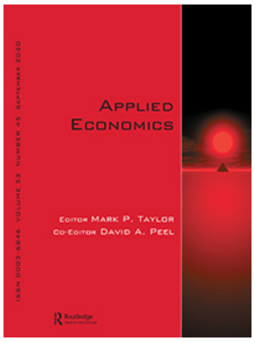


Applied Economics

ISSN: (Print) (Online) Journal homepage: https://www.tandfonline.com/loi/raec20

Systemic risk in the Angolan interbank payment system – a network approach

Maria Rosa Borges, Lauriano Ulica & Mariya Gubareva

To cite this article: Maria Rosa Borges, Lauriano Ulica & Mariya Gubareva (2020) Systemic risk in the Angolan interbank payment system – a network approach, Applied Economics, 52:45, 4900-4912, DOI: 10.1080/00036846.2020.1751052

To link to this article: https://doi.org/10.1080/00036846.2020.1751052

Published online: 19 Apr 2020.

APPLIED ECONOMICS
2020, VOL. 52, NO. 45, 4900–4912
https://doi.org/10.1080/00036846.2020.1751052

Systemic risk in the Angolan interbank payment system – a network approach

Maria Rosa Borges [a], Lauriano Ulica [b] and Mariya Gubareva [c]

[a]ISEG - Lisbon School of Economics and Management, Universidade de Lisboa and UECE - Research Unit on Complexity and Economics, Lisbon, Portugal; [b]Banco Nacional de Angola, Luanda, Angola; [c]ISCAL, Lisbon Accounting and Business School, Instituto Politécnico de Lisboa, SOCIUS - Research Centre in Economic and Organizational Sociology, CSG - Research in Social Sciences and Management, Lisbon, Portugal

ABSTRACT

In this work, we analyse the topology of the network of interbank payment flows settled via the real-time gross settlement system (RTGS) of the Angolan payment system (APS) during the fourth quarter of 2016, with the aim of discussing the APS resilience to systemic risk, focusing on its vulnerability in case of failures in the settlement of any bank payments. We conclude that (*i*) the Angolan RTGS payment network is sparse, characterized by low connectivity, (*ii*) it is a scale-free network with five banks with high connectivity, representing the main origin and destination of the settled transactions and concentrating about 47% of the total volume and amount of payments settled, which adds to contagion risk. However (*iii*) the systemic risk arising from the removal of a single participant from the network is low, since the largest bank in the system, with the greatest transacted volume and amount, accounts only for about 11% of the total transacted amounts. In addition, (*iv*) the adequate risk-mitigating operational processes of each of the RTGS subsystems safeguard the APS from systemic risk.

KEYWORDS
Interbank payment network; systemic risk; real time gross settlement system; Angola

JEL CLASSIFICATION
G20; G21; G28

I. Introduction

In the economy, there is a very high number of daily transactions undertaken by economic agents, which involve transfer of funds. The availability of a reliable and secure payment mechanism for fund transfer is therefore a *sine qua non* condition for the successful realization of economic interactions. A particular type is the real-time gross settlement (RTGS) system, which settles transactions of its participants individually (gross) and immediately (real-time). Each payment is settled individually as soon as the transfer order is submitted and accepted for settlement, provided that the payer has sufficient funds (or facilities for overdrafts) available in his account. Freixas and Parigi (1998) note that pure gross systems are less subject to contagion risk than net settlement systems, but they are more costly, because banks are required to hold more liquid funds, that cannot be invested. Increasingly, central banks have supported and even taken initiatives to implement this type of system, with a rapid increase in the use of RTGS systems throughout the 1990 s. The RTGS system requires high levels of liquidity from its participants.

The development of efficient payment systems has been attracting continuous attention among professionals and academy, and has been a widely researched topic from both theoretical and empirical perspectives (Freeman 1996; Freixas and Parigi 1998; Kahn and Roberds 2001; Williamson 2003; Kahn, McAndrews, and Roberds 2003; Mills and Nesmith 2008; Norman 2010; Triepels, Daniels, and Heijmans 2017; Gibson, Hall, and Tavlas 2018; Yawe and Kiwala 2019).

It is worth noting that a majority of researchers agree that RTGS allows for minimizing systemic risk, but, simultaneously augments liquidity risk (Kahn and Roberds 2001; De Caux, Bredea, and McGroartyb 2016; Nellen 2019). That is why theoretical and empirical studies of RTGS currently are spread across different countries, including both developed economies and emerging markets (Docherty and Wang 2010; Merrouche and Nier 2012; Sun and Chan-Lau 2017; Choi 2019). However, to the best of our knowledge, no research has addressed the Angolan RTGS. The objective of this paper is to evaluate the stability/vulnerability level of the Angolan Payment System (APS) in case

CONTACT Maria Rosa Borges mrborges@iseg.ulisboa.pt ISEG - Lisbon School of Economics and Management, Universidade de Lisboa and UECE - Research Unit on Complexity and Economics, Lisbon, Portugal

of failures in the settlement of any bank payments, and thus fills this gap in the literature.

The rest of the paper is organized as follows. In section 2, we discuss the relevant literature on the topology of financial networks and how it affects systemic risk. Section 3 describes the Angolan payment system. Section 4 develops the methodology and presents the data. The results are discussed in section 5. Section 6 concludes.

II. Systemic risk and the topology of financial networks

Taking together the different aspects of the payment settlement procedures, if these are not properly coordinated and supervised, this may result in upsurge of systemic risk, which arises due to interconnectedness of the banks, representing an open door to contagion (Allen and Gale 2000; Nier et al. 2007; Babus 2016; Sun and Chan-Lau 2017; among others). Berndsen, León, and Renneboog (2016) define systemic risk as the risk associated with any event that threatens the stability of a financial system as a whole. Banks may be capable of absorbing financial imbalances, but if they experience liquidity issues, these can quickly propagate to other banks, due to their interconnectedness (Triepels, Daniels, and Heijmans 2017). Therefore, much research has been devoted to the study of the topology of payments networks and to its systemic risk (Albert and Barabási 2002; Boss et al. 2004; Bech and Atalay 2010; Iori et al. 2008; Soramäki et al. 2007; Santos and Cont 2010; Martinez-Jaramillo et al. 2014).

Allen and Gale (2000) show that the financial system, when interconnected in a highly connected network structure, is subject to a lower risk of contagion than systems with fewer connections. Nier et al. (2007) investigate how systemic risk can be affected by the structure of the financial system. The authors conclude that the effect of bank connectivity is not monotonic and that banking systems with higher concentration are subject to greater systemic risk. Albert and Barabási 2002) show that the distribution of the number of counterparties per bank affects the resilience of the network. If nodes that are connected to many other banks are removed, the structure of the network can change dramatically. Gai and Kapadia (2010) claim that increased connectivity can simultaneously reduce the probability of contagion, but increase its spread in case of the network breaking down, another way of recognizing the robust-yet-fragile characteristic of financial networks.

Boss et al. (2004) analyse the Austrian interbank market based on central bank data and claim that the network structure of the market is scale-free. This means that are few banks have many interbank linkages than the average. Many other existing interbank networks have been reported to resemble scale-free networks, such as the US Fedwire system which Soramäki et al. (2007) study, to analyse the impact of the events of 11 September 2001 in the USA. They find that this financial network has both a low average short path length and low connectivity. The network includes a core of heavily bonded banks, for which most other banks have been connected. Santos and Cont (2010), for the Brazilian interbank network and Martinez-Jaramillo et al. (2014) for the Mexican financial market, reach similar conclusions. Scale-free networks are relatively robust to the random breakdown of nodes, but very vulnerable to the risk of the removal of specific nodes, they are robust-yet-fragile, meaning that targeted attacks on the most central nodes may lead to a breakdown of the entire network. Boss et al. (2004) also show that the most vulnerable banks are those with the highest centrality in the network.

Other studies, by Bech and Atalay (2010), Iori et al. (2008) and Fricke and Lux (2015), claim different findings. Studying the US Federal Funds market, Bech and Atalay (2010) find that the number of counterparties per bank follows a fat-tailed distribution, with most banks having few counterparties and a small number having many, and claim that the degree distribution is not necessarily represented by a power-law distribution. Additionally, they note that there is a significant asymmetry: when a bank is highly connected, it is usually because it borrows from many banks, and not because it lends to many other banks. Iori et al. (2008) find no evidence in favour of scale-free networks in the e-MID (electronic market for interbank deposits) market, but recognize that the degree distribution, though not scale-free, is heavier tailed than a random network. Fricke and Lux (2015) reinvestigate such claims for the e-MID data, and do not find any support for a scale-free network, and demonstrate that many alternative distributions provide a better fit than a power-law. It is important to know the degree distribution of networks, for policy design.

Several studies propose that a core-periphery structure is a better description for many financial networks. A typical core-periphery model assumes that core nodes are all connected to each other, peripheral nodes are not connected within their group at all, and have a limited number of connections to the core banks. Craig and von Peter (2014) propose a measure of distance from an ideal core-periphery structure and identify a core of 45 banks in a network of 1,802 German banks. In't Veld and van Lelyveld (2014) apply the same methodology to the Dutch banking system and identify 10% to 20% of banks as core. Borges and Fernandes (2020) analyse the relationship between interbank connectivity and contagion risk in the Portuguese Banking System, using data on overnight liquidity borrowings and borrowings in the interbank money market. They conclude that the Portuguese overnight IMM has a centralized structure in which several banks simultaneously play the role of lenders and borrowers but that failure of one institution may affect others.

In relation to the network approach, specifically in payment systems, the seminal paper by Eisenberg and Noe (2001) studies the compensation process in an interbank payment network based on a representation of the matrix data, and demonstrates the existence of a single payment vector that optimizes the amount paid after clearing. Using this methodology, a mechanism is proposed to analyse the magnitude of the contagion in the network, in the case of bank settlement failures of a certain bank in the system. This mechanism has been widely used to simulate contagion in banking networks, and is still popular today (Eboli 2019; Khabazian and Peng 2019), although other clearing mechanisms have been proposed, criticizing that the Eisenberg and Noe (2001) model treats all payment obligations as if they had equal priority, assumes that all settlements between banks occur simultaneously, and that the available assets are distributed pro rata to the creditors, which are oversimplifications.

III. The Angolan payment system (APS)

In the last two decades, the APS has evolved significantly, in order to bring it closer to international standards. We can distinguish four stages in the recent evolution of APS.

The first stage lasted until 1996, when the APS was weakly developed. The automation of processes was practically non-existent, with settlement being deferred, resulting in rather long delays in funds crediting onto accounts, especially in comparison to some more developed countries where in the 1990s funds transfers were already made electronically. For example, in the United States, electronic check clearing began in 1956, the automated clearinghouse for electronic funds transfers was implemented in 1960, and in the 1970s, and the Fedwire was the first automated RTGS system (Connolly and Eisenmenger 2000). In the United Kingdom, the same trend began in the 1960s. In respect to African geographies, it is worth mentioning the example of South Africa, whose payment system started a similar development in the late 1980s. Later, the South African Reserve Bank undertook the implementation of the electronic transfers and, finally, of the RTGS (Samos) in 1998.

The second phase, of shorter duration, corresponded to the period from 1997 to 2000, a transition phase marked by a diagnosis of the situation and the design of a strategic plan for the restructuring of the APS. A working group was formed which began its activities in a systematic way in 1997 and published in 1999 a report that served as a basis for the establishment of the APS.

The next six-year phase (2001–2006) was the phase of completion of the SPA project: (i) the implementation of the APS infrastructure, including infrastructure, computer systems, communication networks, and the contracting of financial message transmission services (Swift) for sending/receiving interbank payments, whose handling became mandatory for all banks. With this system, interbank transfers of funds became settled in real-time, in a definitive and irrevocable mode.

Since 2006, the Angolan RTGS has been consolidated, and increased in the number of participant banks, and in the number and amounts of settled transactions. Figure 1 depicts the volume of transactions in the Angolan RTGS system, from 2005 to 2016.

The evolution of the Angolan RTGS system in this period was notable, reflecting the growth in the number of participants (from 16 to 33), the increase in the number of transactions (from 6,188 to more

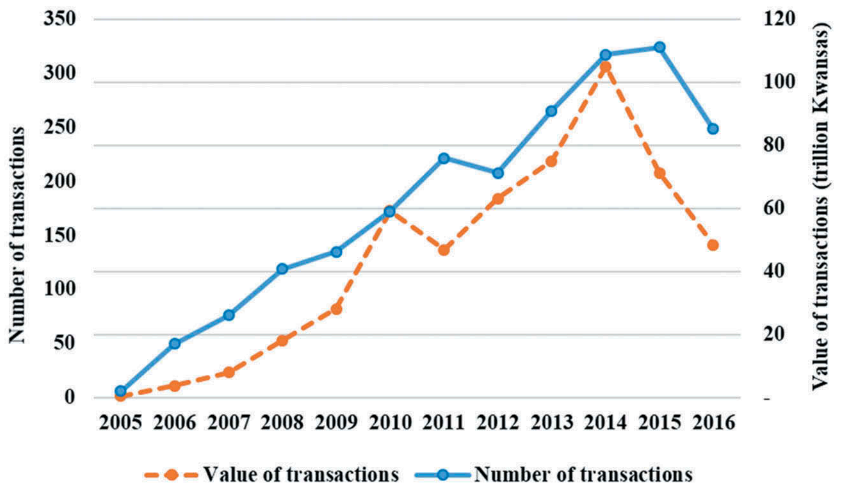


Figure 1. Evolution of the Angolan RTGS: Number and value of yearly transactions from 2005 to 2016.
Source: Angolan RTGS (BNA), authors´ proprietary analyses.

than 300,000 in 2014 and 2015) and the increase in the value of settled amounts (from 470 billion to more than 100 trillion kwanzas in 2015).

IV. Methodology and data

Topology characteristics of networks

Our analysis of the resilience of the APS is based on a topological analysis of the Angolan RTGS, using elements of network theory. Many studies of complex networks employ graph theory, which is used to describe systems in a compact and simple way, focusing on the connection properties of the links existing among a set of system's elements. This approach facilitates the understanding of the properties and the representation of such systems. A few graphical examples of networks topologies are presented in Figure 2.

In a ring network, each node is connected to its two closest neighbours; in a mesh network, the number of links between nodes varies, and the network is not fully connected; in a star network, all nodes are connected to a single central node, designated as the core; in a fully connected or complete network, all nodes are connected to each other. In reality, financial networks are more complex than these examples.

Formally, a network corresponds to a graph defined by a pair of sets $G = \{N, m\}$, where N is the number of nodes (constituting elements) of the network and m is the number of connections, or links, between two network nodes.

The size of the network is determined by the number of nodes (N). A possible way to represent complex networks is through an adjacency matrix, $A(G) = [a_{ij}]$. Two nodes i and j are said to be adjacent if they are connected and $a_{ij} = 1$. If these two nodes are not connected, we have $a_{ij} = 0$. A network will be complete if each node is connected to all other nodes, that is, if in the adjacency matrix the elements outside the main diagonal assume the value one, while the elements on the main diagonal assume the value zero. This applies to both directed and non-directed graphs. In the

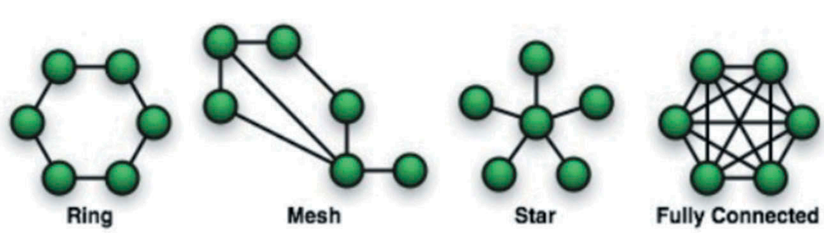


Figure 2. Examples of network topologies: nodes and connections.

latter case, the link-forming nodes are simultaneously the origin and destination of the link.

The degree of connectivity (g_i) of the N_i node of the network corresponds to the number of links in which N_i participates. The degree (g) of the network G is the arithmetic mean of the degrees (g_i) of all the nodes of the network. The analyses of the density, or degree of network connectivity (C) is based the following formula (see, Soramäki et al. 2007):

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

where m stands for the number of connections, and N stands for the number of nodes in the network. If the above expression results in the value one, the network is completely connected. On the other hand, if it equals zero, it means that there is no connection between the nodes. The higher the degree of connectivity, the greater the proportion of established connections and the less sparse the network. A network is defined to be disconnected when there is no path between a specific node and the remaining nodes of the graph.

The geodesic path (d_{ij}), or the shortest path between two nodes i and j, is the minimum number of links necessary to connect those two nodes. The average shortest path length (APL) of the network refers to the average number of minimum connections necessary to ensure the connection of each pair of nodes in the network, and is be determined by:

$$APL = \frac{2}{N(N-1)} \sum\nolimits_{i \neq j} d_{ij} \tag{2}$$

The lower limit for the average shortest path length is one, when the graph is complete, i.e., all nodes are connected to each other. The highest d_{ij} in the network determines its diameter. The diameter is also one, in a complete network.

The connectivity distribution is one of the basic characteristics of network topology. It is the mean number of links a node has, and is simply computed by m/N. According to Soramäki et al. (2007), for the directed graphs, it is necessary to take into account two important characteristics of the nodes, the incoming connectivity and outgoing connectivity degrees, i.e., the numbers of connections, which, respectively terminate and originate at the node.

The clustering coefficient measures the degree to which nodes in a network cluster together, i.e., the tendency of nodes to concentrate in groups with a high density of links. Suppose that a node i has v_i neighbours (adjacent nodes); then, at most $v_i(v_i - 1)/2$ links can exist between the neighbours of node i. Therefore, the clustering coefficient (C_i) of node i is defined as the ratio between the actual number of links between its neighbours, $E(v_i)$, and the maximum number of links that could exist:

$$C_i = \frac{\mathrm{E}(v_i)}{v_i(v_i - 1)/2} \tag{3}$$

It should be noted that C_i always assumes values in the range of $0 \leq C_i \leq 1$. If the local cluster is a tree graph, with node i on the centre, we have $C_i = 0$: if it is a complete network, we have $C_i = 1$. The value of the clustering coefficient of the network corresponds to the arithmetic averages of the values obtained for each node of the graph.

In order to determine the importance of certain links and, consequently, the importance of the nodes in the network, characteristic weights are assigned to all the links. Barrat et al. (2004) define the weight of a node in the network as the sum of the weights of all the connections of this same node, that is, $S_i = \sum^{w_{ij}}$, where S_i is the weight of the node i and w_{ij} is the weight of the links ij of that node i.

In our study, the banks are the nodes of the network and the transfers of funds between the banks are the links between those nodes. Obviously, this corresponds to a directed graph, because the links between banks have a direction, from the originator to the recipient bank. Additionally, as these transactions have a quantity amount, we use the settled amounts as weights of the links and determine the relative strength of the nodes (banks) in the network.

Characterization of the sample

For our empirical study, we analyse interbank data, including volume and amount of payments settled via the Angolan RTGS in the last quarter of 2016, containing observation of 62 banking days. The number of banks involved in these interbank fund transfers is 33.

Given the diversity of institutions participating in the Angolan RTGS, all payments involving BNA and Ministry of Finance are excluded from the analysis of the network, thus including only payments between commercial banks, such as customer transactions, institutional operations, and liquidity borrowing/lending in interbank money markets. Payments between sub-accounts of the same participant, so-called loops, are also not considered for this purpose. Operations of the automatized Angolan clearinghouses, so-called CCAAs, and transactions at the Secondary Public Debt Market, known by the local abbreviation BODIVA, are also excluded.

The Angolan RTGS system is responsible for settlement of all types of large payments (above 5 million kwanzas) processed in the APS, including customer and institutional swift operations, asset market operations (bonds/redemptions of Angola treasury bills, Angolan treasury bonds, BNA securities, coupon interest payments, interbank lending and borrowing, granting/returning of liquidity facilities to commercial banks). The RTGS is also responsible for the settlement of treasury operations, exchange market operations (buying and selling of foreign currency), as well as operations of clearing houses and transactions at the secondary public debt market.

During the period under study, for our sample of banks, 45,461 transactions were settled in the RTGS, totalling 1,887,317.41 million kwanzas (see Table 1). The daily average amount transferred between banks, considering the 62 days of the sample, is around 30,440.60 Million kwanzas, corresponding to 733.24 operations per day. The settled amount reached its maximum value (84.899,78 million kwanzas) on 22 December, and the number of operations peaked on 15 December, with 1805 operations performed.

Figure 3 shows the evolution of the number of transactions during the fourth quarter, as well as the respective value, in million Kwanzas.

It can be seen in Figure 3 that the number of interbank transactions processed in the Angolan RTGS system in the fourth quarter of 2016 exhibits three sharp spikes, one per month, corresponding to the payment of wages. Regarding the value of settled amounts, there is a growing trend in the period under analysis, with some peaks, which are justified by the settlement of IMM operations, traditionally characterized by elevated amounts, which predominantly represent liquidity borrowing/lending operations.

V. Empirical results

Based on the analysis of the Angolan RTGS and taking into account the interconnectivity between its participants, we analyse whether, in the case of occurrence of liquidation failures payments of a banking institution, the APS has the necessary resilience to guarantee the non-propagation of the contagion to the whole system, enabling a mitigation of systemic risk.

We analyse the network topology of the interbank payments processed in Angolan RTGS system, taking as reference the work of Soramäki et al. (2007). Our analysis is based on the common properties of networks (size, connectivity, connectivity distribution, clustering coefficient, average path length, and weight of the links). We study network stability, robustness, resilience, and efficiency in the face of financial turmoil or disturbances caused by one or more participants in the system.

The Angolan interbank payment network

We use the RStudio program, to process the data and to construct the network of interbank transactions flow within the Angolan RTGS. We model the flow of payments as a directed network, where banks constitute the nodes of the network and the transfer of funds from the originator bank to the recipient bank represents a link between them and

Table 1. Descriptive statistics for the daily transactions on the Angolan RGTS.

	Number of transactions	Value of settled amounts (million Kwanzas)	Nodes	Links	Degree of Connectivity
Mean	733.24	30,440.60	26.40	155.42	23.172%
Median	689.50	23,271.89	27.00	157.50	23.148%
Max	1805.00	84,899.78	28.00	187.00	32.619%
Min	465.00	12,032.97	21.00	115.00	17.989%
Standard deviation	15.15	128.84	1.15	3.76	0.153
Number of observ.	62	62	62	62	62
Total	45,461	1,887,317.43	1,637.00	9,636.00	

Source: Angolan RTGS (BNA), authors´ proprietary analyses.

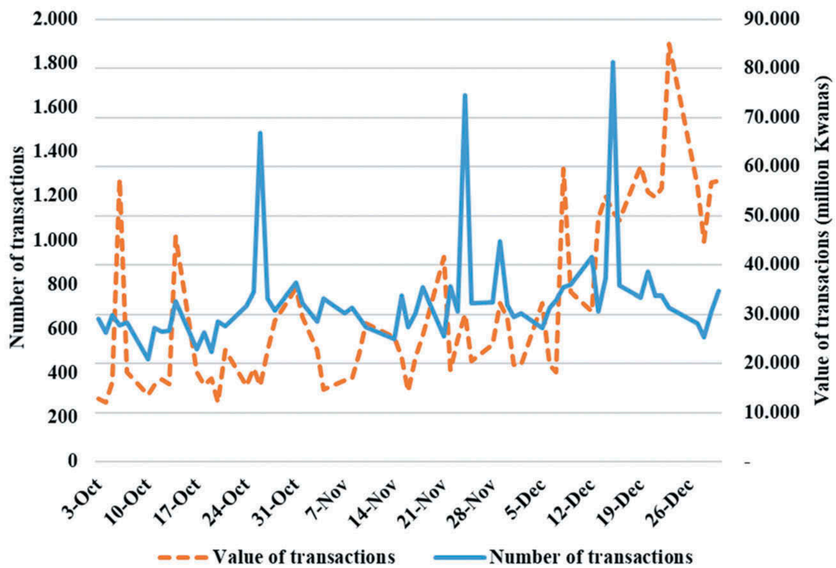


Figure 3. Number and value of transactions in the Angolan RTGS in the fourth quarter of 2016.
Source: Angolan RTGS (BNA), authors´ proprietary analyses.

where the direction of a link is defined by the direction of the payment flow, represented by this link. Arrows depict the links. The weight of each link is defined by the settled transfer amount. Thus, each additional transfer between two banks (provided it is in the same direction) adds the weight to the link between these banks.

Figure 4 shows the variation of the number of nodes and connections occurred during the period under analysis (62 banking days, from 3 October 2016 to 26 December 2016).

To analyse the topological characteristics of the network of the interbank payments processed daily in the Angolan RGTS, a network was modelled for each observed day. As an example, Figure 5(a) represents the graph of the flow of interbank payments on the first day of the sample (3 October 2016).

The network of the first day of the sample (Figure 5(a)) is composed of 26 nodes and 145 links. Graphically, the weights of the links are represented by the thickness of the arrows. The thicker the arrow linking two banks, the greater

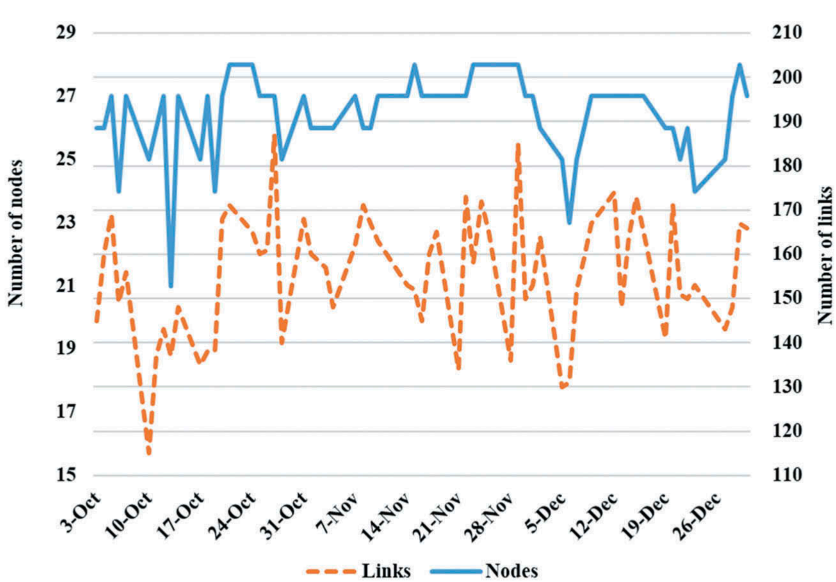
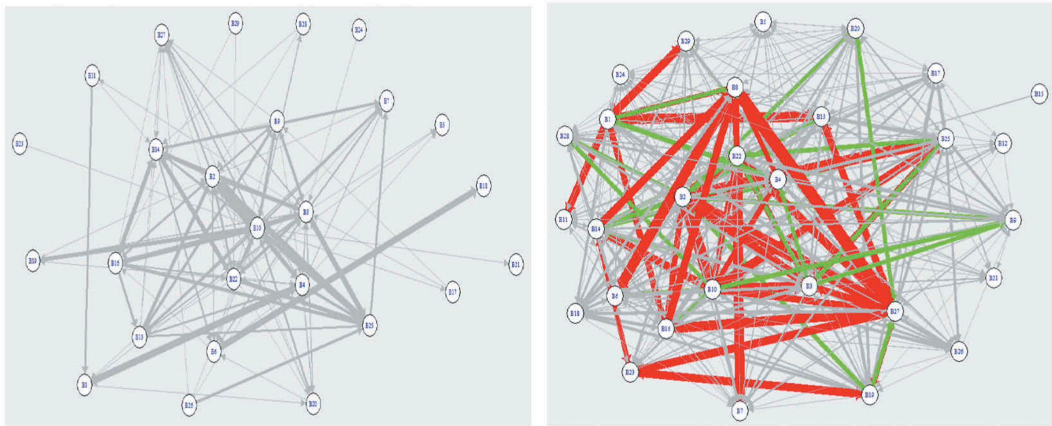


Figure 4. Number of nodes and links in the Angolan RTGS network in the fourth quarter of 2016.
Source: Angolan RTGS (BNA), authors´ proprietary analyses.



(a) (b)

Figure 5. Networks of interbank payment flows.
Source: Angolan RTGS (BNA), authors´ proprietary analyses with R-Studio

the amounts transferred between them. We observe that there is a core formation, consisting of the banks that carry out large-amount transfers, which are called money centres. On the other hand, there exists a set of banks with a more peripheral position in the network, with transactions of relatively low amounts. We also observe some large-amount transfers between nuclear and peripheral banks, but these transfers represent more outflows from the core to the periphery.

Fricke, Finger, and Lux (2013) note that many network statistics display high variability over short horizons, but display more stable statistics at the monthly to quarterly aggregation level, where noise is reduced and the structure of available credit lines is more easily captured. Therefore, for a more robust analysis, the network of payments processed throughout the fourth quarter of 2016 (accumulated data of 62 days) is also represented. The respective graph can be observed in Figure 5(b). This network represents the cumulative inflows and outflows of interbank payments processed in the Angolan RGTS during the fourth quarter of 2016. The red links represent transfers equal to or greater than 10 billion kwanzas, green links represent transfers of between 5 and 10 billion kwanzas, while grey links represent transfers of less than 5 billion kwanzas.

Note that the topological characteristics of the network remains stable, regardless the span of the gauging window. This aggregated network comprises 29 banks, meaning that each of the 29 banks transferred funds to and/or received funds from another bank, in at least one of the 62 days under analysis. Five hundred and thirty-six different links were established among these 29 banks. Figure 5(b) confirms the existence of the money centres, i.e., the core banks that are highly connected among them and, on the other hand, of peripheral banks with few connections.

Topological characteristics of the Angolan RTGS network

In this section, we discuss the topological characteristics of the Angolan RTGS network, taking in consideration the mean of the 62 days banking days.

The number of nodes defines the size of the network. In a typical day, there are 26 banks (nodes) in the network, and 155 links. The degree of network connectivity calculated based on formula (1) is 0.2385, meaning that the network is sparse, since 76.15% of the 650 possible connections between banks were not used. Figure 5(a) also visually corroborates these results, as it exhibits a network graph with little interaction between banks, in general, and, in particular, with especially sparse connections among peripheral banks.

At this point, we perform a Pearson correlation analysis between nodes, links, transactions (number and amount), and the degree of connectivity, based on the 62 days observations, and show our results in Table 2.

Table 2. Correlations between nodes, links and network connectivity.

	Value of Transactions	Number of Transactions	Number of nodes	Number of links
Number of nodes	*−0.0852*	*0.2722*	-	-
Number of links	*0.0745*	*0.4547*	*0.5160*	-
Connectivity	*0.1545*	*0.1167*	*−0.6162*	*0.3476*

Source: Angolan RTGS (BNA), authors´ proprietary analyses.

The size of the network exhibits a weak positive correlation with the number of transactions ($\rho = 0.2722$), that is, an increase in the number of nodes may result in a slight increase in the volume of transactions. The number of links has a modest positive correlation with the volume of transactions ($\rho = 0.4547$), as well as with the number of network nodes ($\rho = 0.5160$), but is not correlated with the amount of transactions. With regard to network connectivity, this has some positive correlation with the number of links ($\rho = 0.3476$), that is, the greater the number of network links, the greater the network connectivity. There is, however, a more significant negative correlation between the connectivity and the number of nodes in the network ($\rho = -0.6162$), that is, the higher the number of nodes in the network, the lower the connectivity. This fact is reflected in the network topology, where it is observed that peripheral nodes, most of them recent Angolan RGTS participants, establish more relations with the central nodes. This analysis is consistent with the graphs presented in Figure 5.

We calculate the 62 days-long average clustering coefficient (C) of the analysed network, using formula (3). The average value of the clustering coefficient is 0.51, which is a relatively low. We can interpret this result as evidence of the fact that certain groups of banks prefer relationships within such groups instead of connecting to all of their neighbours, thus explaining the origin of the low degree of network connectivity.

Another important metrics of the network properties are the average path length (*APL*), computed using formula (2). The value obtained for the mean network is 1.78. This means that the distance separating one node from any other in the network is short, one can navigate through a small number of links. Hence, the network is compact, which is the usual characteristic of small-world networks (Soramäki et al. 2007), where shocks can more easily spread all over the system. Consequently, we can conclude that the Angolan interbank network is sparse with low connectivity (low C) but is sufficiently compact (low *APL*). Hence, it can be easily readjusted if a link is removed from the network. These results can be compared with the findings by Soramäki et al. (2007) in the case of payments processed at Fedwire, who report the clustering coefficient C of 0.53 and an *APL* of 2.6.

Analysing the connectivity distribution, we find that its value equals 5.96, resulting from the mean number of links (155) and the mean number of nodes (26) of the network. From the point of view of the mean outgoing connectivity degree, averaged along 62 banking days, we observe that about 40% of banks send payments to the core six banks (see Figure 6).

On the other hand, we detect the existence of five core banks sending payments on a daily basis to more than 10 different banks. These five banks have on average more than 10 links per day. Regarding the incoming connectivity degree, the observed situation is quite similar too. Twelve banks receive payments originated mainly from six core banks. Out of these 12 banks, only five banks receive payments from 10 or more different banks. Simultaneously we observe that about 42% of the banks have three or less connections per day. These numbers demonstrate the low incoming and outgoing connectivity degrees of the APS network.

This type of connectivity distribution corresponds to the networks where a few nodes have high connectivity, while the majority of nodes have low connectivity, as can be verified in Figure 6. Such type of network is a core-periphery network, similarly to Craig and von Peter (2014) and In't Veld and van Lelyveld (2014).

An important finding related to the distribution of the APS network connectivity is that four of the five banks with higher outgoing concentration degree also belong to the group of the core banks with higher incoming concentration degree. Altogether, five banks concentrate 49% of the network connectivity. This means that these banks are the most active in the APS, acting as the main source and destination of the transactions settled in the Angolan RTGS.

We also calculated the weights of links in order to determine their relative importance and, consequently, the importance of nodes in the network.

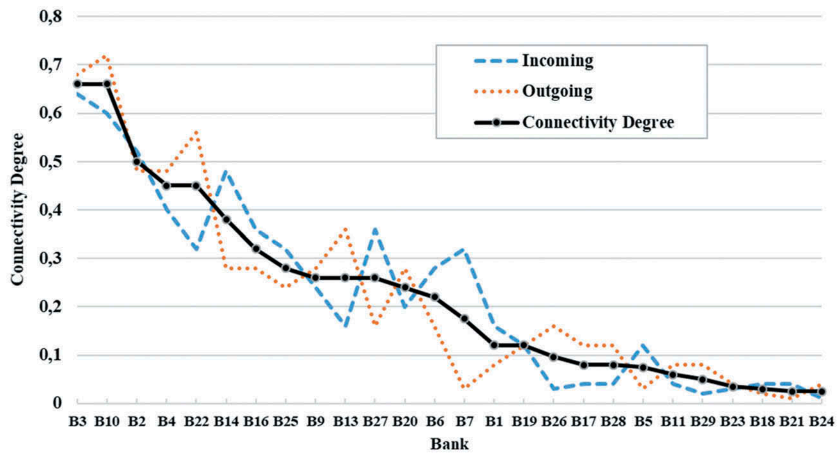


Figure 6. Connectivity degree of the Angolan RTGS.
Source: Angolan RTGS (BNA), authors´ proprietary analyses

We consider the weight of a bank (node) in the network to be equal to the number of interbank transactions, both sent and received by the bank.

For a directional network, the weight of the node can be defined either by the inbound links (received payments) or by the outbound links (sent payments). Herein we opt for analyses based on the outbound links consideration, meaning that we work through the prism of the sent payments. Taking into account the volume and amount of payments executed within the observed period (45,461 transactions and Kz. 1,887,317.41 million, respectively) and also considering the number of nodes in the network (29), the average weight of the nodes in terms of volume and amount is 1,568 payments and Kz. 65,079.91 million, respectively.

Only 13 nodes are characterized by the above-average weights, both in terms of the number of transactions and their amount. The volume-wise and transaction-wise weights are, respectively, 38,563 transactions and Kz. 1,600,965.80 million, representing 84% of the total volume and amount of interbank transfers settled in the Angolan RTGS during the observed period. In order to better observe the connectivity of the 13 banks with the above-average weights, in Figure 7, we present a subgraph from Figure 5b.

The volume and amount of transactions performed only among these 13 banks are, respectively, 73.59% and 61.59% of the total volume and amount registered in the 4th quarter of 2016. The top five banks (banks with dominant positions), which also exhibit the largest incoming and outgoing connectivity degree, together account for about 47% of the volume and amount of the transactions settled in the Angolan RTGS system.

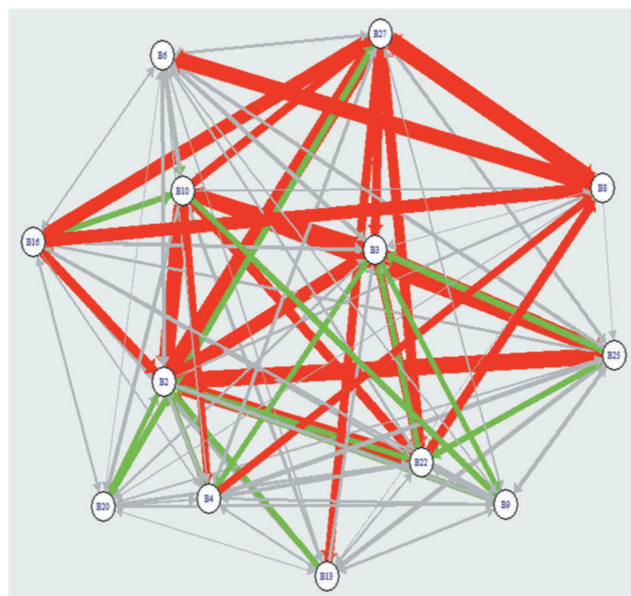


Figure 7. Network connectivity for the 13 banks with above-average weights.
Source: Angolan RTGS (BNA), authors´ proprietary analyses with R-Studio

VI. Conclusions

Systemic risk is the risk that a participant's inability to honour its obligations on the due date may cause other system participants to fail in fulfiling their obligations. This can be caused by operational or financial problems that spread through the system or market, thus threatening the stability of the entire financial system and, in extreme cases, even the real economy. Based on the identified network characteristics, we assess the robustness of the APS to events, which could potentially cause a systemic impact.

We evidence that all the banks are technically connected, that is, all the banks are enabled to send/receive payments to/from other banks. However, in reality, these connections are little used, as the connectivity of the Angolan RGTS network is only 23%. It is, hence, a sparse network, in which 77% of possible connections are not used. The values of clustering coefficient (C) and of average path length (APL) equal, respectively to 0.51 and 1.78, evidence that although the Angolan RTGS payment network is sparse (with low connectivity), it is also compact, with reduced distance between nodes. These findings are indicative of high resilience of the network.

We also investigate the incoming and outgoing connectivity degrees and analyse the weights of the links. We conclude that a group of 13 banks is responsible for the processing of about 84% of the volume and amount of payments settled in the Angolan RTGS system. Within this group, there are five more active banks, i.e. money-centres, which concentrate approximately 47% of the total volume and amount of settled payments. However, the fact that these banks are heavily connected (while most other banks have low connectivity) can represent a potential contagion risk for the system because, in the case of settlement failures of their payments, they may adversely affect the payments of other banks connected to them.

We show that the Angolan RGTS system is a core-periphery network, and therefore, it is potentially vulnerable to targeted shocks. That is, if an intruder knows the topology of the network, a shock to one of the money-centres can trigger system contagion and compromise the settlement of the payments of other system participants. However, the possibility of achieving systemic failure due to the non-settlement of payments by a single participant is not likely, since the largest bank in the system (in terms of transactions volume and amount) represents only about 11% of the total transacted. Regarding to random shocks to networks, as Boss et al. (2004) show, domino effects are lower than then would be if the network was more densely connected.

Nevertheless, ultimately, the system's vulnerability to systemic risk depends on the magnitude and duration of participants' exposure to liquidity and credit risks inherent to the process of interbank transfers' settlement. To reduce this risk, as a guarantor of the Angolan financial system stability, the BNA may grant intraday credits to participants of the payment system, who experience reduced liquidity, in order to allow for the timely settlement of their payments. In extreme cases, the BNA may play the role of lender of last resort, providing liquidity to the banks, and thus mitigating liquidity and credit risks, which may cause systemic risk. The mechanisms for the operationalization of the liquidity concession to the participants are automatic, which already reduces the operational risk and the time-window of the participants' exposure to liquidity and credit risks.

Some policy implications ought to be duly considered and analysed. One of them is related to a possibility of the BNA to use its power of banking supervision in order to make the payment system even more robust and resilient. In this context there are two main areas to act, namely, to the forecast events of potential systemic risk and improve even more the central bank supervision relative to money-centres, for example, demanding an increase of capital holdings by these banks, as they are critical banks in the prevention of contagion risk crystallization. Adequate capital buffers decrease contagion, and increase the capacity of banks to withstand contagious default (Nier et al. 2007). This is important, as the failure of one of these core banks can easily spread to several banks in a very short time (Upper and Worms, 2004).

The network approach can also provide important inputs for the elaboration of regulations aimed at strengthening the role of the BNA as regulator of the financial system. For example, in relation to foreign payments, it is possible to detect the origin and destination of remittances. This information may be important in the drafting of rules on exchange control, as well as extremely useful for combating money laundering and the financing of terrorism.

Disclosure statement

No potential conflict of interest was reported by the authors.

Funding

Financial support from national funds by FCT (Fundação para a Ciência e a Tecnologia). This article is part of the Strategic Project: UIDB/05069/2020 and UID/SOC/04521/2020.

ORCID

Maria Rosa Borges http://orcid.org/0000-0001-5340-471X
Mariya Gubareva http://orcid.org/0000-0001-6829-7021

References

Albert, R., and A.-L. Barabási. 2002. "Statistical Mechanics of Complex Networks." *Reviews of Modern Physics* 74: 48–94. doi:10.1103/RevModPhys.74.47.

Allen, F., and D. Gale. 2000. "Financial Contagion." *Journal of Political Economy* 108 (1): 1–33. doi:10.1086/262109.

Babus, A. 2016. "The Formation of Financial Networks." *The RAND Journal of Economics* 47 (2): 239–272. doi:10.1111/1756-2171.12126.

Barrat, A., M. Barthélemy, R. Pastor-Satorras, and A. Vespignani. 2004. "The Architecture of Complex Weighted Networks." *Proceedings of the National Academy of Sciences* 101 (11): 3747–3752. doi:10.1073/pnas.0400087101.

Bech, M., and E. Atalay. 2010. "The Topology of the Federal Funds Market." *Physica A: Statistical Mechanisms and Its Applications* 389 (22): 5223–5246. doi:10.1016/j.physa.2010.05.058.

Berndsen, R. J., C. León, and L. Renneboog. 2016. "Financial Stability in Networks of Financial Institutions and Market Infrastructures." *Journal of Financial Stability* 35 (C): 120–135. doi:10.1016/j.jfs.2016.12.007.

Borges, M. R., and L. Fernandes. 2020. "Interbank Linkages and Contagion Risk in the Portuguese Banking System." *Studies of Applied Economics* 38 (2): 1–13. doi:10.25115/eea.v38i2.3122.

Boss, M., H. Elsinger, M. Summer, and S. Thurner. 2004. "Network Topology of the Interbank Market." *Quantitative Finance* 4 (6): 677–684. doi:10.1080/14697680400020325.

Choi, H. 2019. "Money, Debit Card, Gross-settlement Risk, and Central Banking." *North American Journal of Economics and Finance* 50: 1–12. doi:10.1016/j.najef.2019.100993.

Connolly, P., and R. Eisenmenger. 2000. "The Role of the Federal Reserve in the Payments System." *Federal Reserve Bank of Boston Conference Series Proceedings* 45: 131–161.

Craig, B., and G. von Peter. 2014. "Interbank Tiering and Money Center Banks." *Journal of Financial Intermediation* 23 (3): 322–347.

De Caux, R., M. Brede, and F. McGroarty. 2016. "Payment Prioritisation and Liquidity Risk in Collateralised Interbank Payment Systems." *Journal of International Financial Markets, Institutions and Money* 41 (C): 139–150.

Docherty, P., and G. Wang. 2010. "Using Synthetic Data to Evaluate the Impact of RTGS on Systemic Risk in the Australian Payments System." *Journal of Financial Stability* 6 (2): 103–117. doi:10.1016/j.jfs.2009.08.004.

Eboli, M. 2019. "A Flow Network Analysis of Direct Balance-sheet Contagion in Financial Networks." *Journal of Economic Dynamics and Control* 103: 205–233. doi:10.1016/j.jedc.2019.04.007.

Eisenberg, L., and T. Noe. 2001. "Systemic Risk in Financial System." *Management Science* 47 (2): 205–336. doi:10.1287/mnsc.47.2.236.9835.

Freeman, S. 1996. "The Payments System, Liquidity, and Rediscounting." *American Economic Review* 86: 1126–1138.

Freixas, X., and B. Parigi. 1998. "Contagion and Efficiency in Gross and Net Interbank Payment Systems." *Journal of Financial Intermediation* 7 (1): 3–31. doi:10.1006/jfin.1998.0230.

Fricke, D., K. Finger, and T. Lux 2013. *On Assortative and Disassortative Mixing Scale-Free Networks: The Case of Interbank Credit Networks*. Kiel Working Paper 1830, Kiel Institute for the World Economy.

Fricke, D., and T. Lux. 2015. "On the Distribution of Links in the Interbank Network: Evidence from the e-MID Overnight Money Market." *Empirical Economics* 49: 1463–1495. doi:10.1007/s00181-015-0919-x.

Gai, P., and S. Kapadia. 2010. "Contagion in Financial Networks." *Proceedings of the Royal Society Series A* 466: 2401–2423. doi:10.1098/rspa.2009.0410.

Gibson, H., S. Hall, and G. Tavlas. 2018. "Measuring Systemic Vulnerability in European Banking Systems." *Journal of Financial Stability* 36: 279–292. doi:10.1016/j.jfs.2018.03.004.

In't Veld, D., and I. van Lelyveld. 2014. "Finding the Core: Network Structure in Interbank Markets." *Journal of Banking and Finance* 49: 27–40. doi:10.1016/j.jbankfin.2014.08.006.

Iori, G., G. De Masi, O. Precup, G. Gabbi, and G. Caldarelli. 2008. "A Network Analysis of the Italian Overnight Money Market." *Journal of Economic Dynamics and Control* 32 (1): 259–278. doi:10.1016/j.jedc.2007.01.032.

Kahn, C. M., J. McAndrews, and W. Roberds. 2003. "Settlement Risk under Gross and Net Settlement." *Journal of Money, Credit and Banking* 35: 591–608. doi:10.1353/mcb.2003.0030.

Kahn, C. M., and W. Roberds. 2001. "Real-time Gross Settlement and the Cost of Immediacy." *Journal of Monetary Economics* 47: 299–319. doi:10.1016/S0304-3932(01)00047-2.

Khabazian, A., and J. Peng. 2019. "Vulnerability Analysis of the Financial Network." *Management Science* 65 (7): 3302–3321. doi:10.1287/mnsc.2018.3106.

Martinez-Jaramillo, S., B. Alexandrova-Kabadjova, B. Bravo-Benitez, and J. P. Solórzano-Margain. 2014. "An Empirical Study of the Mexican Banking System's Network and Its Implications for Systemic Risk." *Journal of Economic Dynamics and Control* 40 (C): 242–265. doi:10.1016/j.jedc.2014.01.009.

Merrouche, O., and E. Nier. 2012. "Payment Systems, inside Money and Financial Intermediation." *Journal of Financial Intermediation* 21: 359–382. doi:10.1016/j.jfi.2012.01.002.

Mills, D., and T. Nesmith. 2008. “Risk and Concentration in Payment and Securities Settlement Systems.” *Journal of Monetary Economics* 55 (3): 542–553. doi:10.1016/j.jmoneco.2008.01.002.

Nellen, T. 2019. “Intraday Liquidity Facilities, Late Settlement Fee and Coordination.” *Journal of Banking and Finance* 106: 124–131. doi:10.1016/j.jbankfin.2019.06.009.

Nier, E., J. Yanga, T. Yorulmazer, and A. Alentorn. 2007. “Network Models and Financial Stability.” *Journal of Economic Dynamics and Control* 31 (6): 2033–2060. doi:10.1016/j.jedc.2007.01.014.

Norman, B. 2010. “Liquidity Saving in Real-time Gross Settlement Systems: An Overview.” *Journal of Payments Strategy & Systems* 4 (3): 261–276.

Santos, E., and R. Cont. 2010. *The Brazilian interbank network structure and systemic risk*. Banco Central do Brasil Working Paper 219.

Soramäki, K., M. Bech, J. Arnold, R. Glass, and W. Beyeler. 2007. “The Topology of Interbank Payment Flows.” *Physica A* 379: 317–333. doi:10.1016/j.physa.2006.11.093.

Sun, A., and A. Chan-Lau. 2017. “Financial Networks and Interconnectedness in an Advanced Emerging Market Economy.” *Quantitative Finance* 17 (12): 1833–1858. doi:10.1080/14697688.2017.1357976.

Triepels, R., H. Daniels, and R. Heijmans. 2017. “Anomaly Detection in Real-time Gross Settlement Systems.” *Proceedings of the 19th International Conference on Enterprise Information Systems (ICEIS 2017)* 1: 433–441.

Williamson, S. D. 2003. “Payments Systems and Monetary Policy.” *Journal of Monetary Economics* 50: 475–495. doi:10.1016/S0304-3932(03)00007-2.

Yawe, B. L., and Y. Kiwala. 2019. “The Role of Real-time Gross Settlement in a World of Instant Payments.” *Journal of Payments Strategy & Systems* 13 (3): 194–200.