. Meanwhile, the z-scores, in the DRG model, of the reciprocated, single, and null links were 43.51, 547.13, and 53.96, respectively. The results showed that the DCM approach, in both RTGS and clearing transactions, can estimate more accurately compared to the DRG approach. The DCM approach, which assumes the presence of heterogeneous probabilities for any interbank relations, can illustrate the real condition of interbank transaction motifs, either in the RTGS or in the clearing.

Once the RTGS and clearing transaction motifs are estimated using the DRG and DCM, then the CCF is performed to find out the indications of relationships between the z-scores of the two types of transactions (RTGS and clearing) with the ISSK. According to Figure 4.3, most of the CCFs between RTGS transactions and the ISSK showed significant results prior to lag 0, indicating that the RTGS transaction is leading towards the ISSK. In other words, the z-score of the RTGS transaction is generally capable of capturing a crisis signal prior to ISSK. In addition, the transaction motif, of the reciprocated link on the DCM z-score, had the highest correlation with the ISSK. This indicated that the DCM approach, using the reciprocated motifs, had the best results in terms of capturing the crisis signal compared to the ISSK.

DRG	DCM
Reciprocated Link	
	
Single Link	

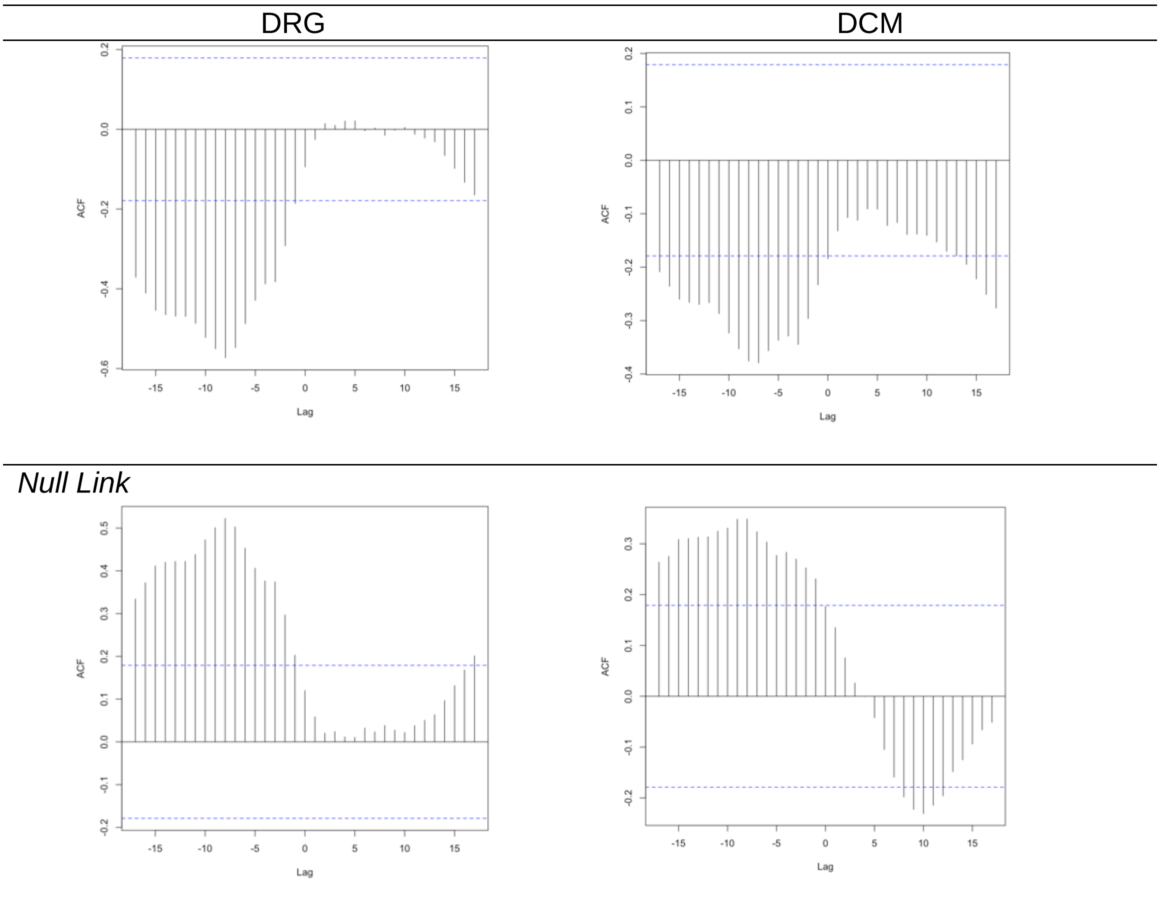
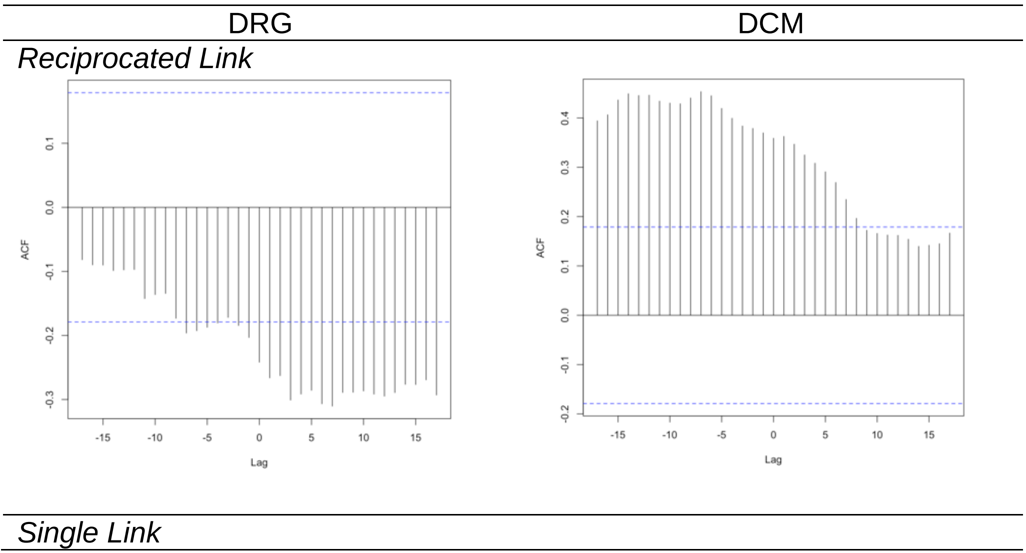


Figure 4.3. CCF results from RTGS to ISSK

Furthermore, in the clearing transactions, the CCF results revealed a significant correlation before and after the lag 0, as shown in Figure 4.4 below, signifying that the lagging status or the clearing leading z-score status towards the ISSK is unknown. The z-score values of the clearing transactions are not as good as those of the RTGS transaction in capturing the crisis signal.



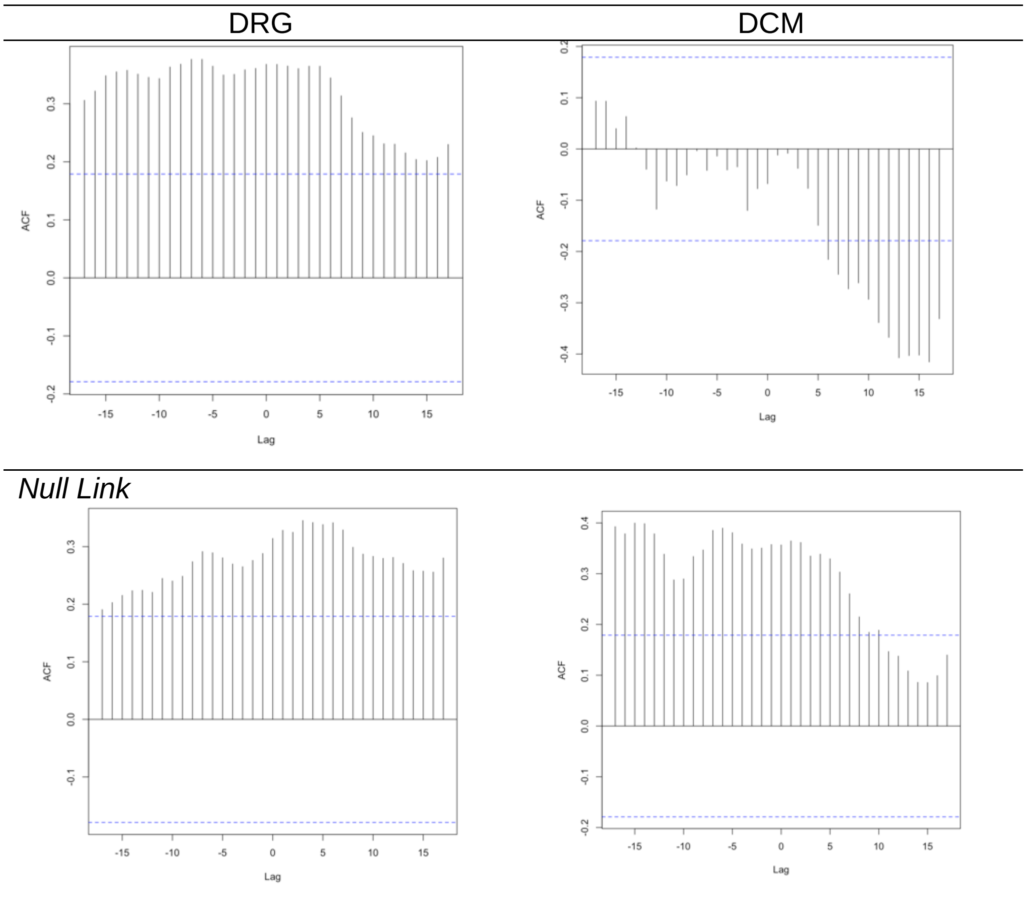


Figure 4.4. CCF results from clearing to ISSK.

The present study also identified the relationship between the z-score in RTGS transactions the z-score in clearing transactions. In Figure 4.5, it can be seen that there was a leading signal from the z-score in the clearing transactions towards the z-score in the RTGS transactions. This is suspected to be due to the fact that the clearing transaction is the beginning of the emergence of a bank liquidity needs. At the end of the settlement of clearing transactions, conducted as netting, a position will arise where there are banks that "lose" and "win". A bank in a negative clearing net position (losing clearing) will seek funds on the interbank market through the RTGS system to cover its shortfall. The clearing transaction becomes one of the sources affecting liquidity needs in the RTGS. Thus, in connection with the early warning signal, the clearing transactions cannot directly predict the occurrence of a crisis. However, the value of interbank transaction motifs, through clearing, can predict the movements of the RTGS transaction motifs.

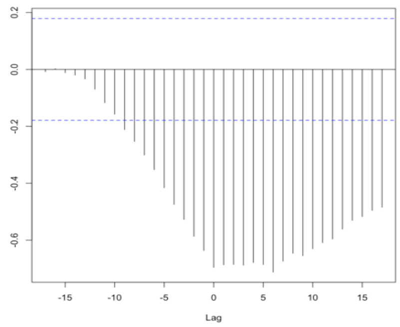
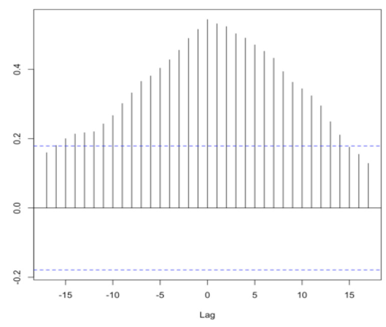
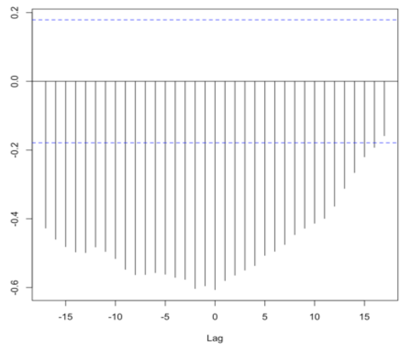
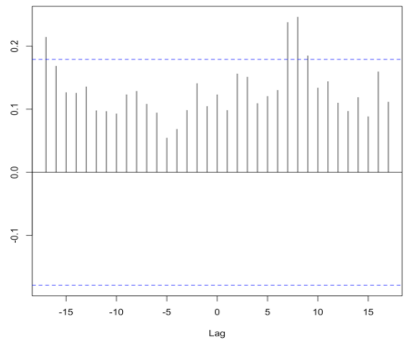
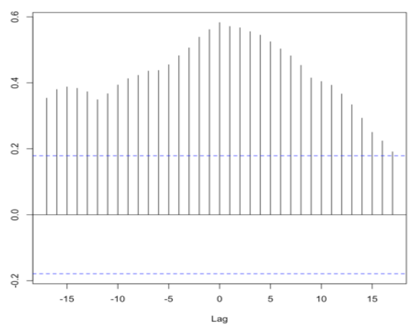
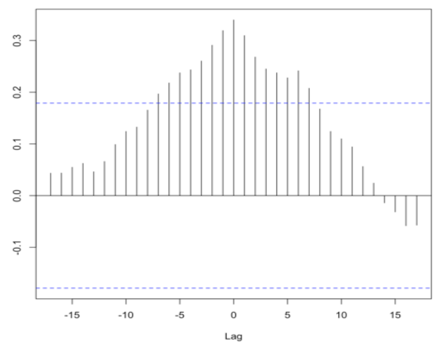
DRG	DCM
Reciprocated Link	
	
Single Link	
	
Null Link	
	

Figure 4.5. CCF results from RTGS to SKN.

V. CONCLUSIONS AND POLICY IMPLICATIONS

5.1. Conclusions

The transaction motifs of interbank relations in the payment system can be observed to determine the liquidity condition of a financial system. Some interbank payment transactions have certain forms of motifs that can be linked to the liquidity conditions, one of which is the dyadic motifs in the forms of reciprocal, single, and null links. The null link motif dominates the RTGS transactions, while the reciprocal link motif commands the clearing transactions in the SKN. This occurs because, in RTGS transactions, the interbank relation is more concentrated in some banks only and do not spread to other banks. While in the clearing transactions, transactions are random since the clearing transactions, in the SKN, are initiated by the customer.

The estimation results in the DRG and DCM models, in both RTGS and SKN transactions, showed that the DCM approach had smaller deviations. The estimation of the DCM approach is more accurate than that of the DRG approach in both types of transactions. This showed that the DCM model, in the RTGS transaction, has a potential as an early warning signal for the liquidity crisis conditions. The result of RTGS transaction correlation towards the ISSK showed that RTGS is leading towards ISSK. The DCM model of RTGS transactions has a potential in becoming an early warning signal for the liquidity crisis conditions. In addition, the reciprocal interbank payment transfer relationship, estimated by the DCM model, is the best motif for early warning signals in the RTGS system. However, the cross-correlation results of the clearing transaction towards the liquidity condition is not as good as the RTGS transaction. Thus, there is still a need for further testing on clearing transactions with regard to liquidity conditions.

Another interesting finding is the presence of leading signals from the z-score of the clearing transaction towards the z-score of the RTGS transaction, indicating that a clearing transaction may affect the liquidity requirement of an RTGS transaction. *Thus, although the clearing transactions do not have the potential to reflect the liquidity conditions, they precisely and firstly signal the RTGS transactions.*

5.2. Policy Implications

In monitoring the liquidity conditions, the RTGS payment transactions can be an indicator of the occurrence of financial liquidity. The DCM model and interbank reciprocal relationship can be used as an early warning signal of the liquidity crisis. The use of payment transactions as an early warning system should still be studied in terms of model stability and robustness.

The present study has not included the threshold measurement of the z-score to determine the value limits used in monitoring early warning signals. Therefore, the next study can be more focused on the z-score threshold measurement. In addition, the payment motif between the three banks (triadic motif) can be an alternative to better understand the interbank payment transaction motifs.

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