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Interbank Market and Monetary Policy in Rwanda

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Abstract

The paper explores the influence of the banks' network characteristics on the spread between the interbank market rate and the central bank rate and, therefore, on the monetary policy transmission. The paper models daily spread at the bank level as a function of bank positions in the interbank network and other bank features in a panel setup. The findings suggest that high centrality in the network market seems to back the monetary policy transmission by narrowing the spread. However, some contradiction in the direction of this influence can emerge as the findings also indicate that the relationship-borrowing and diversification of lenders push up the spread and do not support the transmission of monetary policy. To improve the latter, the central bank should support initiatives that create more hub-banks or encourage banks to actively participate in the interbank market and increase the dynamism that supports the transmission.

Keywords: Network formation, Interbank market, Monetary policy, Transmission mechanism

JEL Classification: E52, L14

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1 Introduction

The 2008 global financial crisis (GFC) altered market-based interbank liquidity distribution and distressed usual banks' business models, especially in developed economies. At the same time, the GFC that centered on dry-ups in wholesale funding liquidity exposed the importance of the interbank market in the financial system across economies. The Interbank market has then attracted the attention of researchers and policymakers for the last decade, partly to remedy disruptions in market-based liquidity distribution that have impaired the conditions of monetary policy transmission.

Monetary policy transmission refers to the influence of monetary policy actions on real economic activity and inflation. The interbank market is vital in the first stage of the transmission linking the central bank and commercial banks (Maehle, 2020). Since central banks do not directly control the supply of credit to the private sector or its pricing, they use reserve balances to exert some influence. The Commercial banks keep reserves at the central bank that they use in settling payments due to other banks from operations between them or on behalf of their customers. They also transact with the central bank and the government in treasury bills, bonds, and foreign exchange.

During these operations, some commercial banks end in a shortage of reserves. Indeed, commercial banks face unforeseen or late-in-day demands for payment that require them to look for funds to meet those obligations. Challenged with these liquidity shocks, banks borrow money from peers that end in excess at a given interest rate; this is the essence of the interbank market. Commercial banks can also resort to central bank money in the Standing Lending Facility or the Discount Window. Since the central bank determines the interest rate on these facilities, it provides a basis for pricing on the interbank market.

Borrower banks look at it as the cost of funds, and lender banks take it as the opportunity cost of not lending before they both engage in interbank transactions. Therefore, when the central bank changes the interest rate on its funds, commercial banks adjust the pricing or the volume of the interbank market since central bank money is an alternative source of funds. By doing so, the interbank market plays a vital role in the conduct of monetary policy through liquidity management. Then, commercial banks pass this adjustment either into retail rates, which will affect loan demand as posited in the interest rate channel, or pass it into loan supply consistent with the bank lending channel. The literature provides supporting evidence on the role of the interbank market in the transmission of monetary policy. Notable studies include Kashyap & Stein, (1997), Freixas, Martin, & Skeie (2009), Freixas, Xavier & Jorge, José (2008) and Bucher, Hauck, & Neyer (2014).

The outlined traditional views have been completed by recent literature on interbank network structure, on the premise that interconnectedness determines the extent of the adjustment in the interbank market. The network structure represents banks' linkages via their bilateral trades. It brings together essential information such as the number of active banks, the number of bank counterparties of each bank, or the value of each bilateral position, de facto revealing the actual interbank market forces. Network analysis contributes to understanding the transmission by synthesizing this vast amount of information in easily usable indicators, taking into account the peculiarities of each banking system.

The debate on network analysis surged in the aftermath of the GFC, which has exposed how network linkages and interactions between banks are critical to systemic risk and monetary policy transmission. A network structure comprises key elements characteristic of its nature, such as centrality, cohesion, and distance, determining how substantial a monetary policy change will be. For example, banks with high network centrality and low centrality pay different prices for interbank borrowings. Consequently, depending on the volume transacted, the network positions of the banks have a direct impact on the interbank rate spread and the effectiveness of the transmission. Studies have shown that banks with strong local network positions are less affected by monetary policy actions since they can get liquidity from different sources. On the other hand, monetary policy actions can alter the interbank network structure. Empirical research found that by changing the width of the interest rate corridor, central banks can affect the mean network density; that is, the number of trading relationships and transactions among banks (Blasques, Bräuning, & Lelyveld, 2015).

Evidence suggests that banks are keen on building relationships because they help hedge against liquidity needs. Interbank relationships are dynamic and can be short-term or long-term. Analysis of the length of the interbank relationships is vital since where long-term relationships exist, they may lead to what (Chiu, Eisenschmidt, & Monnet, 2016) call relationship premium. The latter explains why some banks borrow above the interest rate corridor set by the central bank. (Lelyveld & in' t Veld, 2012) indicate that policymakers should monitor the network structure because it provides insights into the market discipline and relationship lending. It can also inform about the stability of the system and contagion risk.

Most of the research on interbank networks focused on Eurozone economies with developed interbank markets. In recent years, many central banks in developing countries have made several improvements for effective monetary policy to respond to changes that continue to take place in those economies. The recorded progress features notable projects, including setting an appropriate monetary framework, developing market infrastructure, and introducing new market instruments, among others. Some scholars explored these aspects in developing countries (Kireyev, 2015; Primus, 2016). However, the literature on the interbank network in an underdeveloped interbank market is scanty, specifically examining the influence of the network in the context of the conduct of monetary policy. Few studies that explored the role of network analysis in developing countries include (Oduor, Sichei, Tiriongo, & Shimba, 2014), who assess to what extent market segmentation impacts the efficiency of the interbank market and the effectiveness of monetary policy in Kenya. Others include Murinde et al., (2015), who investigate whether the interbank market in Kenya is an effective peer-monitoring and market discipline device.

Since 2017, the interbank network in Rwanda has experienced several changes. The interbank market includes both unsecured and secured transactions among 16 commercial banks and one cooperative bank. The securitizing or not of interbank market transactions is a distinctive aspect characterizing the relationships between banks. The interest rate setting on the interbank market follows a corridor system around the policy rate. The National Bank of Rwanda started the accommodation cycle from the fourth quarter of 2017 to the third quarter of 2020; however, the interbank rate reaction showed some persistence and rigidity close to the upper limit of the corridor. This persistency is another anecdotal evidence of the existence of relationship lending. The latter had shown resistance to the monetary policy actions while it helps to understand some intricacies in interbank trade.

Nonetheless, the volume and the number of interbank transactions overshot recently, and banks that were not active in the market started trading. At the same time, the monetary policy framework changed from monetary targeting to a price-based framework while targeting an optimal level of liquidity during implementation changed to targeting an interest rate corridor. The money market in Rwanda operates in a liquidity surplus setting, but within the past two years, episodes of shortages intensified. These developments indicate likely changes in the interbank network and banks' trading, leading to a different reaction to policy actions.

Against this backdrop, the paper's objective is to examine the effect of the interbank network on monetary policy transmission in Rwanda. It explores the influence of the banks' network characteristics on the spread between the interbank market rate and the central bank rate.

This paper is different from other studies that analyze the interbank market or transmission channels of monetary policy in Rwanda. The existing studies, such as that of Mwenese & Kigabo (2016), look at the direct reaction of the interbank rate to the policy rate controlling for some macroeconomic variables. Others include Kamanzi, Irankunda, & Bagabe (2019), who examine the role of bank-specific characteristics in transmitting monetary policy impulses. The main contribution of this paper is to provide new insights from within the interbank structure that impact the quality of the monetary policy transmission in Rwanda. The study also contributes to the literature on monetary policy transmission mechanisms by bringing into the debate the perspective of an underdeveloped interbank market. It explains how network analysis can help understand areas that need much focus to improve monetary policy transmission in developing economies.

2 Literature Review

2.1 Theoretical literature on interbank network formation

The most commonly used interbank network models are the Erdős-Renyi and scale-free networks. (Erdős & Renyi, 1959) the network consists of a given number of nodes, and each link between nodes forms independently with a given probability P. It is a binomial model of link formation with short average paths and low clustering that assumes low heterogeneity; that is, most nodes have the same number of connections. The other commonly used network model is the scale-free network (Barabási & Albert, 1999). They model the algorithm for generating a random scale-free network using a preferential attachment mechanism. Analysis observes a scale-free network in natural and human-made systems. The degree distribution resulting from the Barabási-Albert model is a power-law distribution.

The scale-free graph has a few but significant nodes with many connections and a trailing tail of nodes with very few links at each level of magnification. A scale-free network is instrumental in modeling financial hubs in the interbank system.

In the past two decades, the theory of network formation has been an active area of research. One strand of literature on network formation considers only linkages and disregards other features of the nodes that make up the network. As a result, this literature models network formation as a random process, using methods from statistical mechanics (Newman, Barabási, & Watts, 2006). Another branch of study on network formation focuses on incentives that push for building relationships. In the model developed by Goyal & Vega-Redondo (2007), individuals form links based on a trade-off between the benefits and the costs involved in creating connections. The idea is that linking with another player gives access to the links of the latter. Some earlier works assumed that the benefits all these players enjoy from the connections are non-rival. By contrast, Goyal & Vega-Redondo (2007) study a setting where the benefits are rival. A critical issue is how different players share the benefits in such a context.

The early network theory (Erdős-Renyi) assumes random link formation that results in homogenous nodes. In contemporary work, a scale-free model predominantly emerging from real-world networks postulates heterogeneous nodes. The latter describes the shape of the interbank network given that banks have different liquidity positions daily where banks with liquidity deficits borrow from those in surplus. One limitation of the aforementioned statistical models is that they do not provide an account of link formation; that is, they do not model the dynamic process by which financial institutions enter into obligations to one another in the first place. This challenge has been taken up recently in the financial networks literature.

This section concentrates on the interbank network literature and identifies three main ways to model network formation. One strand of the literature builds on random link formation, for example, using network growth models. Typically, these are random network models where new nodes are born over time and form attachments to existing nodes when they are born. The literature on financial networks identifies an empty network and mechanically connects nodes. One option is to generate links according to a stochastic process (Anand, Gai, Kapadia, Brennan, & Willison, 2013). Another option is to condition random link formation on the characteristics of the nodes, making it more likely to create links with banks that have higher profits (Lenzu & Tedeschi, 2012) or a higher willingness to extend an interbank loan (Lux, 2015). This process of network formation is called preferential attachment. Trust is a critical element in this regard. Banks trust other banks based on their performance or their reliability in lending. Another feature of preferential attachment is that it provides a mechanism to generate scale-free distributions (Barabási & Albert, 1999), another feature of the interbank network.

A second area uses strategic network formation, where banks assess the costs and benefits of forming a link with another bank. A prominent theme in strategic network formation is rollover decisions by banks, often modeled using global games techniques. Creditors strategically decide to roll over a loan after receiving a signal about the solvency or performance of the borrower (Allen, Babus, & Carletti, 2012; Fique & Page, 2013; Anand, Gai, Kapadia, Brennan, & Willison, 2013). Also, using strategic network formation Farboodi (2014) and in 't Veld & Lelyveld (2014) analyze how bank heterogeneity leads to the formation of a core-periphery network. Further, Acemoglu, Ozdaglar, & Tahbaz-Salehi (2015) show how banks may over connect and diversify in equilibrium, potentially creating excessively prone networks to contagious defaults.

The third area builds network formation based on portfolio optimization by financial institutions. In this line, two approaches stand out. The first is where banks choose the amount of interbank lending or borrowing by optimizing their (heterogeneous) balance sheets (Aldasoro & Alves, 2015; Bluhm & Krahnen, 2014). This optimal amount then gets allocated among the banks. A second option is to fix the overall amount of borrowing and lending (Bräuning & Fech, 2012; Halaj & Kok, 2015). Banks then have the choice of their counterparty.

2.2 Role of the interbank market in monetary policy transmission

The interbank market is among the critical money markets and constitutes the cornerstone of the central banks' implementation of monetary policy. The interbank markets emerge from heterogeneity in banks' liquidity position, which arises when banks engage in their usual lending and deposit activities, where some banks fall short of funds and resort to the peer banks that end up in surplus (Allen & Babus, 2009).

Banks may also solicit central bank money. In this case, banks can adjust their interbank lending in terms of price or loan supply when the central bank changes monetary policy (Kashyap & Stein, 1997). In this adjustment process, the interbank market becomes a conduit of monetary policy to the real economy. Allen & Babus (2009) Posit that in normal times the interbank market should work well without asymmetric information, a view put forward by Chiu, Eisenschmidt & Monnet (2016) that theoretically, the interbank market rate should stay within the corridor band defined for monetary policy implementation.

Freixas, Xavier, Jorge, José (2008), Freixas, Martin & Skeie (2009) and Bucher, Hauck & Neyer (2014) complete this view by allowing the imperfections of the interbank market in their analysis. They establish that under asymmetric information, the interbank market is unable to intermediate liquidity effectively. Concerning monetary transmission mechanism, when liquidity shortage characterized by the positive spread between interbank market rate and policy rate prevails, asymmetric information renders the effect of monetary policy stronger.

2.3 Interplay between interbank network and monetary policy

The literature asserts that network analysis describes well the functioning of the interbank market. This literature includes Kobayashi & Takaguchi (2018), Chiu, Eisenschmidt, & Monnet (2016), Gabrieli & Georg (2016), Blasques, Bräuning, & Lelyveld (2015), and Afonso, Kovner, & Schoar (2014).They argue that network arises endogenously from the fact that banks tend to build relationships with peers to reduce information asymmetry for the lender bank or hedge against liquidity shortage for the borrower bank. This reasoning is consistent with arguments in earlier literature such as (Ehrmann & Worms, 2002). They posit that the distribution of liquidity among banks moves in a network style. However, they suggested that networks are mechanisms that can counteract monetary policy transmission, especially in monetary tightening situations, since banks can react by redistributing liquidity among them.

The analysis of network characteristics revealed essential points on the interbank market vis a vis monetary policy. For example, Chiu, Eisenschmidt, & Monnet (2016) showed how a network structure disappears in an accommodative policy stance in which banks lose incentives to build relationships. In the same line, implementing new central bank instruments can alter the network structure. Barucca & Lillo (2015) found that net borrowing banks became net lending banks while the latter became inactive following the introduction of long-term refinancing operations in the Eurozone. It is important to note that this effect depends on the banking sector structure, as argued by Ehrmann & Worms (2001).

On the other hand, however, the bank's position in the network has been proven necessary in responding to monetary policy. In the network literature, several features describe a bank's position in a network. The degree distribution is one key measure of the centrality of a bank that captures the bank's borrowing diversification. Empirical evidence showed that banks recording a high degree are less sensitive to policy rate variation. On the contrary, Ardekani, Distinguin & Tarazi (2019) found that considering the authority centrality, which measures a bank's lender strength based on outgoing links, stronger banks have a more pronounced reaction to monetary policy.

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2.4 Countries' experiences

Most studies on the linkages between network structure and monetary policy explored developed interbank markets in advanced economies. Some key findings are noteworthy. Network characteristics explain changes in interest rates and their impact on policy transmission. It is the case for the US federal funds market as ascertained by Bech & Atalay (2008), Akram & Christophersen (2010) for the Norwegian interbank market, or Gabrieli & Georg (2016) for the case of the Eurozone. The research established an essential element about computing the network measure, claiming that daily networks are relevant.

The evidence in these economies shows that the interbank structure evolves with time, and its effects vary accordingly. The case studies refer to the 2007/8 GFC and relate the pre-crisis time, the crisis, and the post-crisis times. Some examples include Bräuning & Fech (2012) for the German interbank market and Kobayashi and Takaguchi (2018), who explored the Italian interbank market. Bräuning & Fech (2012) bring out the importance of capturing the composition of the banks, pointing out the role that cooperative banks play in the German bank network. Oduor, Sichei, Tiriongo, & Shimba (2014) provide another supporting evidence on the effect of bank composition by giving the experience from an underdeveloped interbank market. They indicate that banks trade primarily with peers in Kenya and not small banks with large banks. This segmentation impedes monetary policy transmission in the short run.

In summary, this literature outlines the fundamental reasons for banks to form interbank networks. It is either a random process or a strategic move by banks. In the latter case, banks can optimize the income from interbank transactions or choose the counterparties with a fixed amount intermediated on the interbank market. One inference from the literature is that interbank network formation is a dynamic process arising from the heterogeneous liquidity positions of banks. Another key takeaway is that the network analysis describes well the functioning of the interbank market and its role in transmitting monetary impulses. Some differences stem from economies' development levels and the composition of the banking sector.

3 Methodology

In this paper, we follow the approach of Akram & Christophersen (2010), Bech & Atalay (2008), and Gabrieli (2011) in estimating the spread between interbank and central bank rates. We model the spread between the interbank market rate and the central bank rate at the bank level as a function of the bank's positions in the interbank network and other bank characteristics such as size (Bank's total assets). We investigate whether banks considered systemically important can borrow at lower rates than banks deemed comparatively small.

Furthermore, we assess and compare the interbank rate of borrowers with credit relationships in the period before and after adopting a price-based framework in January 2019. Following the adoption of this framework, the number of interbank transactions doubled in 2019 compared to the previous year, evidencing structural changes in the development of network structure, particularly the level of interconnectedness. As a result, it is necessary to explore these two periods separately to capture the aforementioned changes in the network. Trust comes out as a standing pillar in the formation of interbank relations (Lenzu & Tedeschi, 2012); thus, we wish to explore if there is a significant influence of relationship in the network formation of the Rwandan interbank market.

3.1 The model and variables of interest

The study uses an econometric model estimated using panel data of interest rates paid by borrowing banks in the sample period. Particularly, we estimate a random effect model with 16 different commercial banks and consider them as lenders or borrowers depending on specific transactions. The dataset displays an unbalanced panel as every bank does not participate in the market every day.

Bank characteristics in the interbank network are the main determinants of borrowing rates. The connections of banks in the system network explain the interbank market and more often take the form of an adjacent matrix, a square matrix of dimensions NxM with n as the number of nodes (banks in the network) and M_ij as edges(links or connections) or amount bank i lends to bank j. A bank cannot arrange an interbank transaction with itself; thus, $M\_ij = 0$ if $i = j$. Therefore, the connectivity matrix of $n = 3$ can be simplified into:

$$\begin{pmatrix} 0 & M_{12} & M_{13} \\ M_{21} & 0 & M_{23} \\ M_{31} & M_{32} & 0 \end{pmatrix}$$

This network is characterized by incoming connections (borrowing) and outgoing connections (lending), and the common terms in the network analysis are in–degree and out-degree, respectively. This study hypothesizes that as banks diversify more their lenders, the more they get reduced rates. The econometric model considers in-degree k_i^{in} (number of banks that lends to bank i), measured daily for each transaction that happened for a given bank

$$k_i^{in} = \sum_{j=1}^{n} A_{ji}$$

To better capture the significance of any interbank connection relative to others in the network, we normalize the matrix by taking M_{ij} divided by the total amount borrowed in the given quarter. Therefore, this becomes a weighted network. Our interbank network considers 11 quarters starting from 2017Q4 to 2020Q2. In this network, we are more interested in two significant statistics for our research: betweenness centrality and authority, and these serve as measures of centrality and systemic importance.

Betweenness centrality, a concept borrowed from sociology, is the probability that a node (bank in our model) lies on the shortest path between any two unconnected nodes (Freeman, 1979) or the number of these shortest paths that go through the node. This measure takes into account the borrowing and lending activity of each of the banks and its counterparties. The authority variable also portrays the bank's position or centrality in the interbank. This variable measures the importance of each bank's total number of interbank lenders (incoming links) relative to the other banks in the network and considers its lenders' strength based on their outgoing links. Therefore, banks with solid authority connect to strong Hubs (dominant lenders) in the network (Ardekani, Distinguin, & Tarazi, 2019). Authority is calculated based on the HITS algorithm (Kleinberg, 1999). Both betweenness centrality and authority statistics have been calculated quarterly from 2007Q1 to 2020Q2 using Gephi software developed by (Bastian, Heymann & Jacomy, 2009).

Moreover, the study includes a relationship variable to capture the possible effects of banks' credit relationships on the interbank market. We measure relationship as the share of funds obtained from a bank's two primary lenders in the sample period (Akram & Christophersen, 2010). After identifying two primary lenders of a given bank, we create a dummy variable of relationship that equals one if a transaction is a trade with any of those two primary lenders and 0 otherwise.

The position of a bank in borrowing activities at the market also matters in influencing the interbank rate; we assume that large banks borrow relatively high amounts than small banks. As a result, we control for the bank's borrowing share in the total daily borrowing. The previous studies found that larger banks borrow at a lower cost than small banks (Furfine, 2001; Cocco, Gomes, & Martins, 2009; Akram & Christophersen, 2010).

The study also considers other bank characteristics, such as the effect of the bank's total assets on the interest rate spread, assuming that larger banks (systemically important banks) borrow at lower rates and small banks relatively trade at higher rates.

Finally, the study adds another control dummy variable size that takes 0 if a bank has a microfinance background and one otherwise. Therefore, the study estimates the following model in panel random effects setup:

$$spread_{it} = \alpha_i + \beta_1 in\_degree_{it} + \beta_1 betweenness_{it} + \beta_3 authority_{it} + \beta_4 relationship_{it} + \beta_5 dayshare_{it} + \beta_6 l\_size_t + \beta_7 dum\_size_i + \varepsilon_t \tag{1}$$

$day - share$ stands for the bank's share in the total daily borrowing. size represents the importance of the bank, computed as the log of the bank's total assets. dum_size is the dummy variable that equals zero for having a microfinance background and one otherwise.

Empirical evidence asserts that microfinance banks are more inclined to build a relationship than other commercial banks in a bid to have a liquidity hub. Other categories such as saving banks and cooperative banks, rarely intervene in the interbank market since they can get liquidity from their union or head institutions (Affinito & Pozzolo, 2017). This dummy variable allows us to consider these aspects in the model.

4 Results

4.1 Descriptive statistics

The degree statistic shows that from 2017 to 2020, a bank borrowed from 1.4 banks on average, where a bank with the highest counterparties totals 5. Around 72 percent of transactions banks borrow from one bank. Few banks borrow from many counterparties.

Table 1: Summary statistics

VARIABLES	(1) N	(2) mean	(3) sd	(4) min	(5) max
degree	1,071	1.385	0.701	1	5
betweenness	1,072	5.798	9.347	0	33.57
day-share	2,354	0.221	0.319	0	1
rel	1,071	0.508	0.500	0	1
spread	1,071	0.289	0.339	-2.500	1.017

Source: Authors' computations

The betweenness centrality reveals that around 55 percent of the interbank borrowing transactions are small and do not influence the system's flow, while just one percent of borrowing from 2 banks can influence the flow. This is related to the fact that 2 banks that cover around 30 percent of the borrowing transactions are generally small and are not the bridges of the interbank system. The bank with the lowest betweenness is the same bank with the highest degree. That is, the bank that has the most diversified lenders does not influence the market. Regarding authority centrality, banks connected to strong hubs in the network, meaning that they transact with dominant lenders, represent less than 20 percent of the transactions.

Table 2: Summary statistics

rel	(1) degree 1 Freq (Percent)	(2) degree 2 Freq (Percent)	(3) degree 3 Freq (Percent)	(4) degree 4 Freq (Percent)	(5) degree 5 Freq (Percent)	(6) degree. Freq (Percent)
0	356***	126**	32	12	1	
	(46.35)	(57.53)	(52.46)	(57.14)	(50)	
1	412***	93**	29	9	1	
	(53.65)	(42.47)	(47.54)	(42.86)	(50)	
Total	768	219	61	21	2	0

Source: Authors' computations

Around 51 percent of the borrowing transactions go through the same lenders, indicating a strong relationship with lending in the Rwandan interbank market. About 8 percent of the time, the interbank market recorded one transaction.

4.2 Regression analysis

To decide the fitting model, the Hausman test and the Breusch-Pagan Lagrangian multiplier test assert that the random-effects model is appropriate, and there are significant differences across banks (Table 3 & 4).

Table 3: Hausman test results

	(b) fixed	(B) random	(b-B) Difference	sqrt(diag(V_b-V_B)) S.E.
degree	.0481569	.0478147	.0003422	.0007082
betweenness	-.003623	-.0036708	.0000478	.0001858
authority	.1074356	.1237637	-.0163281	.0152498
rel	.0839159	.084517	-.0006012	.0009153
dayshare	-.2836281	-.2841008	.0004727	.0018555

```
                 b = consistent under Ho and Ha; obtained from xtreg
     B = inconsistent under Ha, efficient under Ho; obtained from xtreg

Test:  Ho:  difference in coefficients not systematic

            chi2(5) = (b-B)'[(V_b-V_B)^(-1)](b-B)
                    =        2.64
          Prob>chi2 =      0.7548
```

Table 4: LM test results

```
spread[bank_id,t] = Xb + u[bank_id] + e[bank_id,t]

Estimated results:
```

	Var	sd = sqrt(Var)
spread	.1145887	.3385095
e	.0830325	.2881536
u	.0214682	.1465204

```
Test:   Var(u) = 0
                       chibar2(01) =   398.19
                    Prob > chibar2 =   0.0000
```

Source: Authors' computations

Table 5 presents the results of the model. Columns 1 and 2 solely look at the network features, and the results assert that degree and relationship have a positive and significant effect on the spread while betweenness centrality has a negative effect. The authority variable is not significant. A bank with a high degree position, meaning that it can get interbank loans from a different bank, increases the spread, which means it borrows at higher rates. These results contrast with other findings in the literature, such as those (Ardekani, Distinguin,Tarazi & 2019).

On the contrary, the betweenness centrality shows that banks that constitute the bridges among banks in a network borrow at lower rates. This result is in line with (Bräuning & Fech, 2012) findings that the more the bank moves towards the center, the more it gets better rates, as other banks assume that they can get liquidity quickly.

Similarly, in column 2, our findings indicate that a bank that tends to build a relationship with its peers by regularly borrowing from the same lender cannot negotiate a lower rate and increase the spread. This contradicts the findings of (Temizsoy, Iori & Montes-Rojas, 2015) that relationship lending delivers better rates for both traders.

The findings reported in column 3 of table (5) indicate that banks that borrow higher amounts on the interbank market are likely to negotiate for a reduction in rates. Column 4 presents parameter estimates of the model, including bank-specific characteristic variables as bank size and a dummy variable representing if the bank comes from a microfinance background or not. The coefficients are significant but respectively positive and negative. The findings suggest that when a bank grows in assets, it borrows at increasing rates on the interbank market; however, this situation reverses when the bank is in the category of commercial banks, contrary to former microfinance banks.

Table 5: Regression results

	(1) Spread	(2) Spread	(3) spread	(4) spread
degree	0.0232	0.0271*	0.0476***	0.0427**
	(1.69)	(1.98)	(3.57)	(3.23)
betweenness	-0.00401**	-0.00414**	-0.00383**	-0.00267*
	(-3.01)	(-3.14)	(-3.02)	(-2.16)
authority	0.0576	0.0582	0.123	-0.0760
	(0.66)	(0.67)	(1.49)	(-0.92)
rel		0.0936***	0.0852***	0.0814***
		(4.99)	(4.72)	(4.53)
day-share			-0.285***	-0.234***
			(-9.39)	(-7.87)
l_size				0.282***
				(7.78)
size_3				-0.592***
				(-5.45)
_cons	0.207***	0.155**	0.241***	-4.607***
	(3.64)	(2.65)	(4.72)	(-7.25)
N	1071	1071	1071	940

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Source: Authors' computations

The network features change as the network evolves based on the interbank transactions; the study examines whether the effect of the network on the spread changes over time. The analysis refers to February 2019, the first monetary policy committee date in the price-based framework. There is a significant difference in the estimated coefficients in the period before and after the new framework. In the pre-period, the authority is the sole network feature that is significant and negative, suggesting that building a strong hub of counterparts helps banks to negotiate a reduction in the borrowing rates (see table 6). However, the coefficient of the relationship variable is significant and positive, indicating that borrowing from the same bank puts a bank in a weak negotiating position and borrows at increased rates. In the post-period, all the variables are significant except the network variable degree. Other network variables are significant and negative, indicating that the changes in the network structure narrow the spread in this period. The coefficient of the relationship variable remains the same in both periods. Another noteworthy difference is that larger borrower banks pay lower rates in the post-period while this variable was insignificant in the pre-period.

Table 6: Regression results

	(1) Spread	(2) Spread
degree	0.0204	0.0195
	(0.84)	(1.50)
betweenness	0.00146	-0.00580***
	(0.71)	(-4.90)
authority	-0.319**	-0.244*
	(-2.62)	(-2.50)
rel	0.0647*	0.0464**
	(2.13)	(2.59)
day-share	-0.0680	-0.117***
	(-1.49)	(-3.35)
l_size	0.0987	0.182***
	(1.25)	(5.92)
size_3	-0.239	-0.311***
	(-1.16)	(-5.44)
_cons	-1.629	-2.712***
	(-1.20)	(-5.14)
N	351	591

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Source: Authors' computations

4.3 Discussion

The results show a significant influence of the network structure on the spread between the interbank and central bank rates and, therefore, on monetary policy transmission. For the whole sample, the results show some contradiction in the direction of this influence. Diversification of lenders is still low and seems not to support the transmission as more diversified banks push up the spread. However, more pivotal banks in the market seem to back the monetary policy transmission by narrowing the spread. Relationship borrowing is present in the Rwandan interbank market and takes a substantial weight in transactions. Banks seem to prefer this mechanism though the latter widens the spread. It is important to note that both relationship and diversification affect the spread upwardly. The latter likely stems from the fact that small banks initiate both actions; while they do not have enough power to negotiate a reduction in rates.

As the network structure evolves, changes in the effect of the network appear in the way that facilitates the transmission of the monetary policy. In the period after adopting the price-based framework, the dynamism in the network resulted in banks surrounding themselves with strong hubs and improving their interbank businesses at both ends of the network. One can deduct this from the changes in the coefficients of betweenness and authority variables. At the same time, the degree coefficient representing diversification becomes insignificant while that of the relationship eases though it remains significant. Another critical point to note is that as a bank borrows more considerable amount on the interbank market, it gains some power to negotiate for a better rate. Nevertheless, this is not always the case looking at the period before the new framework. The coefficient of the variable of interest (bday-share) is not significant. It may imply that the increase of the amount intermediated on the interbank market does not always support monetary policy transmission. These findings align with the literature, especially (Chiu, Eisenschmidt & Monnet, 2016) and (Barucca & Lillo, 2015) , who demonstrate that network structure can disappear or banks change positions constantly where a borrower bank becomes a lender and vice versa.

5 Conclusion and Recommendation

The objective of the paper is to study the effect of the interbank network on monetary policy transmission in Rwanda. It explores the influence of the banks' network characteristics on the spread between the interbank market rate and the central bank rate. The motivation stems from the evidence that interbank network structure and relationship lending determine how much monetary policy change affects the economy. At the same time, the Rwandan interbank market continues to record the progress that alters its structure and, therefore, the monetary policy transmission. The empirical literature demonstrates that the position of a bank in the network, expressed in terms of degree and centrality measures, has been proven essential in responding to monetary policy. The study applies a random-effects model to a panel of 12 banks active in the interbank market.

The main finding is that the network structure influences the spread between the interbank and central bank rates and, therefore, monetary policy transmission. Specifically, the finding is that building relationship borrowing and diversification of lenders do not support the transmission of monetary policy. On the contrary, the dynamism in the interbank structure leads to active business at both ends of the network back the transmission. These findings have some policy implications. The central bank should support initiatives that create more hub- banks or encourage banks to actively participate in the interbank market and increase the dynamism that supports the transmission.

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