Structure and Stability of the Jamaican Payment System: Assessing Systemic Risk in the JamClear-RTGS System through Network Analysis & Simulations

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Abstract

This study seeks to examine the network topology and stability of the Jamaican payment system during January 2014 and December 2015. The operational resilience of payment infrastructures is important to maintain financial stability as disruptions in routine payment flows can result in unwanted risk exposures. To better understand the financial network and minimize systemic risk in Jamaica, this paper examines the network topology of the JamClear-RTGS in periods of tight liquidity and normal liquidity, identifying systemically important payment institutions (SIPIs) as well as uses counterfactual simulations to quantify the contagion impact of the inability of SIPIs in submit payments. Results indicate relatively high connectivity with over 50.0 per cent of potential payment flows being realized. Notably, commercial banks dominated the strongly connected sub-group of participants. Commercial banks were also the most influential and systemically important participants based on degree centrality. Closeness and betweenness centrality, however, highlighted the importance of primary dealers within the network. Increased concentration risk and a lower speed of contagion risk was observed for December 2015 relative to January 2014. Counter-factual simulations revealed a resilient payment system to various participant defaults. Given the network structure observed and the importance of commercial banks and primary dealers within the Jamaican financial system, potential shocks to the payment system network have implications for the formulation of appropriate liquidity management policies.

Keywords: Network Topology, Systemic Risk, Contagion, Payment System
JEL Classifications: D58, G21, G20, G28

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1. Introduction

The most recent global financial crisis experienced in 2008 has raised concerns on the adverse consequences related to externalities intrinsic to financial systems. One particular association with the increased pace of globalization and financial integration is interconnectedness risk or too-connected-to-fail (Chan-Lau, 2010). With increased interconnectedness in financial markets, systemic risk has become a key concern for central banks, especially as it relates to their responsibility for financial stability. The heightened levels of interconnectedness also broadens the base of the number of potentially destabilizing institutions beyond that determined by the traditional banking-focused approach to systemic risk. As such, there is the need for methodologies capable of coping with complex cross-dependent, context-dependent non-linear systems (Leon *et al.*, 2011). This, the authors posit promulgates a shift in ideology from the too-big-to-fail to too-connected-to-fail.

The interconnectedness of the modern financial system is generally observed to have been a key contributing factor to the recent financial crisis (Glasserman and Young, 2014). With the existence of intricate interlinkages between institutions, risk emanating from one section of the system can be transmitted throughout the system to other areas, thereby creating a system-wide threat to financial stability. Recent work on the stability of banking systems suggests a systematic relationship between network structure, system stability and contagion (Schmitz and Puhr, 2009). As such, effective financial systems surveillance requires the monitoring of direct and indirect financial linkages whose disruption could have important implications for the stability of the entire financial system.

One method of analysis that has come to the fore in tackling the issue of interconnectedness is network analysis which involves the mapping and measuring of relationships and flows within a group of agents[2]. The main advantage of network analysis is that it provides both a visual and a mathematical analysis of relationships from which the answers to key questions about the characteristics and performance of a network can be obtained (Espinosa-Vega and Solé, 2011a). Network analysis allows for the design of simple metrics for measuring contagion that can be used to augment contemporary stress testing techniques.

[2] Espinosa-Vega and Solé (2011a).

An evaluation of the evolution of networks, more specifically financial networks, is important in the management of systemic risk. Network analysis on financial systems provides an assessment of the possible systemic exposures of the system to arbitrary or direct failures. In identifying the structure of financial/payment networks we are able to capture particular features of the financial/ payment system which can then be monitored to capture the dynamics within the system.

This study attempts to examine the network topology and stability of the Jamaican payment system. The analysis focuses on the large value transfer system, the JamClear-RTGS system which represents the core of the payment system and the backbone of the overall financial system. The operational resilience of payment infrastructures is important to maintain financial stability as a disruption in routine payment flows can result in unwanted risk exposures. Therefore, this paper seeks to assess the payment system network topology and stability under normal and stressed conditions so as to gauge the target areas for liquidity management policies.

The study seeks to first examine the topology of the large value payment network, concentration and contagion risk. We then utilize the network topology to identify systemically important payment institutions (SIPIs) that are then incorporated in various simulation scenarios to assess the systems stability to withstand liquidity shocks. The analysis was conducted within the context of tight and normal liquidity and it was observed that commercial banks are the most influential participants. Notwithstanding, an increased influence of the primary dealers within the network was also observed. A large portion of the liquidity within the network was observed to flow between commercial banks highlighting high levels of concentration within the JamClear-RTGS system. It was also observed that generally, the simulations results illustrated that the JamClear-RTGS network was robust to significant distress, thereby signaling a stable and resilient network to systemic risk.

2. Literature Review

Several authors have employed the technique of network analysis in examining financial markets (Eisenberg and Noe, 2001; Inaoka *et al.*, 2004; Allen and Badus, 2009; Cont *et al*., 2010; Demange, 2012; Elliot *et al.*, 2013; Glasserman and Young, 2015; *inter alia*). These studies explore networks from a balance sheet perspective, focusing on the generation of matrices of interbank exposures that identify gross lending and borrowing among institutions in an effort to facilitate the simulation of plausible stresses to specific institutions and assessing the systemic effect to other institutions within the financial system. Espinosa-Vega and Solé (2011a) proposed a network analysis tool to measuring direct and indirect systemic interconnectedness. Through simulation of credit and funding shocks, they analyzed cross-country interbank exposures, noting that simulations are beneficial as they allow for the modelling of the institutional specific impact in subsequent rounds of contagion spill overs.

The examination of financial markets through network analysis in developing countries remain sparse which poses a challenge in the comparison of results from financial markets at similar levels of development. Milwood (2014), however, examined the network structure of the Jamaican financial system from the balance sheet perspective and found that the network was generally sparse with few institutions having a large number of connection. The author also employed a similar technique to that of Espinosa-Vega and Solé (2011a) in the examination of the resilience of the system to credit and funding shocks. The analysis revealed a relatively resilient network to contagion risk.

In recent times there has been some growth in the body of literature examining financial networks from a payment systems perspective (Bech *et al.*, 2002; Boss *et al.*, 2004; Inaoka *et al.*, 2004; Schmitz and Puhr, 2006, 2007; Soramäki *et al*., 2006; Roberts, 2011; *inter alia*). These studies use the actual transfer of funds between participants to construct matrices of interbank/inter-institution connections. Soramäki *et al*. (2006) describes the topology of interbank payment flows between participants in the large value payment system (LVPS), Fedwire Funds Service, examining the impact of the 11 September 2001 terrorist attacks on the Fedwire network. They found that massive damage to property and communication systems made it more difficult or even impossible for some Fedwire participants to send payments. Cheung (2002) also assessed the impact of the 11 September 2001 attacks on the payment flows of the Canadian LVTS, identifying a reduction in connectivity within the network. Albert *et al.* (1999 & 2000) noted that the stability of networks is conceptualized as the connectivity of the remaining nodes and is measured by the size of the largest cluster in the network as well as the average path length. The studies examining payment networks outlined previously focus on the assessment of network stability based on network metrics/ statistics only, assessing the network topology during periods of disruption. Network statistics alone, however, do not provide adequate information to deduce the stability of financial networks. Boss *et al.* (2015) in their analysis of the Austrian Real Time Interbank Settlement (ARTIS) network noted that as it relates to payment systems, the network metric of connectivity– as used by many studies, is not a useful conceptualization of stability. They posit that as the ARTIS is a complete network, the stability issue is not that a participant cannot make a payment because of a broken link, but that a participant might not have adequate liquidity to make the payment. Furthermore, similar to studies that examine financial network and network stability from using gross credit exposures from the balance sheet, they propose that the measure of the contagion impact should focus on the effects of shocks on the flow of liquidity which they measure through simulating the number of accounts with unsettled payments and the value of unsettled payments within the network.

Humphrey (1986) was the first to quantify systemic risk in payment systems. He proposed the method of *unwinding* to assess the potential disruptive effects of systemic risk. Using transactional data on the Clearing House Interbank System (CHIPS), Humphrey (1986) calculated multilateral net balances of all participants within the network and simulated the failure of a major participant by *unwinding* all the day's transaction to and from the troubled participant. Multilateral net balances are then recalculated and compared to the participant's capital to identify whether the net exposure is greater than the capital available to absorb shocks.

Angelini *et al.* (1993) employed similar methods to that of Humphrey *et al*. (1986) in assessing the level of systemic risk in the Italian clearing system. They executed their simulations based on two assumptions. First they assumed that no two or more banks can fail at the same time due to internal or external shocks. Secondly, they assumed that the probability that an institution defaults due to internal or external shocks is an exogenous event for each institution.

Their approach also had two major differences. Firstly, they simulated the default of all the members of the system, one at a time for all the business days to allow for computation of a relative frequency estimate of conditional probabilities. Secondly, they grouped banks into categories by size. The authors executed two types of simulations, one to examine insolvency and the other to examine liquidity issues. In quantifying a participant's ability to settle, the authors proposed the use of participants' capital and liquid assets, with the former being an indicator of solvency and the latter as an indicator of a participant's liquidity condition. Their results demonstrated that systemic risk was unlikely to be significant for the period under examination.

In summary, there has been increased focus on the financial networks. There is also a growing interest in the analysis of financial interlinkages through payment systems. In analyzing network stability, tracking network topology metrics also does not provide a sufficient assessment of the stability of financial networks. Stress-testing through counterfactual simulations provide a more fulsome view of the level of resilience of financial networks. *Unwinding* is a simple but effective method of simulating the contagion effect and essentially the resilience of a financial network. This study seeks to employ this method to the analysis of the resilience of the Jamaican large value payment system.

3. The JamClear-RTGS System

The JamClear-Real-Time Gross Settlement (RTGS) system was commissioned in 2009 and is the official infrastructure for the movement of funds through Jamaica's financial system. Its primary purpose is to provide a settlement mechanism in which processing and final settlement of participant payment instructions occur continuously throughout the business day. The settlement of funds occur on a transaction by transaction basis and are checked for funds availability as well as settled individually, continuously in real time across central bank settlement accounts, provided the sending participant has sufficient covering balance or credit. The infrastructure enables participants to move large value and time critical payments between each other in real time and obligations are settled without netting debits against credits.

The JamClear-RTGS facilitates fast, secure, final and irrevocable clearing and settlement of payments. It also enhances transparency of banking activities; offers a reduction in payments system risks such as settlement risk; improves speed for the settlement of payment obligations; provides efficiency gains for treasury management; improves financial stability through the reduction of systemic risk and increases system efficiency, safety and reliability.

The system rules categorize participants into three groups: (1) full members that have direct access and are permitted to undertake financial transactions with other members; (2) restricted members that maintain settlement accounts but have no access to intraday liquidity; and (3) indirect members that do not have direct access to the system but are able to submit multilateral net settlement files in prescribed payment windows.[3, 4] Currently, the system has 22 full members and operates between the hours of 8:00 a.m. and 5:00 p.m. each business day. The participants are categorized into commercial banks, merchant banks, building societies and primary dealers (broker dealers). The Jamaica Central Securities Depository (JCSD) as well as the Accountant General Department (AGD) are also participants along with the Bank of Jamaica (BOJ).[5,6] As a result of the reforms to the retail repurchase agreement (repo) market, there was an inclusion of a participant to facilitate the transfer of funds to and from the designated Trustee account created for retail repo transactions.

3.1. Trends in Large Value Payments in Jamaica

During 2015, the JamClear-RTGS settled an average of 1 351 transactions daily, valuing approximately J$62.7 million. This outturn represented an increase relative to 2014 when there were on average, 1 164 transactions per day, valued at approximately J$58.0 million.

The Large-Value System Concentration Risk Index (LSCRI) developed by BOJ is used to measure the share of payment activity between the two most active participants relative to all other participants. It is computed based on the value payments made and received by each participant as a share of overall payments for the system and excludes the activities of the AGD, BOJ as well as participants designated as indirect members. The LSCRI revealed that payment activity was concentrated among few participants in the JamClear-RTGS. It also indicated a high level of liquidity concentration as the flow of funds was largely between the top two participants. For December 2015, there was a marginal reduction in concentration risk within the system with the average share of payment activity for the two most active institutions decreasing to 33.7 per cent relative to 36.1 per cent for December 2014. This was coupled with an increase in the share of activity for all other institutions to 3.2 per cent from 2.6 per cent between the same periods (see Figure 9 in Appendix).

[3] Full members are required to maintain a settlement account at the central bank and are allowed access to any credit services offered by the central bank including the intraday liquidity facilities.
[4] Indirect members include the Automated Clearing House (check clearing system) and MultiLink (card network providers).
[5] The JCSD provides depository and settlement services for securities traded electronically on the floor of the Jamaica Stock Exchange.
[6] The AGD is Jamaica's Treasury and the operational department within the Ministry of Finance and Planning, charged with facilitating and reporting on the flow of funds within the public sector.

Concentration risk within the payment system was also evident based on the outturn in the Herfindahl index of JamClear-RTGS Liquidity Concentration. This index is a measure of the extent of a financial institution's payment activity in relation to the other participants in the system. It is also an indicator of the level of concentration of liquidity with the system. The Herfindahl index signaled persistence in the level of liquidity concentration within the JamClear-RTGS, averaging 0.2 points, in line with the annual average over the period (see Figure 10 in Appendix).

4. Data & Methodology

4.1. Network Measures & Metrics

Network statistics provides a mathematical representation of complex systems such as that of payment networks. These measures simplify the payment flows to unweighted links (payment flows), allowing for ease of analysis. There is a wide variety of network statistics that could possibly be used, however, the focus in this study was limited to measures such as centrality, connectedness and contagion measures given the relative size of the payment network in Jamaica.

4.21. Centrality Measures

Degree Centrality

Degree refers to the number of edges connected to a node. Degree centrality equates centrality directly to the degree of a node and hence does not consider indirect relationships. Therefore, the most central participant in the system is the one with the most direct relationships. Directed networks allow for both an in-degree and an out-degree. For payments systems, in-degree centrality highlights participants that are net-debtors while out-degree centrality identifies net-creditors. The important point to note is that those participants connected to many others might have more influence on and/or have more access to liquidity.

The study utilizes a modified measure of degree centrality, the eigenvector centrality. This is an extension of degree centrality, however, instead of awarding one centrality point for every network neighbour a node has, it provides each node with a score proportional to the sum scores of its neighbours (Newman, 2010). This is important since not all nodes are equivalent. Furthermore, the importance of a node increases as its connection to other important nodes that are also important increases. Participants with high eigenvector centralities are those which are connected to many other nodes which are, in turn, connected to many others (and so on) [7].

Closeness Centrality

Closeness centrality measures how many steps are required to access every other node from a given node. The closeness centrality of a node is defined by the inverse of the average length of the shortest paths to/from all the other nodes in the graph:

$$C_i = \frac{1}{\frac{1}{n}\sum_j d_{ij}} \tag{2}$$

Here d_{ij} is the length of the geodesic (shortest) path from i to j. This simplifies to:

$$C_i = \frac{n}{\sum_j d_{ij}} \tag{3}$$

This measure shows the importance of participant as it relates to the ease of providing liquidity. Furthermore, it can be used as an indicator to identify the more systemically important participants in the event of liquidity crises. Notwithstanding, the closeness centrality measure has its issues. The major one being that its value spans a rather small dynamic range from largest to smallest (Newman, 2010). With distance, d_{ij} between vertices in most networks being small, increases in distance typically changes logarithmically with the size of the entire network. As such, the ratio between the smallest distance 1 and the largest distance being of order log n is itself only of order log n which is also small (Newman, 2010).

Betweenness Centrality

The betweenness centrality measures the extent to which a node lies on paths between other nodes. Nodes with high betweenness centrality may have considerable influence within a network by virtue of their control over information passing between others (Newman, 2010).This measure highlights the importance of a participant with regards to their impact on the flow of payments

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[7] This Eigenvector centrality can be denoted as follows: $x_i' = \frac{1}{\lambda}\sum_j A_{ij}x_j$

Where x_i is the centrality for each node i, A_{ij} is an element of the adjacency matrix (a square matrix used to represent a finite graph), x_j is the centrality of neighbouring vectors and λ is the largest eigenvalue in absolute value of matrix A. Here λ is a non-negative constant ($\lambda \neq 0$).

between other participants in the system that may not be directly connected. The node betweenness of node i is defined by:

$$B_i = \sum_{s \neq i \neq t} \frac{\sigma_{st}(i)}{\sigma_{st}} \tag{4}$$

Where s and t are nodes in the network different from i, σ_{st} denotes the number of shortest paths from s to t, and $\sigma_{st}(i)$ is the number of shortest paths from s to t that i lies on.

4.1.1. Distance Measures

The geodesic distance between a pair of nodes is the length of the shortest path connecting them. Embree and Roberts (2009) notes that for payment networks, distance provides an indication of how shocks affecting one financial institution could travel through links to affect others. This paper focuses on the average path length, the diameter and the radius as key distance measures.

Average Path Length

Embree and Roberts (2009) defines a path as a sequence of nodes and links beginning and ending with nodes, where any link or node can only be included once. They allow for the measurement of the relative closeness of two nodes in the network at any given time. Further, for large value transfer systems, all participants can make payments to all others and as such paths do not reflect the course that payments can travel. They can, however, highlight the path that liquidity or contagion may follow in the event of shocks to the network.

The length of this path is measured by its number of links. The average path length is the average distance for any combination of two nodes in the network. An average path of one indicates that all participants have sent a payment to all others. Longer average path lengths indicate that activities are concentrated among fewer pairs of participants.

Diameter

The eccentricity of a node is the maximum length of the shortest path between nodes within a network. It is calculated by measuring the shortest distance from (or to) the node, to (or from) all nodes in the graph, and taking the maximum. Embree and Roberts (2009) defines the diameter as the largest eccentricity in the network indicating the maximum distance between any two nodes in the network. In large value transfer systems, a participant may be faced with operational or liquidity issues which will affect their ability to meet payment obligations. Other participants with direct connections to this troubled participant might experience liquidity issues sooner than those who are only connected indirectly to that participant. These indirect participants as well as other robust participants directly linked to the troubled participant may be along the diameter and may be able to absorb the shock associated with the troubled participant.

Consequently, this measure can provide an indication of the potential speed of contagion as well as the robustness and resilience of the network to liquidity shocks. The greater the number of intermediate participants in the diameter the greater the probability of participants being able to absorb the shocks of a troubled participant. Additionally, the longer the diameter, the slower the speed of contagion within the network.

4.1.2. Connectivity

Connectivity calculates the measure of network completeness. It is the ratio of the number of actual links that exists in the network to the total number of potential links:

$$C = \frac{m}{N(N-1)} \tag{5}$$

Here *N* is the number of nodes and *m* is the number of direct links. For payment networks, connectivity is a measure of payment activity and indicates whether participants are transacting, in general, with many or only a few of the other participants within the network (Embree and Roberts, 2009).

4.2. Counterfactual Simulations

In the evaluation of payment system stability we employ counterfactual simulations, using the method of *unwinding* first explored by Humphrey (1986) and later Angelini *et al*. (1993). The multilateral net positions of all participants within the network was calculated and then used to simulate the failure of major participants by removing all transactions sent and received by those participants for a particular period. [8] The net balances of the remaining participants were then recalculated, highlighting those with a negative balance. The change in the net balances of these institutions were then compared to the contingent liquid indicators[9]. A participant who experienced

[8] Multilateral net positions are calculated as the sum of all payments received by an institution minus the sum of all payments sent by the institution.
[9] Institutions' capital was used to gauge insolvency and their liquid assets was used to gauge liquidity issues.

an increased level of exposure greater than or equal to their ability to withstand/absorb the shock were assumed to '*have failed'* due to systemic effect. The payment activity of this participant was then removed from the network and new settlement positions calculated. Several iterations of this process was conducted until all participants were able to settle their transactions.

In this study, simulations are geared towards assessing the JamClear-RTGS system's susceptibility to liquidity shocks based on idiosyncratic issues impacting participants' ability to meet their payment obligations and thereby poses systemic risk concerns for the financial system. As a measure of the ability to withstand liquidity shocks, the change in the net balance of participants with negative net balances are compared to the participants' JamClear-RTGS transaction account closing balance, cash reserves and stock of liquid assets. For the purpose of this study, tiers of contingent liquidity were established based on their ease of accessibility in the event of shocks to payment flows. Participants' average transaction account closing balances over the periods examined were deemed as Tier 1 contingent liquidity, as this is where all transactions originate and funds can easily be reallocated if necessary. Cash reserves are deemed Tier 2 contingent liquidity, as this is the most liquid form of assets in the event that the transaction account closing balance was insufficient to absorb the shock. Additionally, Tier 3 contingent liquidity are participants' liquid asset with a maturity time of up to 90 days.[10] Unlike previous studies, we adjust liquidity measures by accounting for the absorption of shocks in each iteration. This was done by reducing the stock of contingent liquidity by the proportion of the change in the participant's net balance for each iteration of the simulation.

As an augmentation to the *unwinding* methodology employed in Humphrey (1986) and Angelini *et al*., (1993), this research incorporates network topology in the counterfactual simulations. Systemically important payment institutions (based on participants being too-connected-to-fail) are identified through their presence in the giant strongly connected component (GSCC) as well as their degree centrality scores. Out-degree centrality is used to identify and rank the top four (4) systemically important payment institutions (SIPIs) within the GSCC which are then used as

[10] Liquid assets include: liquid funds excluding items in the course of collection; Investments in BOJ securities deemed eligible as liquid assets; Investments in Government of Jamaica (GOJ) Treasury Bills; GOJ local registered stock eligible as liquid assets; Other GOJ securities eligible as liquid assets; other public sector securities eligible as liquid assets; domestic securities purchased with a view to resale from other counter-parties normally eligible as liquid assets (for securities/primary dealers only).

troubled participants within various scenarios. [11] Out-degree centrality is used as opposed to in-degree centrality since these participants are net creditors[12] and are expected to have a greater impact on the network.

This paper also proposes proportional payment defaults where a percentage of the most influential participant's overall sent payments are removed and the impact on the GSCC is examined. We propose focusing on the even restriction of the sent payments from the most influential participants to others within the GSCC while assessing the impact on both the sent and received payments of the other participants within the GSCC. This is seen as a more realistic scenario. A similar approach to the method previously outlined is employed where participants that are deemed to have *failed* then have their ability to make payments restricted. This iterative process is continued until all remaining participants are able to meet their payment obligations either through settlement or using their contingent liquidity. This augmentation to the *unwinding* process was seen as more realistic than a participant failing to meet all of its obligations over a given period of time.

4.3. Data

The dataset included actual daily payments for 2 January 2014 to 31 January 2014 and 1 December 2015 to 31 December 2015, collected from the JamClear-RTGS database and included all transaction types within the JamClear-RTGS system except system charges and other transactions denoted as general ledger. The data includes information on the sender, receiver and the value of each individual payment. The central bank was removed from the dataset as their influence on the network is understandably significant and therefore they were not necessary for inclusion in the study.

Given the potential impact of tight liquidity conditions on financial market flows, it was important to examine the network structure during periods of tight liquidity. The BOJ's TRE spread and intra-day liquidity usage were used to identify periods of tight liquidity.[13] Higher percentages denote tight liquidity in the market. A liquidity facility is also available to the full member participants of the JamClear-RTGS system in an effort to offset liquidity shocks to participants.

[11] The GSCC is largest cluster in the network. Within this cluster, all nodes are connected with each other, forming one completely connected network.
[12] Net creditors refer to central participants that have a greater level of outgoing payments relative to other participants.
[13] The TRE spread measures the premium priced in the repo rate for default risk. It captures both counterparty risk and liquidity risk in the money market. It is computed as the difference between the private money market 30-day repurchase agreement rate and the BOJ's 30-day Treasury Bill rate.

Both indicators identified January 2014 as the period with tightest liquidity in recent times. As such, the daily transactions for January 2014 were included in the analysis (see Figure 8 in appendix).

5.1. JamClear-RTGS Network Topology

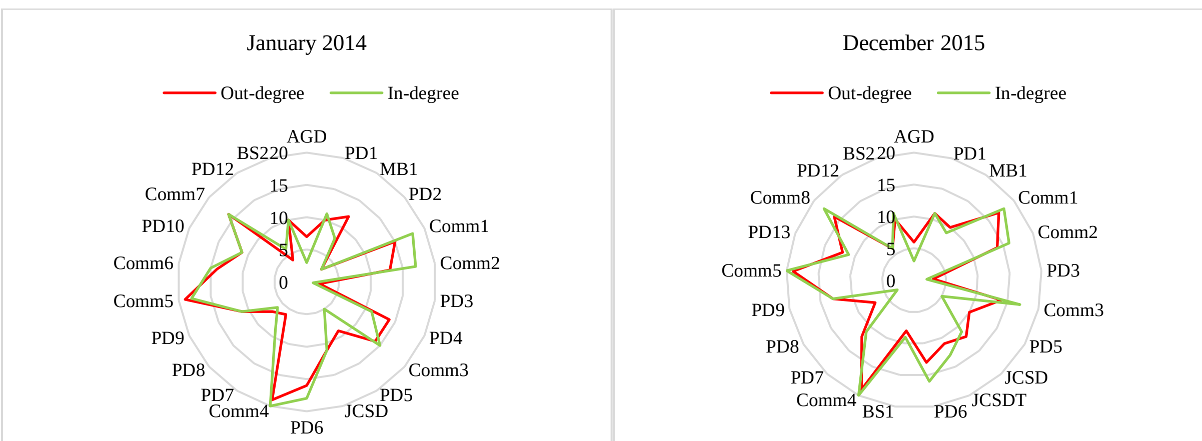
5.1.1. Centrality Measures

Centrality measures assign scores to nodes, allowing for the ranking of participants based on their level of influence or importance within the network. Having different centrality measures allow for the observation of different patterns within the network that can be used to assess stress points or the emergence of risks.

Degree Centrality

Based on degree centrality, commercial banks are the most influential nodes within the network. This is highlighted by commercial banks having the higher levels of both in-degree and out-degree centrality in both periods examined (Figure 1).[14]

Figure 1: *Degree Centrality of Participants*



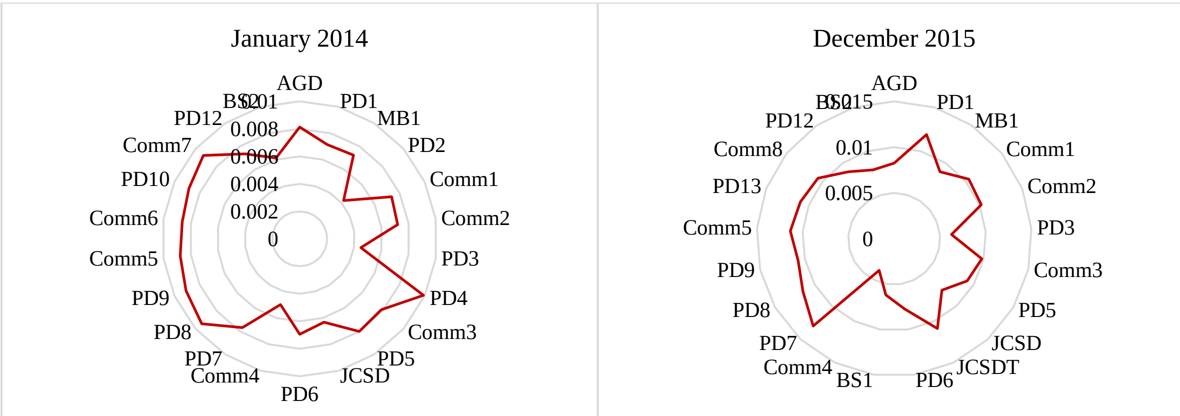
Closeness Centrality

As it relates to closeness centrality for both periods examined, it was observed that primary dealers followed by commercial banks were the most influential nodes within the network. Given that

[14] Out-degree is used along with the GSCC in the simulations to identify more influential/ important participants as failures from net senders of payments is expected to have a greater impact on the participants' liquidity.

closer nodes allow for ease of liquidity flow, it can be said that primary dealers are important in the transfer of liquidity throughout the network (see Figure 2).

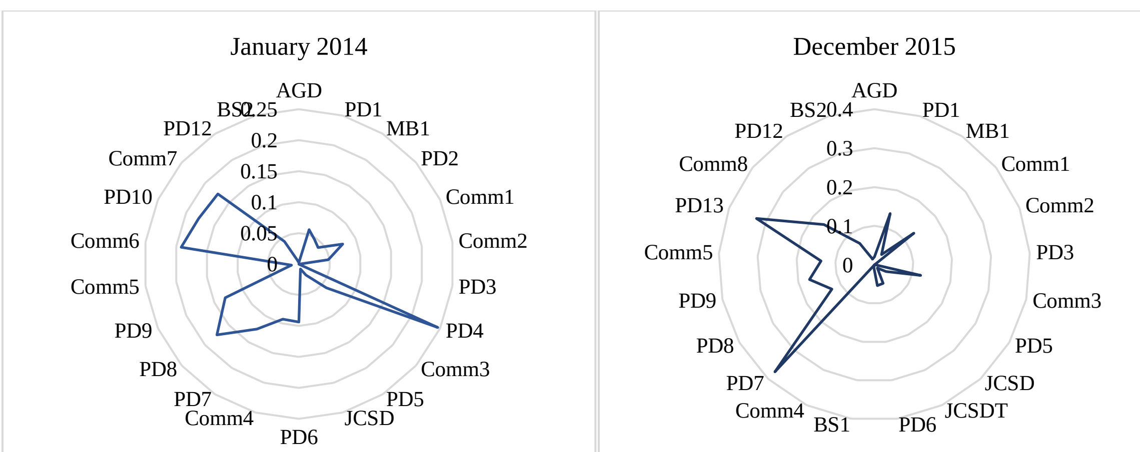
Figure 2: *Closeness Centrality of Participants*



Betweenness Centrality

Primary dealers were generally observed to have the largest betweenness centrality values in both periods. This indicates that primary dealers have a greater probability of being an intermediary on the shortest path between any two other participants. This underscores the importance of primary dealers in linking payments flows between other participants within the network that would have otherwise not been connected (see Figure 3).

Figure 3: *Betweenness Centrality of Participants*

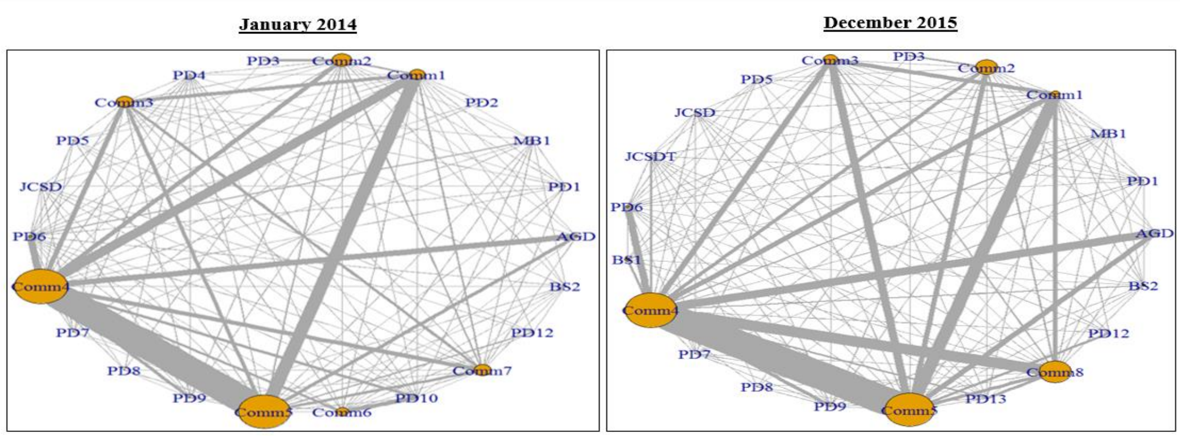


5.1.2. Structural Graphics & Network Indicators

For payment systems and more specifically the JamClear-RTGS, a network is a structure of system participants, connected by payment flows over a given period. Links in this case are payment flows that are directed and assigned weights according the value of payments that occurred between the sender and recipient.[15] Arrows directed towards a node indicate the direction of the payment flow. Nodes are weighted based on how connected a participant is to other connected participants within the system. Furthermore, links are weighted by the gross value of payment flows between participants.

Similar to Milwood (2014), the JamClear-RTGS network like many real world networks, was observed to be a scale free network whereby a few nodes have a large number of links while most nodes have a few links.[16] Within the network, payments are observed to be concentrated among commercial banks. Commercial banks were also the most influential nodes within the network as evidenced by the size of the nodes (see Figure 1). This highlights the function of commercial banks as intermediaries within the financial system as well as provides evidence of an active interbank market within the JamClear-RTGS system. Liquidity within the network tends to flow primarily between commercial banks with a significant flow of funds between the Treasury Single Account, (the GOJ’s transactional account) and the two most central participants within the network (Comm4 and Comm5).

Figure 4: *JamClear-RTGS Network*[17]



Note: Nodes represent the financial institutions and the flow of funds from sender to receiver are represented by links. Arrows directed towards a node indicates that the node is a receiver while arrows directed outwards indicates that the node is a sender. Nodes are weighted based on how connected a participant is relative to many other participants within the network. Links are weighted by the value of payments. Larger nodes represent more important institutions in the network and thicker links indicate larger payment flows. Participants are assigned codes based on the bank identification code (BIC) registered in the system in the given period where Comm# are codes given to commercial banks, PD# are codes given to primary dealers, MB# are codes given to merchant bank, BS# are codes given to building societies. AGD, JCSD and JCSDT represents codes for the transactional account of the GOJ, the Depository for Corporate Securities and the Trustee Arrangement for Retail Repurchase Agreement arrangement respectively.

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[15] A directed link originates in a source actor and reaches a target actor.

[16] The degree distribution of scale free networks follow a power law $P(k) \sim k^{-\Upsilon}$, that is, the probability that a node has k degrees is $k^{-\Upsilon}$.

[17] The number of participants within the system changed primarily due to mergers and acquisitions over the two periods examined.

Figure 4 illustrates the JamClear-RTGS network in a period of tight liquidity (identified by increased intra-day liquidity usage and the TRE spread) in January 2014 and a period of normalcy in December 2015. A scale-factor was assigned to the graphs in both periods for ease of comparison. Links were weighted by the value of transactions between participants while nodes were weighted by eigenvector centrality. Larger values of funds transfer were observed for December 2015 relative to January 2014. The network size and structure was observed to be relatively similar for both periods examined. Connectivity, however, was observed to be lower in the period of tight liquidity with 52.8 per cent of potential links being completed relative to 57.9 per cent in the period on normal liquidity.

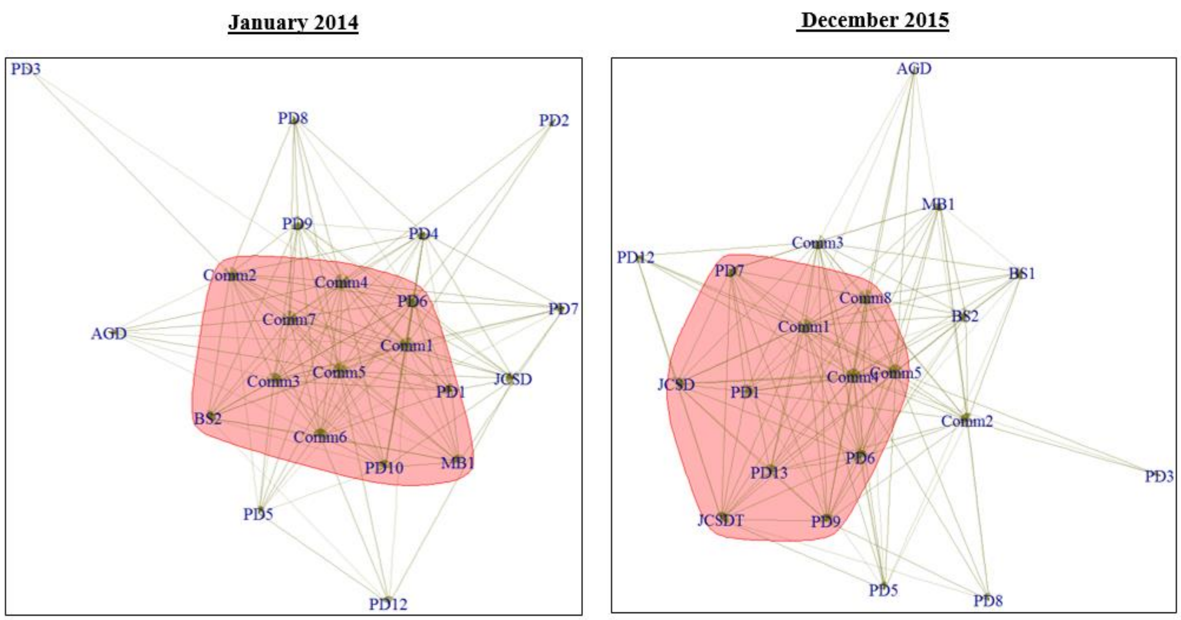
Table 1: *JamClear-RTGS Network Indicators*

	Jan-14	**Dec-15**
Payments		
Average Daily Volume (Average Number of Transactions)	1,045.350	1,568.400
Average Daily Values (J$Bn)	83.34	65.25
Average value per Transaction (J$Bn)	0.080	0.042
Network Size		
Nodes	22	21
Links	244	243
Connectivity Measures		
Density (%) – Connectivity	52.814	57.857
Distance Measures (Speed of Contagion)		
Average Path Length	1.487	1.421
Diameter	5	7
Systemically Important Payment Institutions (SIPIs) – Measure of Concentration		
Size of Giant Strongly Connected Components (GSCC) –Number of Institutions	11	11

Concentration Risk

Concentration risk within the network was highlighted through both the average path length and the size of the GSCC. We propose that the smaller the size of the GSCC, the greater the concentration risk as a smaller subset of participants are totally connected thus increasing the likelihood of failure of the network in the event that these participants are faced with liquidity constraints (see Figure 5).

Figure 5: *JamClear-RTGS Giant Strongly Connected Component*



Note: Shaded area represents the Giant Strongly Connected Component (GSCC) of the network. Participants within the shaded region are deemed systemically important.

Both measures however provided conflicting reviews when closely interrogated. The average path length was observed to be higher in the period of tight liquidity relative to the period of normal liquidity. This illustrated a relatively higher concentration risk in the period of tight liquidity relative to the period of normalcy. Concentration risk, measured by the size of the GSCC within the JamClear-RTGS was observed to be the same in both periods with 11 participants being deemed SIPIs. Important to note however, is that 9 institutions were observed to be SIPIs in December 2015. The other two participants were the JCSD, a depository for corporate securities and the trustee account for retail repurchase agreement arrangements. If these two participants were removed, it would mean an increase in the level of concentration within the system. The structure of the GSCC changed significantly in December 2015 relative to January 2014 with only commercial banks and primary dealers making up the SIPI group. Of significance as well, was the increase in the number of primary dealers within the GSCC, underscoring the increasing importance of these institutions within the financial sector.

A comparison of the concentration measure with the LSCRI revealed contradictory results where the LSCRI reported a decrease in level of concentration within the system for December 2015 relative to January 2014. It should be noted, however, that the LSCRI is constructed using the value of transactions sent and received for the two most active participants relative to the other participants within the system while the JamClear-RTGS network was developed using the number of transactions between participants. The LSCRI was subsequently recomputed using the number of transactions of the top two participants and it was observed that payment activity by the top two participant for December 2015 was 46.3 per cent of all transactions relative to 41.5 per cent for January 2014, thus supporting results from the network analysis.

Contagion Risk

The speed of contagion is assessed using the length of the diameter. There are two divergent views in graph theory associated with the diameter. On the one hand, it is believed that a longer diameter would have a greater number of nodes along it and as such greater contagion risk. On the other hand, it is believed that the greater the number of participants along the diameter, the more likely the probability that one or a few participant can act as an intermediary and fill the gap of a participant facing liquidity issues. The latter is adopted in this study as the more plausible viewpoint in the analysis of the speed of contagion. Consequently, the results revealed a faster speed of contagion within the period of tighter liquidity, as indicated by a shorter diameter of 5 participants relative to 7 participants in the period of normal liquidity.

5.2. Simulation Results

The resilience of the JamClear-RTGS system was assessed in a period of tight liquidity (January 2014) as well as period of normalcy (December 2015). Several scenarios were examined starting with the most catastrophic to the more routine failures. This study explored scenarios involving the joint failure of central participants, individual failure of central participants and the proportional settlement failure of central participants.

5.2.1. Joint Failure of Central Participants

Unlike Angelini *et al*. (1993), we relax the assumption that no two or more participants can fail at the same time and begin our simulations by first examining the effect of the joint failure of central participants within the JamClear-RTGS network. However, the assumption that participants' failures are exogenous events was maintained. Firstly, the failure of the four most central participants was examined followed by the failure of the three most central and then finally the two most central participants within the network (see Table 2 in Appendix).

5.2.1.1. Failure of Four Most Central Participants

The four most central participants identified during the period of tight liquidity included three commercial banks and a securities dealer (SD) and had a combined asset size of J$710.9 billion. This accounted for 70.1 per cent of the aggregated asset size of the institutions within the GSCC. During the normal liquidity period, the four most central participants were all commercial banks and has a combined asset size of J$771.3 billion, approximated 68.1 per cent of the aggregated asset size of the institutions within the GSCC.

Following the removal of the four most central participants during the period of tight liquidity, four participants were observed to have negative net balances. Using Tier 1 liquidity, it was observed that two participants, from the deposit taking institution (DTIs) sector and the SDs sector would have failed. The system was observed to be stable on the third iteration with four institutions having negative net balances which were adequately covered by their Tier 1 liquidity. Using Tier 2 liquidity, it was observed that four participants would have failed. All four failed participants were from the DTIs sector. The system was observed to be stable on the third iteration with only one institution having a negative net balance. Furthermore, they had sufficient levels of Tier 2 liquidity to cover the negative balance. Regarding Tier 3 liquidity, four participants had negative net balances, however, all were able to absorb the shock using their Tier 3 liquidity.

Examining the impact of the failure of the four most central participants during normal liquidity conditions (December 2015) revealed a more resilient network with only two participants having a negative net balance following the initial shock. The system was reported to be stable after one iteration based on both the Tier 1 and Tier 3 liquidity measures. Using the Tier 2 measure, it was observed that only one participant from the SDs sector failed after two iterations. The system was observed to be stable after the second iteration with two institutions having negative net balances that were sufficiently covered by their Tier 2 liquidity.

5.2.1.2. Failure of Three Most Central Participants

In examining the three most central participants during the period of tight liquidity it was observed that the group included two commercial banks and a securities dealer (SD) and had a combined asset size of J$659.7 billion. This accounted for 65.1 per cent of the aggregated asset size of the institutions within the GSCC. A similar examination of the three most central participants during the normal liquidity period revealed that all commercial banks and has a combined asset size of

J$674.4 billion, approximated 59.6 per cent of the aggregated asset size of the institutions within the GSCC.

On the removal of the three most central participants, five participants were observed to have negative net balances. Using Tier 1 liquidity, it was observed that one participant from the DTIs sector failed in the tight liquidity period. The system was observed to be stable after two iterations with four participants having negative net balances which were, however, sufficiently offset by each participant's Tier 1 liquidity. Using Tier 2 liquidity, it was observed that a total of three participants from the DTIs sector failed. The system became stable after two iterations with two participants having negative net balances as well as sufficient Tier 2 liquidity to offset their net balances.

For December 2015, the system showed greater resilience following the failure of the three most central participants. Only three participants had negative net balances after the removal of the three most central participants. Based on the tier 1 measure of liquidity no participant failed and the system was observed to be stable after one iteration with three participants having negative net balances but adequate Tier 1 liquidity to offset their net balances. Using Tier 2 liquidity, it was observed that one participant from the DTIs sector failed. The system was observed to be stable after three iterations and two participants were observed to have negative net balances which was, however, sufficiently covered by their Tier 2 liquidity. The system was again considered stable based on the Tier 3 measure of liquidity in both the tight and normal liquidity periods after the one iteration.

5.2.1.3. Failure of Two Most Central Participants

The two most central participants identified during the period of tight liquidity included two and had a combined asset size of J$528.8 billion. This accounted for 52.1 per cent of the aggregated asset size of the institutions within the GSCC. During the normal liquidity period, the four most central participants were all commercial banks and has a combined asset size of J$655.9 billion, approximated 57.9 per cent of the aggregated asset size of the institutions within the GSCC.

The failure of the 2 most central participants within the system was also examined. Examining the system during tight liquidity revealed that on removal of the two most central participants, five participants were observed to have negative net balances. The system was observed to be stable based on Tier 1 and Tier 3 liquidity measures after one iteration. On the other hand, using Tier 2 liquidity, two participants from the DTIs sector were observed to have failed. The system was observed to be stable after three iterations with three participants having negative net balance. Their Tier 2 liquidity levels was, however, sufficient to offset the negative net balances.

Examining a period of normal liquidity conditions revealed a more resilient system with three participants having negative net balances after the two most central participants were removed. The system was observed to be stable after the removal of the two most central participants based on the Tier 1 and Tier 3 measures of liquidity. Based on the Tier 2 liquidity measure, three participants two DTIs and one SD were observed to have failed. The system was observed to be stable after three iterations with two participants having negative net balances, however, participants had sufficient Tier 2 liquidity to offset these negative balances.

5.2.2. Individual Failure of Central Participant

The impact of the individual failure of the four most central participants within the SIPI group of the JamClear-RTGS network was also examined (see Table 3 in Appendix).

5.2.2.1. Failure of Most Central Participant[18]

For January 2014, on the removal of the most central participant within the JamClear-RTGS network, it was observed that five participants had negative net balances. The system was observed to be stable based on the Tier 3 liquidity measure. Using Tier 1 liquidity, however, it was observed that one participant failed. The system was observed to be stable after two iterations with five participants having negative net balances which were sufficiently covered by their Tier 1 liquidity. Using Tier 2 liquidity, it was observed that three participants failed. The system was observed to be stable after three iterations with three participants having negative net balances but holding sufficient Tier 2 liquidity to offset negative net balances.

An examination of the failure of the most central participant during a period of normal liquidity revealed a more resilient network with only two participants having negative net balances. Based on all three liquidity measures, no participant failed and the system was observed to be stable after one iteration (see Table 3 in Appendix).

[18] Participant is from the DTIs Sector with total assets of J$296.6 billion, 29.3 per cent of the aggregated assets of the GSCC during the tight liquidity period and J$ 368.2 billion or 32.5 per cent of the aggregated asset of the GSCC in the period of normal liquidity.

5.2.2.2. Failure of Second Most Central Participant[19]

An examination of the removal of the second most central participant from the network revealed four participants had negative net balances during the period of tight liquidity. The system was observed to be stable after one iteration using Tier 1 and Tier 2 liquidity measures. Using Tier 2 liquidity, it was observed that two participants failed. The system was observed to be stable after three iterations with three participants having negative net balances but also with sufficient Tier 2 liquidity to offset negative net balances.

Similar to earlier results, the JamClear-RTGS showed greater resilience during the period of normal liquidity than in the period of tight liquidity. With the removal of the second most central participant, it was observed that only two participants had negative net balances. The system was observed to be stable after one iteration based on all three tiers of liquidity measures.

5.2.2.3. Failure of Third Most Central Participant[20]

Further examination was conducted with the removal of the third most central participant in the network for January 2014. On removal, it was observed that six participants had negative net balances. The network was observed to be stable after one iteration based on Tier 1 and Tier 3 liquidity measures. Using Tier 2 liquidity, it was observed that four participants failed. The system was observed to be stable after four iterations with three participants having negative net balances but with sufficient Tier 2 liquidity to offset negative balances.

Examining the resilience of the network to the failure of the three most central participant during a period of normal liquidity revealed that the network again was more resilience than in a period of tight liquidity. On removal of the third most central participant, it was observed that four participants had negative net balances. The system was observed to be stable after one iteration based on Tier 1 and Tier 3 liquidity. Using Tier 2 liquidity, it was observed that only one participant failed. The system was observed to be stable after two iterations with three participants having negative net balances that was sufficiently covered by their Tier 2 liquidity.

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[19] [19] Participant is from the DTIs Sector with total assets of J$232.1 billion, 22.9 per cent of the aggregated assets of the GSCC during the tight liquidity period and J$ 287.6 billion or 25.4 per cent of the aggregated asset of the GSCC in the period of normal liquidity.

[20] [20] Participant is from the SDs sector with total assets of J$130.9 billion, 12.9 per cent of the aggregated assets of the GSCC during the tight liquidity period. On the other hand, during the period of normal liquidity, the participant was from the DTIs sector with assets amounting to J$18.6 billion or 1.6 per cent of the aggregated asset of the GSCC.

5.2.2.4. Failure of Fourth Most Central Participant[21]

On removal of the fourth most central participant within the JamClear-RTGS network it was observed that six participants had negative net balances. The system was observed to be stable after one iteration based on all three tiers of liquidity measures.

An examination of the resilience of the network with the removal of the fourth most central participant revealed that two participants had negative net balances. This again is an indication of the network being more resilient in a period of normal liquidity. The system was observed to be stable after one iteration based on all three tiers of liquidity measures.

5.2.3. Proportional Settlement Failure of Central Participants

The most central participants were subject to failure of various proportions of their outgoing transactions starting with 100 per cent failure then 10 per cent reductions in the proportion of failure payments until the system was observed to be stable. This assessment was conducted on the peak days (based on the day with the highest transactional activity) of both the period of tight and normal liquidity.[22] Proportional settlement failures were considered to be more realistic as they relate to payment defaults or transactional delays of participants. With these simulations being conducted on daily data, only the Tier 1 liquidity measure, the transactional account closing balance of the previous day was used to evaluate the stability of the network.

5.2.3.1. Proportional Defaults for the Most Central Participant

An examination of the system in a period of tight liquidity reveals that five participants had negative net balances. All outgoing payments from the most central participant were restricted and it was observed that one other participant from the DTIs sector failed. The system was observed to be stable after two iterations with eight participants having negative net balances. However, they had sufficient levels of Tier 1 liquidity to offset by the negative balances.

Examining the network on a peak day during normal liquidity conditions revealed that four participants had negative net balances. On the restriction of all outgoing payments from the most central participant, one participant failed. The system was observed to be stable after two iterations

[21] [21] Participant is from the DTIs Sector with total assets of J$51.2 billion, 5.0 per cent of the aggregated assets of the GSCC during the tight liquidity period and J$ 96.9 billion or 8.6 per cent of the aggregated asset of the GSCC in the period of normal liquidity

[22] Peak day for period of tight liquidity: January 31, 2014. Peak day for normal liquidity period: December 18, 2015.

with six participants having negative net balances but sufficient Tier 1 liquidity to offset the negative net balances.

The system was also observed to be stable following proportional defaults by the second, third and fourth most central participants. Several iterations were carried out and it was found that the system remained stable during both periods based on the levels of Tier 1 liquidity.

6. Concluding Remarks

This paper provides an examination of the structure of the JamClear-RTGS which is the core infrastructure of the Jamaican payment system. It further provides an assessment of the JamClear-RTGS network topology metrics in a period of tight liquidity as well as a period of normal liquidity conditions in an effort to gauge the target areas for liquidity management policies. The study also sought to assess the stability of the JamClear-RTGS network by using counter-factual simulations of disruptions of influential participants within the network. Unlike previous studies using simulation, influential participants (SIPIs) were not identified by expert-knowledge. Instead, the simulations were informed by metrics from the network analysis, more specifically, out-degree centrality and the components of the GSCC – the largest cluster within the network.

The results revealed that commercial banks are the most influential participants, based on degree and eigenvector centrality. It was also observed that a large portion of the liquidity within the network flows between commercial banks. This was consistent in both periods examined. This finding was not alarming as commercial banks function as the main intermediators within the financial system. The findings also highlighted the active interbank market within the JamClear-RTGS system.

Increased concentration risk was observed in December 2015 relative to January 2014. This was observed in the reduction of the size of the GSCC and signals the need for closer attention to be paid on this developing area of fragility. This was corroborated by the re-calculated LSCRI (using transaction volume rather than value). Of importance as well was the increase in the number of primary dealers as SIPIs. Added to the increased importance of primary dealers in the December 2015 period, it was also observed that these participants were the most influential based on closeness and betweenness centrality. This was observed in both periods. This underscores the need for more focus on these participants as systemically important institutions. The speed of contagion was, however, observed to be relatively faster in the period of tight liquidity than in the normal liquidity period. This was highlighted in the relatively smaller diameter in January 2014 when compared to December 2015.

This study employed augmented simulations based on the method of *unwinding* from existing literature as well as proposed a more realistic method wherein the defaults of the most central participants' outgoing payments were explored. Similar to Milwood (2014), results revealed a relatively resilient network in both periods with the largest number of failed institutions being three participants. This was, however, in two instances where cash reserves (Tier 2 liquidity) were used as the participants' contingent liquidity. As expected, the JamClear-RTGS network was observed to more resilience in the period of normal liquidity.

Based on the proportional counterfactual simulations of outgoing payment defaults proposed in this paper, the system was observed to be very resilient with only one participant failing in both periods examined when all outgoing payments were restricted from the most influential participant in both periods. Results also suggest that the system was able to with stand 100 per cent of individual outgoing defaults from the second, third and fourth most influential participants within the network in both periods. This was due to the significant level of opening balances in their transactional accounts that can be used as contingent liquidity.

The simulations results presented demonstrate that the JamClear-RTGS network is robust to significant distress, thereby signaling a stable and resilient network to systemic risk. Notwithstanding, the large value system simulation of systemic stress using proportional defaults proposed in this research paper, proves to be an essential tool regulators can utilize for the continued assessment of the stability of payment system.

The structural analysis of the JamClear-RTGS network also provides useful information on identifying systemically important payment institutions as well as concentration and contagion risks within the system. The analysis provided can be used to inform the development of macro-prudential tools to curtail negative externalities related to interconnectedness. Network metrics in the form of concentration, systemic importance and speed of contagion measures can be used to advise the setting of prudential taxes or capital requirements to mitigate these risks.

The network topology analysis presented highlights the need for more focus on primary dealers in the Jamaican financial system given their increasing importance for financial intermediation. This, coupled with increased concentration risk emanating from the group, accentuates the importance of the implementation of macro-prudential tools to target concentration of systemically important institutions in a relatively small and concentrated financial sector.

References

Albert, R., & H.Jeong, A.-L. B. (1999). Diameter of the World Wide Web. *Nature 401*, 130-141.

Albert, R., & H.Jeong, A.-L. B. (2000). Error and attack tolerance of complex netowrks . *Nature 406*, 378-381.

Allen, F., & Babus, A. (2009). Networks in finance. *Wharton Financial Institutions Center Working Paper No. 08-07* .

Allen, F., & Gale, D. (2000). Financial Contagion. *Journal of Political Economy 108(1)*, pp. 1-33.

Angelini, P., Maresca, G., & Russo, D. (1993). An assessment of Systemic Risk in the Italian Clearing System. *Banca D'Italia*.

Bech, M. L., Chapman, J. T., & Garratt, R. (2008). Which Bank Is the 'Central'Bank? An Application of Markov Theory to the Canadian Large Value Transfer System An Application of Markov Theory to the Canadian Large Value Transfer System (November 2008). *FRB of New York Staff Report*, (356).

Boss, M., Elsinger, H., Summer, M., & Thurner 4, S. (2004). Network topology of the interbank market. *Quantitative Finance, 4(6)*, 677-684.

Boss, M., Krenn, G., Metz, V., Puhr, C., & Schmitz, S. (2015). Systemically Important Accounts, Network Topology and Contagion in ARTIS. *Financial Stability Report 15*, 93-111.

Chan-Lau, M. J. (2010). Balance sheet network analysis of too-connected-to-fail risk in global and domestic banking systems (No. 10-107). *International Monetary Fund*.

Cheung, L. (2002). Understanding Intraday Payment Flows in the Large Value Transfer System. *Bank of Canada Financial System Review*, 49-52.

Cont, R., Moussa, A., & Santos, E. (2010). Network structure and Systemic Risk in Banking Systems. *SSRN.<http://ssrn.com/abstract=1733528*.

Demange, G. (2012). Contagion in Financial Networks: A Threat Index. *Working Paper 2012-02, Paris Scholl of Economics, Paris*.

Eisenberg, L., & Noe, T. H. (2001). Systemic risk in financial systems. *Management Science, 47(2)*, 236-249.

Elliott, M., Golub, B., & Jackson, M. (2013). Financial Netowrks and Contagion. *Working Paper, California Institute of Technology, Passadena, California*.

Embree, L., & Roberts, T. (2009). Network analysis and Canada's large value transfer system. *Bank of Canada Discussion Paper*, No.2009-13.

Espinosa-Vega, M. A., & Solé, J. (2011a). Cross-border financial surveillance: a network perspective. *Journal of Financial Economic Policy, 3(3)*, 182-205.

Espinosa-Vega, M. A., & Sole, J. (2011b). Introduction to the network analysis approach to stress testing. *A Guide to IMF Stress Testing: Methods and Models*, 205-208.

Glasserman, P. &. (2015). How likely is contagion in financial networks? *Journal of Banking & Finance*, *50*, 383-399.

Humphery, D. (1986). Payments finality and risk of settlement failure. *Technology and the Regulation of Financial Markets: Securities, Futures, and Banking (Heath, Lexington), 31(3)*, 97-120.

Inaoka, H., Ninomiya, T., Taniguchi, K., Shimizu, T., & Takayasu, H. (2004). Fractal Network derived from banking transaction–An analysis of network structures formed by financial institutions. *Bank Jpn Work Pap, 4*.

León, C., Machado, C., Cepeda, F., & Sarmiento, M. (2011). Too-connected-to-fail institutions and payment system's stability: assessing challenges for financial authorities. *Borradores de Economía* , 644.

Milwood, T. (2014). Contagion Risk in the Jamaican Financial System. *Bank of Jamaica Working Paper*.

Newman, M. (2010). *Networks: an introduction.* Oxford university press.

Roberts, T. (2011). The impact of operational events on the network structure of the LVTS. *Bank of Canada*.

Schmitz, S. W., & Puhr, C. (2006). Liquidity, Risk Concentration and Network Structure in the Austrian Large Value Payment System. *Available at SSRN: http://ssrn.com/abstract=954117*.

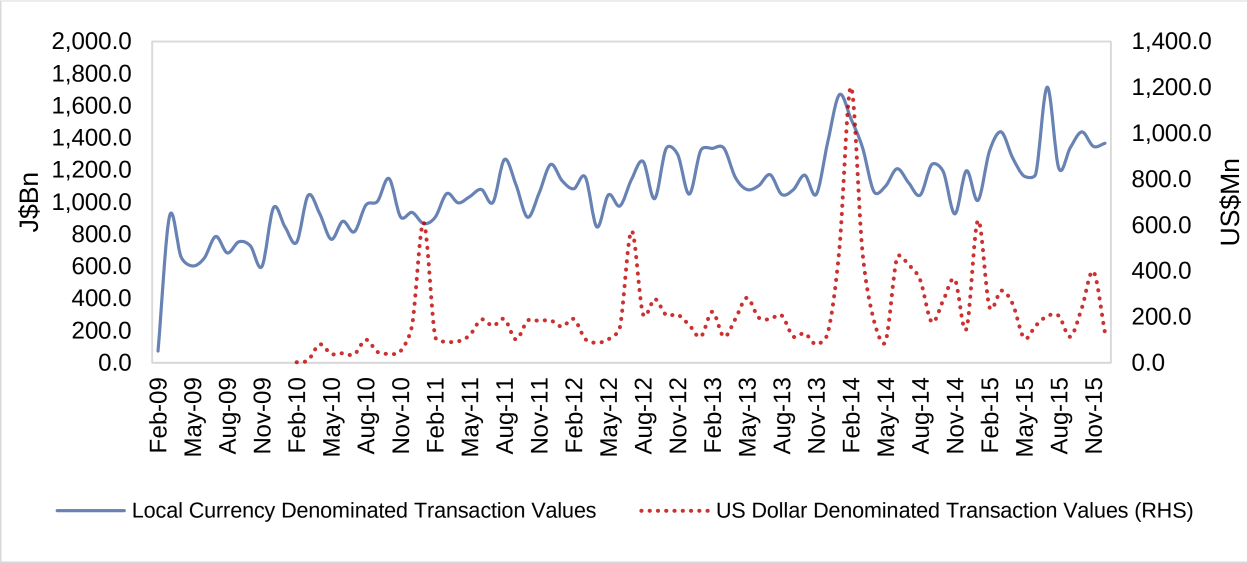
Schmitz, S. W., & Puhr, C. (2007). Risk concentration, netowrk structure and the assessment of contagion in the Austrian large value system. *H. Leinonen (ed.), Simulation studies of the liquidity needs, risks and efficiency in payment netowrk, Bank of Finland Scientific Monograph E:39, Helsinki*, 183-226.

Schmitz, S., & Puhr, C. (2009). Structure and Stability in Payment Networks-A Panel Data Analysis of ARTIS Simulations. *Available at SSRN 1400883*.

Soramäki, K., Bech, M. L., Arnold, J., Glass, R. J., & Beyeler, W. E. (2007). The topology of interbank payment flows. *Physica A: Statistical Mechanics and its Applications, 379(1)*, 317-333.

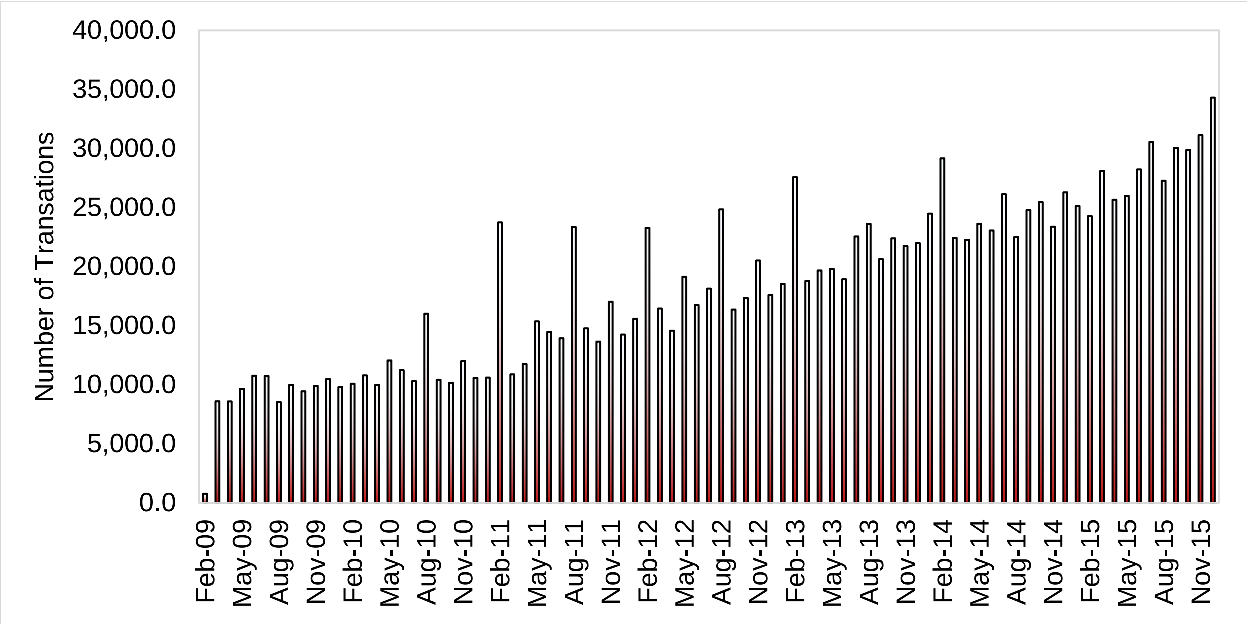
Appendix

Figure 1: *Trends in JamClear-RTGS payment value*



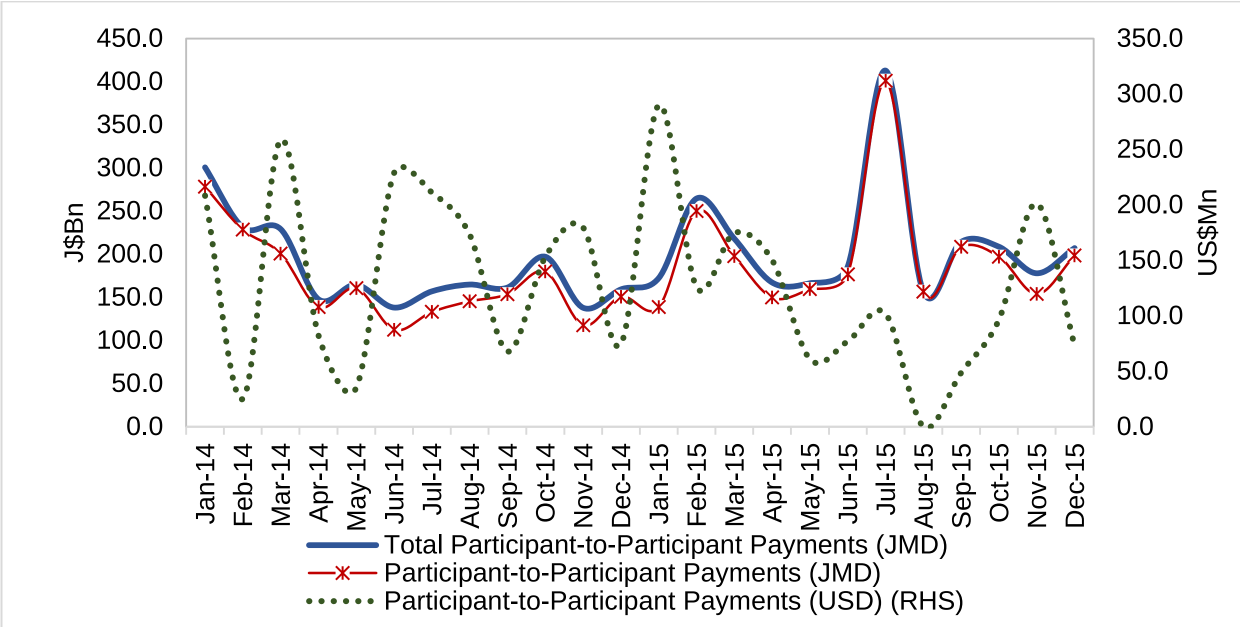
Source: Bank of Jamaica

Figure 2: *Trends in JamClear-RTGS payment volume*



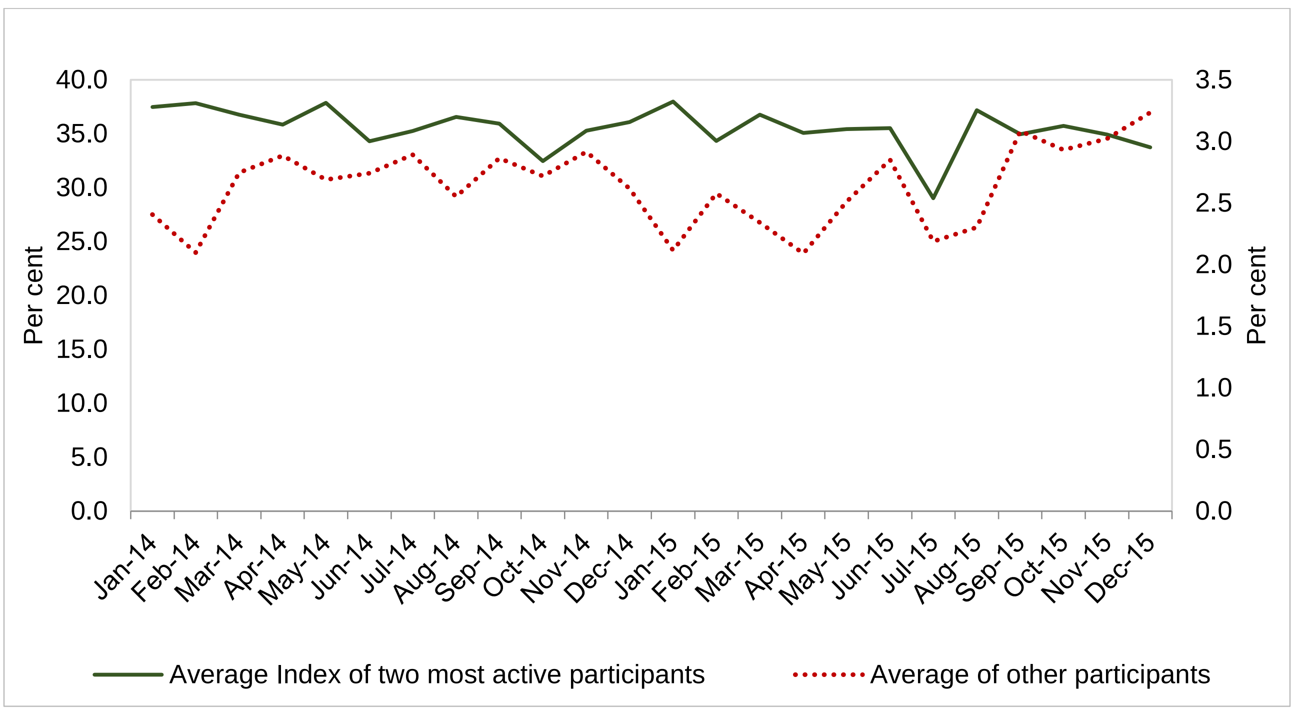
Source: Bank of Jamaica

Figure 3: *Trends in Participant-to-Participant Payments*



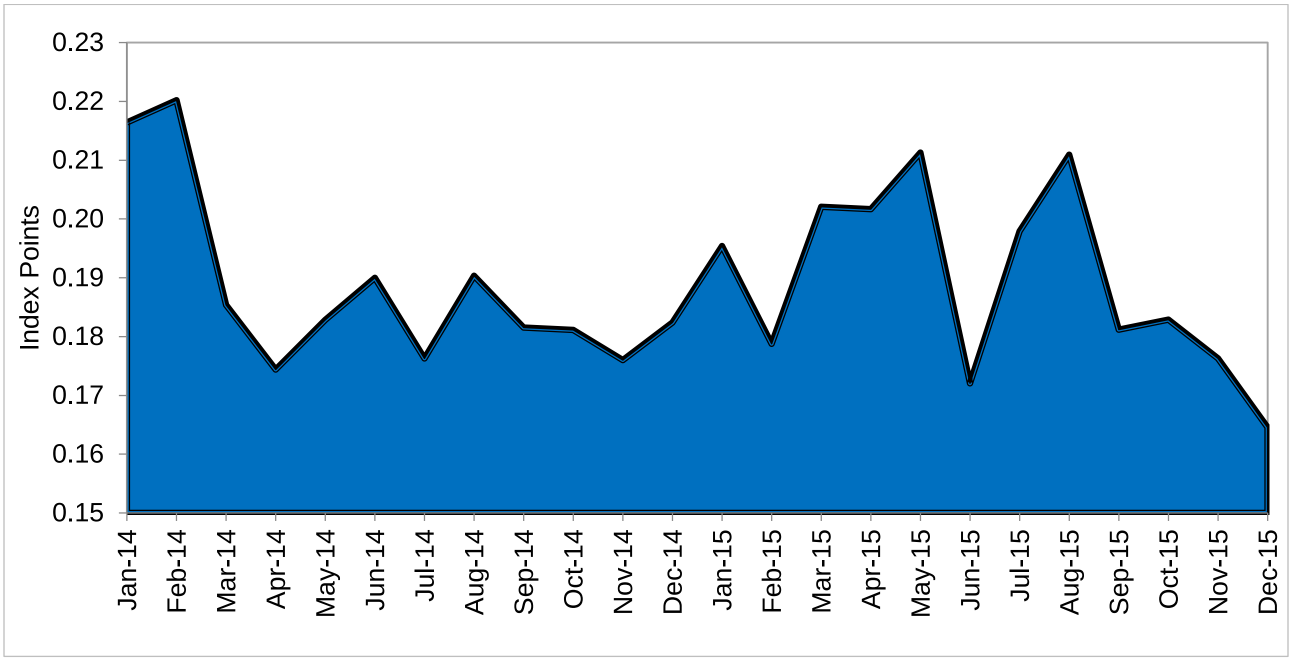
Source: Bank of Jamaica

Figure 4: *Payment Concentration*



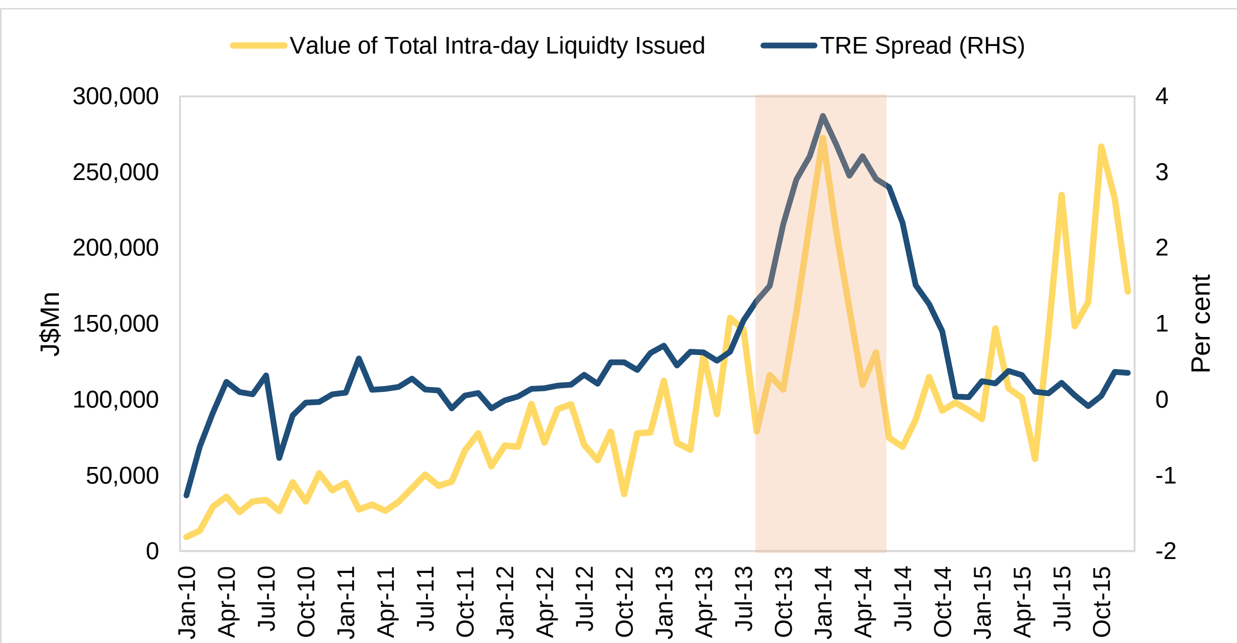
Source: Bank of Jamaica

Figure 5: *Herfindahl Index of JamClear-RTGS liquidity Concentration*



Source: Bank of Jamaica

Figure 6: *Measures of Liquidity Tightness within the Jamaican Financial System*



Source: Bank of Jamaica

Table 2: *Simulation Results of Joint Participant Failure*

Period	Scenario	Iterations	Tier 1 Liquidity: *No. of Participants with Negative Net Balances*	Tier 1 Liquidity: *No. of Failed Participants*	Tier 2 Liquidity: *No. of Participants with Negative Net Balances*	Tier 2 Liquidity: *No. of Failed Participants*	Tier 3 Liquidity: *No. of Participants with Negative Net Balances*	Tier 3 Liquidity: *No. of Failed Participants*
Period of Tight Liquidity January 2014	**Scenario 1**: *Joint Failure of 4 Most Central Participants*	-	7*	-	7*	-	7*	-
		1	4	1	4	3	4	0
		2	3	1	2	1		
		3	4	0	1	0		
	Scenario 2: *Joint Failure of 3 Most Central Participants*	-	7*	-	7*	-	7*	-
		1	5	1	5	3	5	0
		2	4	0	2	0		
	Scenario 3: *Joint Failure of 2 Most Central Participants*	-	7*	-	7*	-	7*	-
		1	5	0	5	2	5	0
		2			3	0		
Period of Normal Liquidity December 2015	**Scenario 1**: *Joint Failure of 4 Most Central Participants*	-	3*	-	3*	-	3*	-
		1	2	0	2	1	2	0
		2			2	0		
	Scenario 2: *Joint Failure of 3 Most Central Participants*	-	3*	-	3*	-	3*	-
		1	3	0	3	1	3	0
		2			2	0		
	Scenario 3: *Joint Failure of 2 Most Central Participants*	-	3*	-	3*	-	3*	-
		1	3	0	3	2	3	0
		2			2	1		
		3			2	0		

**Represents the number of participants with negative net balances prior to the removal of troubled participant(s)*

Table 3: *Simulation Results of Individual Participant Failure*

		Iterations	Tier 1 Liquidity		Tier 2 Liquidity		Tier 3 Liquidity	
			No. of Participants with Negative Net Balances	*No. of Failed Participants*	*No. of Participants with Negative Net Balances*	*No. of Failed Participants*	*No. of Participants with Negative Net Balances*	*No. of Failed Participants*
Period of Tight Liquidity January 2014	**Scenario 4**: *Failure of Most Central Participant*	-	7*	-	7*	-	7*	-
		1	5	1	5	2	5	0
		2	5	0	4	1		
		3			3	0		
	Scenario 5: *Failure of 2nd Most Central Participant*	-	7*	-	7*	-	7*	-
		1	4	0	4	1	4	0
		2			4	1		
		3			3	0		
	Scenario 6: *Failure of 3rd Most Central Participant*	-	7*	-	7*	-	7*	-
		1	6	0	6	1	6	0
		2			6	2		
		3			4	1		
		4			3	0		
	Scenario 7: *Failure of 4th Most Central Participant*	-	7*	-	7*	-	7*	-
		1	6	0	6	0	6	0
Period of Normal Liquidity December 2015	**Scenario 4**: *Failure of Most Central Participant*	-	3*	-	3*	-	3*	-
		1	2	0	2	0	2	0
	Scenario 5: *Failure of 2nd Most Central Participant*	-	3*	-	3*	-	3*	-
		1	2	0	2	0	2	0
	Scenario 6: *Failure of 3rd Most Central Participant*	-	3*	-	3*	-	3*	-
		1	4	0	4	1	4	0
		2			3	0		
	Scenario 7: *Failure of 4th Most Central Participant*	-	3*	-	3*	-	3*	-
		1	2	0	2	0	2	0

**Represents the number of participants with negative net balances prior to the removal of troubled participant(s)*