Assessing the Systemic Importance of Banks in Rwanda using Portfolio Similarity and Clustering Methods

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Abstract

This paper assesses the similarity among Rwandan banks, especially looking at how the assets side and lending portfolios have been evolving, and their implications on systemic risks in the Rwandan banking system. The aim was to gauge a systemic risk that might originate from a cluster(s) of small banks, which is not well captured by traditional means of using the size or interconnectedness in network analysis. We used a variety of empirical approaches to tackle this aspect in the context of Rwanda, with data from 2016 to 2019. Our key findings suggest that the general measure of the portfolio similarity between individual banks is quite stable over time and driven predominantly by big banks. Conversely, we noted that some medium-sized banks have been consistently similar in terms of the loan portfolio and associated risks in the last four years, and therefore they can be exposed to common risks with impactful consequences, as the cluster is more sizeable than banks have taken individually.

Keywords: *Systemic risk, Banks' portfolios, Cluster analysis*

JEL Classification: *G01, G11, C38*

1. Introduction

Assessing linkages and complexity in financial systems has gained more interest in literature and policy making, especially in the aftermath of the 2008 Global Financial Crisis (GFC). The existence of linkages and feedback loops is seen as leading to a high propensity of bank failure(s), which would affect the whole banking system and the real economy (Lux, 2016; Krause and Giansante, 2012).

The occurrence of bank failure(s) does not necessarily lead to similar consequences on financial system stability and the real economy. Some bank failure(s) are very consequential as the affected bank(s) can be systematically important due to different reasons. According to IMF, Bank for International Settlements (BIS) and Financial Stability Board (FSB) (2009), systemic importance is difficult to define. Still, in practice, a financial institution can be established as systemic if its failure or malfunction causes general distress in the financial system, either as a straight impact or as a cause for wider contagion. The systemic importance of a bank(s) implies a high propensity that failure can affect the stability of the whole financial system. In the 2008 GFC, the failure of some systemically important banks spilled over the entire financial system, with dire consequences on the latter and the real economy (Brechler et al., 2014).

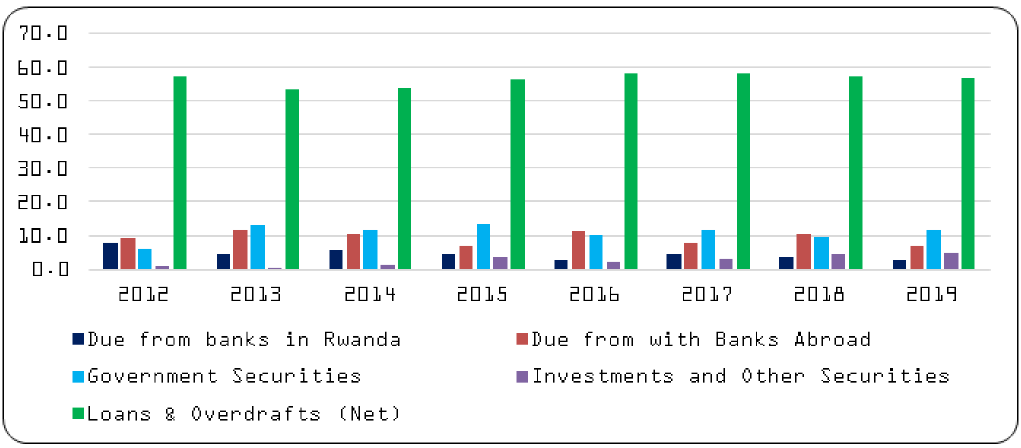
The literature on assessing the systemic importance of institution(s) in the banking system has mostly focused on direct channels. Direct channels involve direct contractual obligation between banks, for instance when a given bank has borrowed from another bank on the interbank market. These direct channels imply that a bank failure rapidly spills over to the whole financial system through linkages mostly in the form of financial exposure between banks as the failing bank will not be able to honour its contractual obligation. By domino effect, this will spread over the whole banking system. The financial exposure may be exacerbated by a subsequent negative impact on the real economy and existing feedback loops with the financial sector.

Direct channels often consider three criteria, namely: substitutability, size, and interconnectedness. *Size* in this situation denotes the volume of financial services and products provided by a certain bank in the banking system. The extent to which other banks can provide the same services is what is defined as *substitutability*. Lastly, *interconnectedness* refers to the degree of interdependence between banks or the extent to which an individual bank is linked to other banks (e.g. exposure on the interbank market, which may cause bank failures when a bank is unable to pay what it owes to other banks in the financial system (IMF, BIS and FSB, 2009). Despite numerous challenges in measuring systemic importance, recent literature such as Leon, Machado and Murcia (2015) and Leon, Machado and Sarmiento (2018) focused on interconnectedness and used network analysis methods to assess banks' systemic importance through centrality in money markets and payment systems.

However, another strand of recent literature (e.g. Brechler et al., 2014 and Leon, 2017) considers additional features of the banking system by looking at similarity/homogeneity in banks' portfolios as a possible source of systemic risks. The similarity of banks' portfolios (i.e., when banks have invested in similar assets such as loans per sector, government securities, etc) can be across the whole financial system or concentrated in different clusters within the banking system (Brechler et al., 2014). The reason is that similarity of balance sheets makes exposure to common economic shocks more likely and intense (Leon, 2017) and this may have substantial implications on financial stability as losses in those financial institutions may be highly correlated. Indeed, common asset holdings (that is when banks invest more or less in the same assets) have been the main factor of contagion during the 2008 GFC (Caccioli et al., 2014). The issue with common assets holding is that when one bank fails and its failure is followed by assets fire sales, the negative impact on prices of those assets will lead to failures of other banks as the latter have the same assets in their portfolio.

In Rwanda, the banking system has experienced significant mutations over the last two decades. Its size has been consistently expanding along with the real sector. The number of banks has tripled from 5 banks in early 2000 to 16 banks in 2017, and the size of the balance sheet has grown following mostly increasing volume of loans to finance economic activities. The level of concentration in terms of assets, loans, and deposits has also been declining, although at a slower pace in recent years. Despite recent developments in the interbank markets, the share of the amount due to other domestic banks in total assets is still relatively low.

Figure 1: Evolution of share of main assets categories in total assets of the banking system



Source: Authors' calculation using data from the National Bank of Rwanda

In a landscape of the banking industry with a low level of concentration and exposure to other banking institutions, assessment of systemic importance through size or interconnectedness in interbank markets may suggest a situation with lower systemic risks. Nevertheless, in the context of less developed financial markets, banks are likely to hold similar investment and risk management strategies, and that homogeneity can contribute to systemic risks (Leon, 2017). In Rwanda, lending has been the primary income-earning activity with the highest share on all bank balance sheets. Also, banks' lending has consistently been channeled to some key sectors such as a mortgage, trade, and transport, and this common exposure may predispose the banking industry to systemic risks once some sectorial shocks erupted. From that perspective, one would wonder how similarity in terms of the structure of financial statements across banks has evolved in Rwanda, and its implications on the assessment of systemic risks.

This study aims to assess how similarity among Rwandan banks, especially on the assets side and lending portfolios, has been evolving, and implications on systemic risks in the Rwandan banking system. This study borrows from (Brechler et al., 2014) in their study for the case of the Czech Republic. It applies a similar methodology to measure similarity and identify the existence of clusters of similar banks, which may turn out to be systemic.

Similarity and clustering methods allow us to gauge systemic risks stemming from a cluster(s) of small banks, which is not well captured by traditional ways of using the level of interconnectedness in network analysis. Similarity and clustering methods help to assess vulnerabilities, which do not directly come from a breach of contract by another bank, and they can help to discover the importance of small banks, which usually have lower centrality in network analysis.

Given that in Rwanda, contractual obligations notably interbank transactions and other due from one bank to another bank have remained relatively low over time, it is worthy to look at indirect channels to evaluate whether homogeneity in exposure to a given sector/market/debtors may be a source of systemic vulnerability. Therefore, this study proposes an additional systemic risk monitoring tool to complement existing ones based on direct channels (size, concentration, stress test and network analysis through cross exposure in interbank markets). It will inform financial regulation and ensure appropriate monitoring of systemic risks build up and timely actions to protect the financial system against threats coming from common exposure or clusters.

The structure of this study is as follows: the next section reviews the empirical literature on measuring systemic importance within the banking system. Section 3 overviews the evolution of banking system in Rwanda. Section 4 explains the methodology used while section 5 details empirical results and section 6 concludes.

2. Empirical literature

Systemic risk is at the centre of all financial stability practices, and the 2008 Global Financial Crisis (GFC) awakened interests in the subject. The literature on measuring systemic importance has been growing with different approaches, mostly in line with various forms through which systemic importance may materialize. European Central Bank (ECB) (2010) distinguished three primary types, namely contagion risks from individual firms (using measures such as expected shortfall, conditional value at risk), the common exposure to adverse macroeconomic shock (using stress testing, etc) and the dangers from widespread financial imbalances (e.g. credit cycles, leverage, maturity mismatch, etc). In addition to these, other new approaches emerged in the last decade, including the network analysis to understand the structure and interconnectedness in the banking system. Recent studies such as Brechler et al. (2014), Cai, Eidam and Saunders (2018), and Leon (2017) adopted measuring similarities/homogeneity among institutions providing financial services and the existence of clusters within the financial system as a new approach to gauge systemic importance in financial systems.

Assessing portfolio similarity is one of the promising avenues in the broad literature analyzing the implications of financial institutions' homogeneity on systemic risks and overall financial stability. Leon (2017) referred to homogeneity as lack of diversity in financial institutions and highlighted uniform diversification (Beale et al., 2011) and herding (Sornette, 2003) as one of the main sources of homogeneity among financial institutions. According to Beale et al. (2011), uniform diversification refers to the state where banks adopt the same set of exposure. Portfolio similarity is one manifestation of it.

In line with the objective of this study, this literature review covers previous studies that aimed at assessing homogeneity/portfolio similarity in banking institutions. As mentioned in previous sections, the interest in this area of research has been growing since the 2008 GFC as commonalities in financial institutions (especially banks) positions led to contagion across financial system. The one of contagion mechanism is through spillovers from assets fire-sales; that is when banks are obliged to sell illiquid assets and with constrained demand. The resulting fall in assets prices leads to distress to other banks holding the same type of assets (Greenwood, Landier and Thesmar, 2015).

Given that the objective of this study is to assess how portfolio similarity have evolved in Rwandan banking sector, this review focuses mostly on studies with almost the same objectives. While this strand of literature is relatively new, authors have come up with different approaches to gauge banks similarity, such as measuring the distance between banks portfolio using the Euclidian distance (e.g. Cai, Eidam and Saunders, 2018); Leon, 2017), measuring similarity through cosine similarity (e.g., Blecher et al., 2014), etc. Each of these methods has its own merits and details about the method adopted in this study.

One of the main insights from these studies is that similarity in banking system across different economies had been quite significant and this phenomenon is more salient in big banks, which could be a source of vulnerability with regard to financial stability. One example is Colombia where banks homogeneity in terms of lending, funding, and investment portfolios is found to be more evident in large banks (Leon, 2017). Another example is the US where bank size in addition to the level of diversification and specialization are positively correlated with banks interconnectedness, according to Cai, Eidam and Saunders (2018). Moreover, In Czech Republic, in addition to big banks, similarity was also present in small banks, which could make them systemically important (Brechler et al., 2014).

Looking at other empirical evidence from these studies, starting with the US, Cai, Eidam and Saunders (2018) used Euclidian distance as a measure of similarity, focusing on the US syndicated loans market from 1988 to 2011. They also calculated the aggregate interconnectedness index, which indicated an increase in the interconnectedness between 1989 and 1994 and a significant decline in 2008 and 2009 before a pick up afterwards. Evidence also suggested that banks tended to concentrate syndicate lenders, and that bank size, the level of diversification and specialization are positively correlated with its interconnectedness, and diversifications matters more.

In the Czech Republic, Brechler et al. (2014) applied similarity and clustering methods to examine banks' systemic importance. Their approach was different as they used the cosine similarity function to measure the similarity between bank assets and loan performance instead of Euclidian distance, which is a measure of dissimilarity. Evidence from data spanning from 2002 to 2013 suggests that overall similarity has generally been stable and not excessively high. Nevertheless, the similarity was high in big and deep-rooted commercial banks, and some clusters of small banks which could turn out to be systemically important were identified. Aldasoro and Alves (2016) also used cosine similarity in their study of similarity between layers on the multiplex interbank network of large European banks.

Applying clustering methods to evaluate similarity has been somehow popular in this literature, though the scope was not always on banks portfolio. One of the most comprehensive study was by Leon (2017). He studied homogeneity (defined as lack of diversity due to some forms of uniform diversification) in the Colombian banking system by measuring their similarity in terms of lending, funding, and investment portfolios. His study delved deeper into bank granular data and used agglomerative clustering with machine learning techniques. Besides, similarity and clusters were identified using the Euclidian distance between banks and the Ward linkage method. The results revealed the existence of some degree of similarity in the Colombian banking system, especially with regard to lending and funding, while investment portfolios are relatively less homogenous. Also, as discussed above, shreds of evidence suggested that homogeneity was more substantial in the largest banks.

Another study conducted by Dardac and Boitan (2009) applied cluster analysis to assess homogeneity in terms of risk profile and profitability in Romania banking industry, and identified large and complex banking groups as a potential source of systemic risk in Romania. They used financial intermediation data from the period of 2004 to 2006 and applied the clustering techniques for each of the three years, taking into account single linkage, complete linkage, and centroid clustering for computing distance functions. This study focused on homogeneity in terms of profitability, cost and risks exposures.

Moreover, Tabak et al. (2014) used a directed clustering coefficient in a complex banking network in Brazil. The authors employed daily data on loans collected from financial services providing institutions within the Brazilian financial system for all deposit-taking corporations that have exposures in the interbank market system from January 2004 to November 2007. Their results showed that the directed clustering coefficients are an indicator of a systemic risk, and that these indicators vary over the financial institutions, and they are negatively associated with the change in interest rate. They concluded that banks change their risk exposure with changes in interest rates. Generally, systemic risk in Brazil was found to be very limited (Tabak et al., 2014).

One caveat in this review is that it focused on which approach used, and on the degree of similarity in different jurisdiction. It does not deeply discuss empirical evidence on implications of bank similarity on systemic risks or financial stability, which is beyond the scope of the present study.

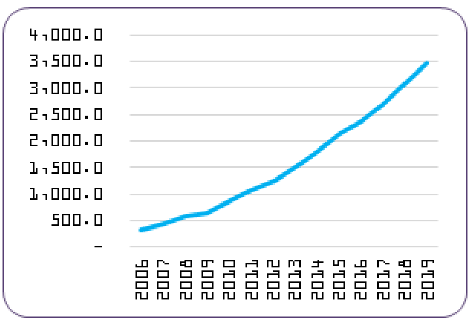
The present study implements the similarity and cluster analysis to examine systemic risk based on similar features of the credit exposure and balance sheet in the Rwandan banking system. It heavily borrows from Brechler et al. (2014) and Dardac and Boitan (2009). Their methods are well suited to the case of Rwanda, where portfolio of most banking institutions is concentrated in loans, thus the probability of having a similar position is real. Secondly, the banking industry includes large, medium and small banks and, as seen in the literature, the small banks can be equally important when they form a cluster; therefore, investigating the presence and evolution of clusters in the banking sector is vital. The empirical strategy is detailed in the next sections.

3. Overview of the banking sector in Rwanda

The banking system in Rwanda has undergone significant progress in the last two decades in various areas. The number of banks has grown from 6 in 2006 to 16 in 2020, including several foreign banks entering the market. Expansion in terms of banking institution size is also noticeable in line with growth in the real sector. Increasing the banking sector lending to the economy has also played a role in the process (Nyalihama and Kamanzi, 2019).

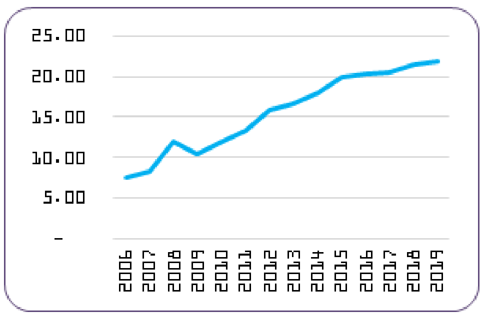
Figures 2 and 3 illustrate the rising role of the banking industry of the Rwandan economy. Total assets of the banking industry have grown over four times in the last ten years, driven particularly by lending activities. Loans to GDP ratio doubled during the same period from 11.9% in 2010 to 21.9% in 2019. Nevertheless, this level is still relatively low compared to emerging economies.

Figure 2: Banking sector total asset (FRW billion)



Source: Authors' calculation using data from the National Bank of Rwanda

Figure 3: Banks loans to GDP ratio (%)



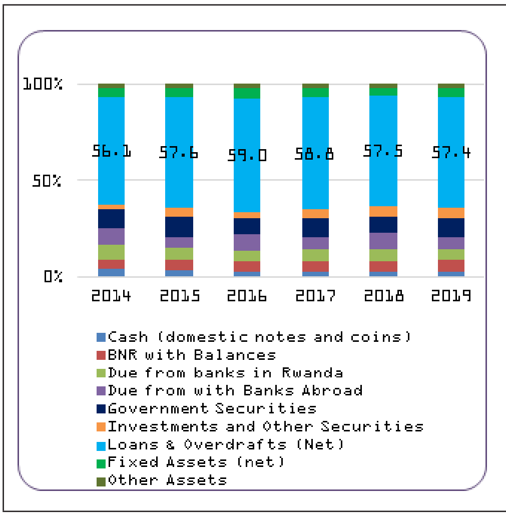
Source: Authors' calculation using data from the National Bank of Rwanda

Financial market development is still at an early stage in Rwanda, and financial intermediation is generally deposit-taking and lending by commercial banks, where lending is the primary income-generating activity (Figure 6). Deposits are the primary source of funds (Figure 5). For the last seven years, loans share in total assets has remained steady, around 57%, followed by Government securities with a share of about 10% (Figure 4). Deposits are the primary source of funds, with the share in total liabilities currently at 63.0%, down from 68.4% in 2014 (Figure 5). Funds from other banks have been gradually expanding along with the deepening of interbank markets.

On deposits, the bulk of them are highly liquid demand deposits. By the end of 2019, the share of demand deposits stood at 43% against 34% for time deposits. On the type of depositors, household's share is still the largest, although dwindling amid the expansion of institutional deposits. Despite these improvements, the banking sector still over-relies on short-term funds, and this poses a challenge for maturity transformation.

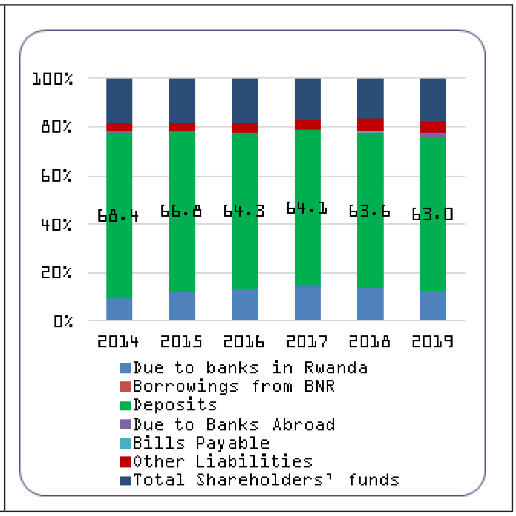
The leverage ratio has remained high, and the capital adequacy ratio remained above 20% at the industry level, well above the minimum required of 15%. Banking sector profitability has improved in the last two years, as shown by the return on equity for the industry (Figure 7). However, it has been volatile in the past and is mostly driven by well-established banks. Moreover, efficiency gains and improvement in asset quality, especially loans, as shown in Figure 8 below, have contributed to this observed gain in banking sector profitability.

Figure 4: Banking sector assets decomposition



Source: Authors' calculation using data from the National Bank of Rwanda

Figure 5: Banking sector source of funds

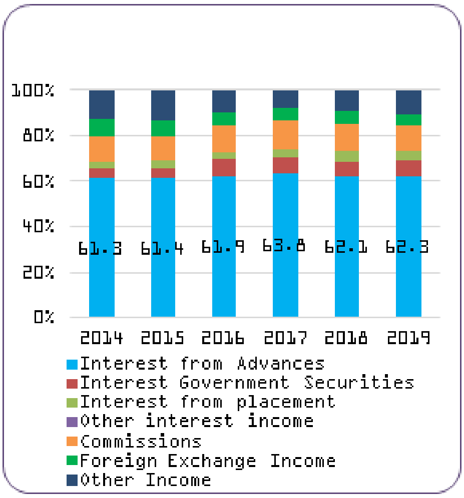


Source: Authors' calculation using data from the National Bank of Rwanda

Figure 6: Banking sector source of income Figure 7: Banking sector return on equity

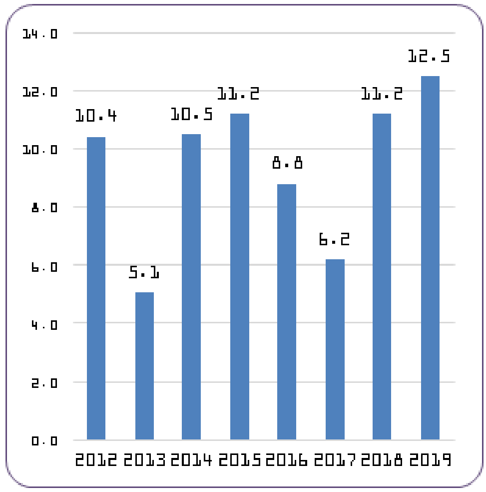
Source: Authors' calculation using data from the National Bank of Rwanda
Source: Authors' calculation using data from the National Bank of Rwanda

Figure 6: Banking sector source of income



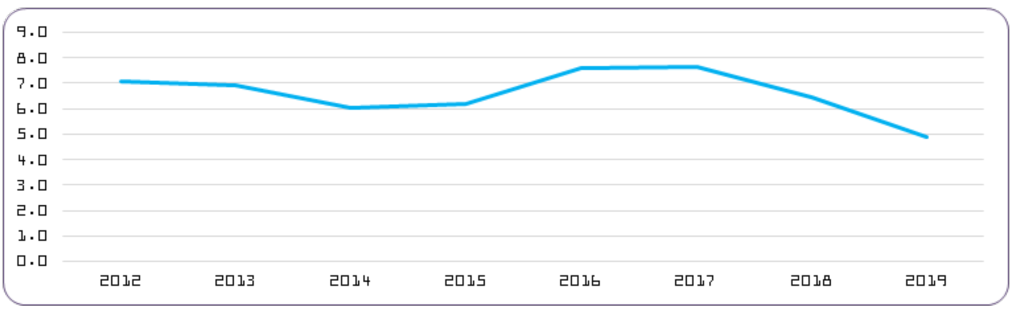
Source: Authors' calculation using data from the National Bank of Rwanda

Figure 7: Banking sector return on equity



Source: Authors' calculation using data from the National Bank of Rwanda

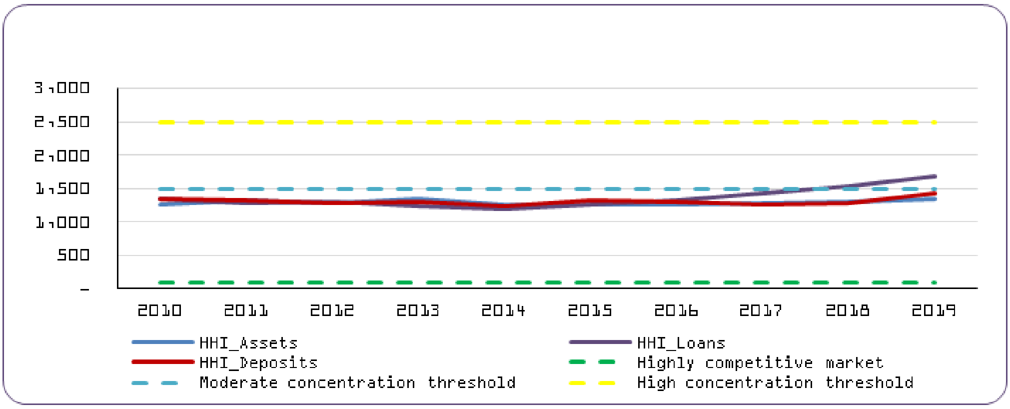
Figure 8: Non-performing loans to gross loans (%)



Source: Authors' calculation using data from the National Bank of Rwanda

Overall, banking sector development in Rwanda is evident, and indicators of capital adequacy, liquidity, assets quality, and profitability have remained generally sound. Nevertheless, as shown in the previous sections, the source funds and assets remain concentrated in deposits and loans, respectively, which may turn out to be a vulnerability at the bank level. Besides, at the industry level, some progress recorded in previous years on assets, loans, and deposits market concentration has been waning for the last two years, as shown by Figure 9 below. In particular, Herfindahl-Hirschman Index (HHI) for the loan market suggests that, currently, the loan market is moderately concentrated.

Figure 9: Evolution of HHI on banks assets, loans and deposits markets



Source: Authors' calculation using data from the National Bank of Rwanda

Even though the banking sector in Rwanda heavily relies on short-term resources, the recent stress test on liquidity coverage ratios suggest that the banking sector in Rwanda was resilient to a sudden withdrawal of 10% of institutional investors' deposits and a simultaneous dry of 5% inflows from loans repayments (NBR, 2019).

4. Methodology

In the subsequent section, we describe the steps undertaken to assess systemic importance in the banking system using similarity and clustering methods. As mentioned in the previous sections, this study follows the methodology used by (Brechler et al., 2014) for the case of the Czech Republic.

Data description and estimation

This paper used secondary annual data from the National Bank of Rwanda in the Financial Stability Database, spanning from the period 2016 to 2019. The choice of this period is informed by the availability of disaggregated data per economic activity (sector) on all deposit-taking corporations or banks in Rwanda regarding the variable of interest. Prior to this period, the sector of economic activity classification was not harmonized across the banking industry. The dataset is composed of sector of economic activity, loans portfolio, non-performing loans, ratio of Non-Performing Loan (NPL) over Loan, and all categories of balance sheet assets, equity and liabilities per bank. All the deposit-taking corporations were used in this study. The data analysis and estimations were carried out in R language.

In the beginning, we designed a measure of banks portfolios' similarity, which considers the similarity of categories of assets between individual banks. This measure helps to visualize the risk of banking system fragility, which links up with contagion risk; however, the system remains stable and unwavering with the absence of adverse shocks.

The analysis of common risks could thus be vividly crucial in understanding the vulnerability of the banking system, which may transform into financial system instability. Specifically, the similarity of banks' portfolios can be analyzed in different facets, namely the typical risk profile and the whole banking system without account for assets risk. In Rwanda, as most banks are in the traditional commercial banking business, the main item on their balance sheet is loans as discussed in the previous sections. For this reason, we also investigate similarity in Rwandan banks' loan portfolio and their risk profile. Similar to Brechler et al., (2014), considering loans risks per sector helps to better gauge systemic risks as loan portfolio similarity, and the exposure to the same risks would exacerbate vulnerabilities.

Lastly, measures of similarity of the balance sheet, loan portfolio, and risks adjusted loan portfolio will help to identify clusters of very similar banks in Rwanda and how those clusters' dynamics over time. Because the Rwandan banking system includes both bigger and smaller banks in terms of assets, identifying clusters could help see whether a cluster of smaller banks can turn out to be systemic if taken as a group.

Balance sheet similarity

Although banks can be characterized by the structure of the asset side of the balance sheet, its liquidity conditions, leverage conditions, among others, this study focuses on the assets side of 16 Rwandan banks' balance sheets, notably bank loans portfolio given the importance of bank lending as the main source of external funds for corporate sector and households in Rwanda. The methodology described below could be applied on the liability side, and this may be undertaken in future studies.

Specifically, in the first place, we consider the assets side components and narrow down to one asset category, namely loans portfolio thereafter. As in Brechler et al. (2014), let us consider a vector $a = \{a1...ak\}$, where k stands for data granularity and a, denotes the asset portfolio, characterized by the combined gross nominal value of each asset category $i \in 1,..,k$. In our case, assets categories are cash, balance with the central bank, due from other banks in Rwanda, due from other banks abroad, Government securities, investment and other securities, loans, fixed assets, and other assets. Regarding loans, granularity is according to the economic sector in which loans are directed to.

Following Brechler et al. (2014), we measure the similarity between the portfolios of any two banks (e.g. x and y) using a cosine similarity function. Cosine similarity has several advantages, including the fact that it is a scale-independent measure and is bounded to $\{a, b \in R\} \rightarrow [-1, 1]$ by definition. Furthermore, given that balance-sheet assets only take non-negative values, we further find $\{a, b \in R+\} \rightarrow [0,1]$, 0 for orthogonal vectors, which is the complete dissimilarity and 1 for identically oriented vectors, which is the completely identical portfolio composition. The cosine similarity between two vectors (a and b) is defined as the cosine of the angle between the vectors:

$$similarity(a,b) = \cos(\theta) = \frac{a.b}{\|a\|\|b\|} = \frac{\sum a_i b_i}{\sqrt{\sum a_i^2 \times \sum b_i^2}} \quad (1)$$

The above formula is used to measure similarity in banks' asset categories and loans per sector. In the second phase, loans per sector are adjusted with a measure of credit risks (details in the next sections). In line with Brechler et al., (2014), the weighted cosine similarity is defined as follows:

$$similarity_{wt}(a, b, w) = \frac{\sum w_i a_i b_i}{\sqrt{\sum w_i\, a_i^2 * \sum w_i b_i^2}} \tag{2}$$

As indicated above, a measure of credit risk is included as a weight in equation 2. Following Brechler et al. (2014), the level of credit risk associated with a certain asset category at time *t*, *μt*, is measured by the combined value of NPLs ratio per sector for the whole banking industry in a period under consideration. We also consider the coefficient of variation of those NPL ratios per sector to gauge the overall similarity of NPL ratios across banks, and the risk weights are derived as the level of NPLs and the inverse of the coefficient of variation. The latter is inverted because the higher coefficient of variation indicates dissimilarity instead of similarity. The formula used is as follows:

$$W_t = \mu_t * V_t^{-1} \tag{3}$$

$$V_t = \frac{s_t}{\mu_t} \tag{4}$$

Where μ_t is NPL ratio per sector at time t and s_t is standard deviation at time *t*. If we compute a (*di*) similarity measure (3.1) for each pair of *n* banks, we get an *n*×*n* symmetric similarity matrix *S = {si, j}* that denotes an essential input for deriving several characteristics of the banking system. From similarity matrix *S*, we derive a measure of the overall similarity in the Rwandan banking system during the sample period. Secondly, in addition to matrix *S*, the matrix with risk-adjusted loans also helps to identify clusters of banks exposed to joint risks, which can eventually turn out to be systematic.

To identify clusters, we use multivariate visualization methods, which imply "optimally" restructuring the rows and columns of the matrix *S* and put banks with a similar balance sheet or diversification in loan portfolio closer to each other and different banks far from each other.

We considered another standardized measure for objects based clustering (hierarchical clustering), which does not require predetermining the number of clusters (k) to be computed, and this characteristic makes it the best measure in grouping clusters. One type of this measure is agglomerative clustering in which each data point is primarily taken as a cluster of its own (leaf). Thereafter, the most alike clusters are continuously merged till there is only one single cluster called the root. The final result of hierarchical clustering is a graphical representation in a tree-based form of the objects, commonly known as dendrogram. To visualize the clusters, we used the R package dendextend.

5. Results and discussion

In this study, we used the above presented methodology focusing on the balance sheet assets, loan portfolio, and loans adjusted with NPLs ratios as a risk measure. The analysis shows that assets expose several commercial banks to shared risks. The loan portfolio also echoes the message from the assets as some banks present the same similarities in assets. When we adjust the loan portfolio with risk element, the separation of the hitherto identified clusters of banks becomes even more pronounced. Both empirical methods turn out to be useful matches and reveal how credit risk can concentrate on banks with a similar source of funding and credit exposures to the real economy.

Banking sector loans share and concentration

Table 1 below provides an overview of Rwandan banks' exposure to the different economic sectors and suggests that dynamics across sectors have been mixed. Since 2010, the mortgage sector has had the highest share, and continues to get bigger. As at end of 2019, it had 37% of total outstanding bank loans, higher than its last ten years average (32.5%). The construction sector continued to expand, with many big projects especially in Kigali City and leads in terms of loan concentration. Other main sectors include trade, manufacturing, transport, and warehousing, personal (consumer) loans and, lastly, hotels and restaurants. Among these, the share of personal loans and loans to the trade sector has declined recently while manufacturing and transport sector share increased. The share of hotels and restaurants has generally remained stable.

Table 1: Banking sector loans share and concentration per sector

Sectors	Share in total loans (average 2010-2019)	Share in total loans in 2019	HHI (average 2010-2019)	HHI in 2019
Mortgage industries	0.325	0.370	0.168	0.176
Trade*	0.175	0.145	0.137	0.152
Manufacturing activities	0.088	0.120	0.204	0.179
Transport and warehousing	0.081	0.112	0.181	0.306
Personal loans	0.126	0.075	0.209	0.18

continued next page

Table 1 Continued

Sectors	Share in total loans (average 2010-2019)	Share in total loans in 2019	HHI (average 2010-2019)	HHI in 2019
Restaurant and hotel*	0.082	0.073	0.272	0.253
Water and energy activities	0.022	0.052	0.5	0.47
Services sector	0.034	0.029	0.197	0.139
Agricultural, fisheries and livestock	0.026	0.012	0.284	0.257
Other Financial Institutions (OFI) and Insurance	0.013	0.011	0.406	0.41
Mining activities	0.001	0.001	0.775	0.778

*Average for trade sector and restaurant and hotels start in 2016 as the two sectors were separated that time

Regarding concentration, the analysis of HHI per sector helps us to unmask important implications. As discussed in the previous section, the market for loans had remained unconcentrated in the last ten years, except in the last two years where the level of concentration moderately increased. The HHI per sector in Table 1 shows strong heterogeneity across the sectors in terms of loan market concentration, as the latter is exceptionally high for the mining sector, transport and warehousing sector, water and energy sector, and other financial institutions and insurance sector. High HHI in those sectors means that the big chunk of loans directed to those sectors is given by a few banks. Generally, the current level of concentration is closer to the ten years average in most sectors, except in transport where concentration is increasing while the market in the services sector has recently become unconcentrated.

One positive point to mention with some implications to systemic risks is that in sectors where banking system exposure is higher as shown by sector share in total loans (see Table 1), the market is relatively less concentrated except for the transport sector and hotels and restaurant sectors. Nevertheless, for hotels and restaurants sector, the situation is improving as the market became moderately concentrated in 2019 from being highly concentrated in previous years. The fact that sectors with higher share are financed by many banks may reduce the severity of impact from a sectoral shock on a given bank balance sheet. It reduces the likelihood of having concentrated exposures to an individual or few borrowers, thus limit the maximum loss a bank can incur in case of sectoral shock. Details on the evolution of the share of loans per sector in total banking loans and growth of HHI are provided in Appendix 3.

Similarity in credit risk performance

We primarily give the descriptive statistics to show the basic characteristics of bank portfolios in terms of credit risk materialization (NPL ratios). The NPL stands for Non-Performing Loan ratio, whereas CV stands for Coefficient of Variation. The results based on the NPL ratio as a proxy for credit risk materialization are provided in Table 2.

Table 2: Non-performing loans mean and coefficient of variation (2016-2019)

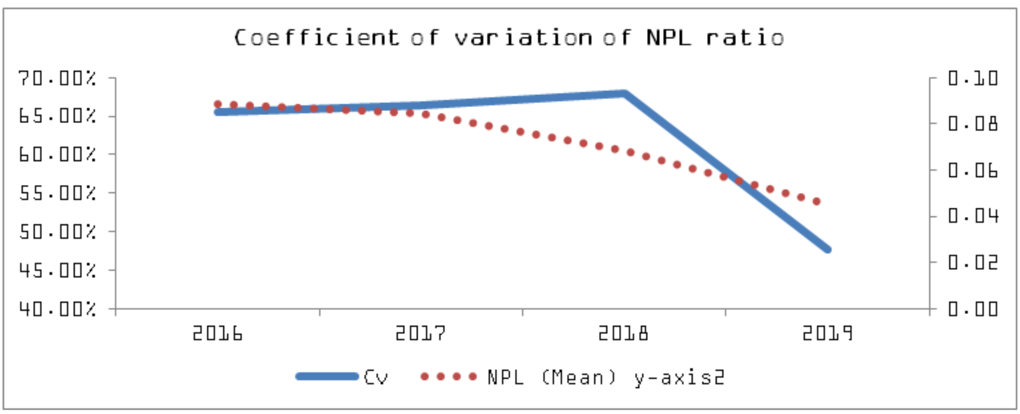
Sector	NPL	CV
Personal loan	0.07	0.98
Agricultural, fisheries and livestock	0.15	1.66
Mining	0.02	2.97
Manufacturing	0.06	2.19
Water and energy	0.01	3.00
Mortgage industries	0.06	1.28
Trade	0.10	0.88
Restaurant and hotel	0.05	1.86
Transport and warehousing	0.05	1.23
Other Financial Institutions (OFI) and insurance	0.03	2.80
Service sector	0.07	1.65

Source: Authors' calculation using data from the National Bank of Rwanda

Several sectors present a relatively high level of non-performing loans. In particular, agricultural, fisheries and livestock; trade; services sector; and personal loans exhibit relatively risky exposures for banks. The risk of indirect contagion through these exposures is even more pronounced given that the coefficient of variation is comparatively small for most of the asset groups.

Conversely, the following sectors, namely water and energy activities, mining activities, and other financial institutions (OFI) and insurance manifest reasonably lower NPL ratios, mixed with a high coefficient of variation, thus resulting in relatively low risk. Despite the current low-risk profile of these sectors, the observed low overall dispersion across the banking sector throughout the period under review, as shown in Figure 10, might contribute to a higher level of systemic risk.

Figure 10: Evolution of non-performing loans



Source: Authors' calculation using data from the National Bank of Rwanda

Balance sheet similarity

Underlying banks' balance sheet similarity was high homogeneity at 88.35% on average in 2019, resulting from observed common assets portfolios for the banks, with the only distinction in the level of asset categories. However, this picture does not fully uncover which banks are most similar and which are less similar. For that reason, Figure 11 displays a similarity matrix for all pairs of banks active as at the end of 2019. Its rows and columns represent individual banks in the same order. Each cell thus stands for the similarity between two banks of the corresponding row and column. The darker blue cell represents the greater similarity between the two banks, while the lighter blue cell symbolizes the lower similarity between two individual banks. The diagonal elements of the similarity matrix show the cosine similarity between a bank and the very same bank, which is equal to 1, by definition.

Using both similarity matrix and cluster analysis, Figure 11 shows that two big clusters emerge, with the other two small clusters with only one bank in each. Particularly, cluster analysis distinctly describes a yellow-colored cluster, which contains bank 1, 2, 3, 5, 6, 8, 9 and 10. The second big cluster (with blue color) has the subsequent banks, namely banks 12, 14, 16, 13, 15 and 11. The remaining two clusters are considerably small, with bank 7 in the red-colored cluster and bank 4 in green. Banks are named as numbers for confidentiality.

The largest banks operating in the system mostly belong in the first big cluster, while the smallest banks assembled in the second big cluster. This result corroborates earlier research (Brechler et al., 2014). In the Czech Republic and (Aldasoro and Alves, 2016) in European banks who found that the similarity was substantial in big and diversified banks, and correspondingly some small banks could be systemically important.

Figure 11: Banks' similarity matrix in the left and clusters in the right as of end 2019

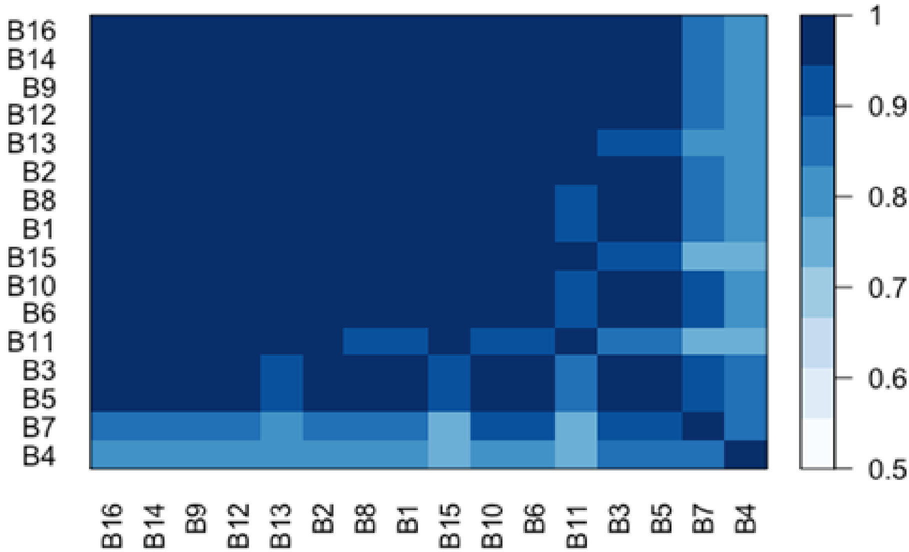


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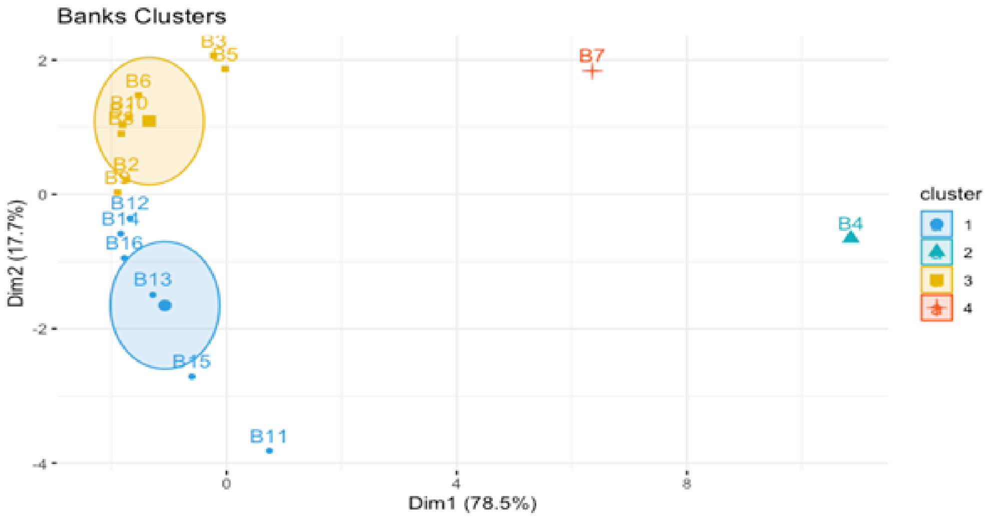
Figure 11 Continued



Source: Authors' calculation using data from the National Bank of Rwanda

Similarities between individual banks' loans portfolio

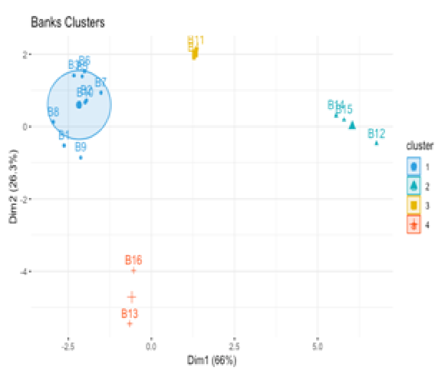
The overall similarity based on loans by sector in the banking system has noticeably loosened from 0.92 in 2016 to relatively stable around 0.63 from 2017 to 2019. Figure 12 highlights four clusters of similar banks in three consecutive years and three clusters in the last period. Also, several clusters invariably remained stable in the period under consideration. These include the following: the cluster of banks 12, 14 and 15; the cluster of banks 3, 5, 6, 7, 11 and a group of banks 1, 9, 10 and 13. It is also important to note that banks 4 and 16 were in the same cluster in the contemporary two years.

Interestingly, a stable cluster of banks 12, 14 and 15 seemed to be the subset of the observed cluster of small banks considering balance sheet size, while the cluster of banks 1, 9 and 10 includes some of the largest banks. This reflects that these groups of banks share the same exposures in underlying loans bestowed in different sectors, namely agriculture, mining, trade, and so forth. The risk-adjusted similarities based on credit exposures to the real economy, however, portray a different but meaningful picture of banks' similarity. To that end, overall banks' similarity was somewhat unchanged in the first three years at 0.75 and peaked to 0.79 in 2019. As a result, this unmasks the increasing similarity in non-performing loans in particular sectors.

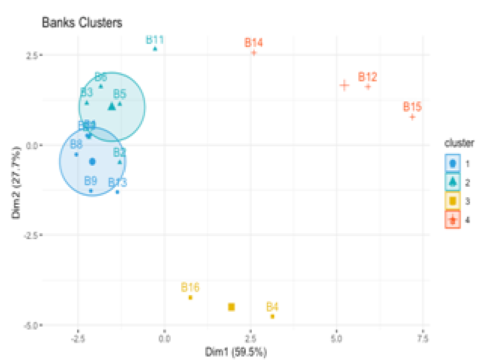
Looking at Figure 13 that describes risk-adjusted similarity clusters, the number of clusters remained stable at four (4) in the period under review and, specifically, two (2) big clusters are present. Similar to non-risk adjusted similarity, the sub-cluster of banks 12, 14 and 15 persisted the homogeneity in recent four years and, more interestingly, this cluster has in common the lowest financing of the economic activities, except for the trade and mining financing where they are the second last. This group of banks falls in small-sized banks that are less important individually. Even though their total size taken as a group is still relatively small, in event of a common shock to a sector they have lent to, a simultaneous crisis in 3 banks could be seen as a bad sign for financial system stability.

In addition, within clusters, there emerged another group of five (5) banks that moved together, underlying high similarity in 2016-2019, namely banks 2,3,6,7 and 10. This group has the properties of being the second-lowest lender in the banking system, and they almost finance every activity at an average level compared to other clusters. It is worth noting that banks 1,8 merged with this cluster in 2016-2018. However, in 2019, they moved to a separate cluster of big lenders in every economic sector, except for agriculture where they are the second largest. These results are in the same line with what was revealed in the study done by Leon (2017) in Colombia where it found the existence of some degree of similarity with regard to lending and funding, while investment portfolios are relatively less homogenous. Thus, in Rwanda, the aforementioned group of banks that include large and mid-sized banks deserve keen attention as some of them are already big and, when considered as a group, they are systemically important.

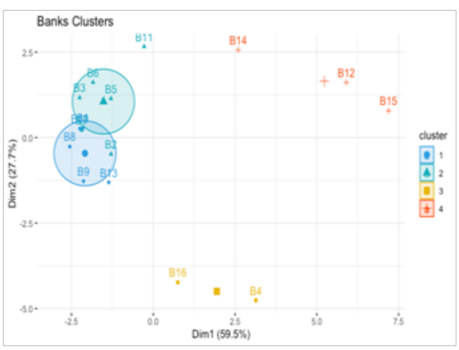
Figure 12: Clusters based on loans by sector



2016



2017



2018

2019

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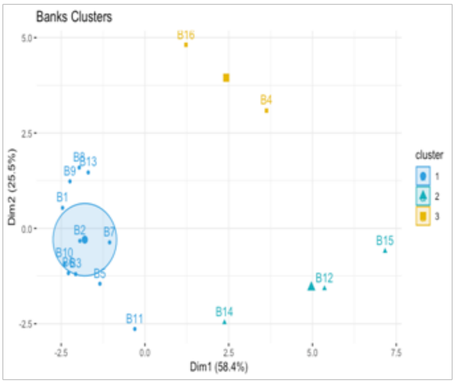
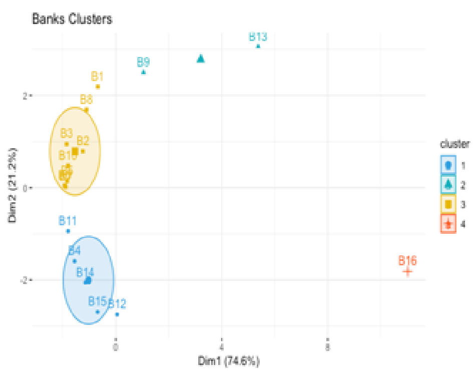
Figure 12 Continued



Source: Authors' calculation using data from the National Bank of Rwanda

Figure 13: Risk-adjusted similarities between individual banks



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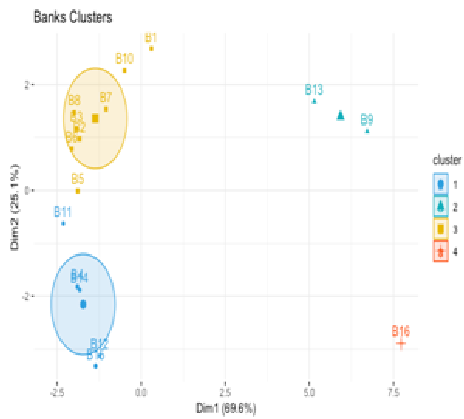
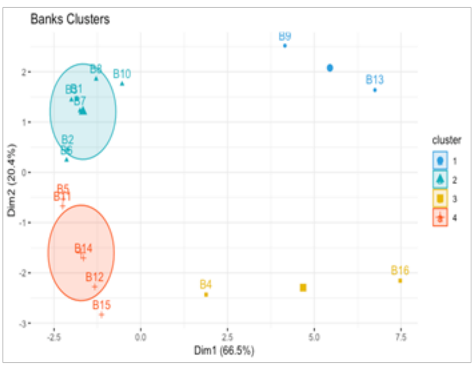
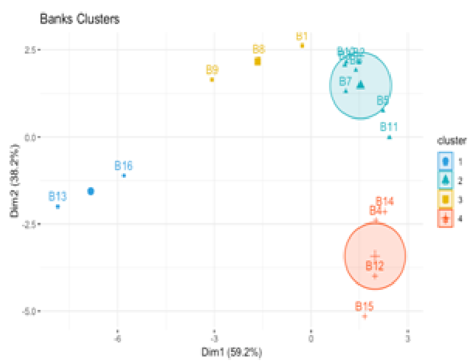


2017



2018



2019

Source: Authors' calculation using data from the National Bank of Rwanda

To understand the characteristics of the clusters based on the loans with risk-adjusted for the year 2019, we computed the sectoral average loans and ranked clusters accordingly. As shown in Figure 14, cluster one has the banks that finance the economic activities moderately, except for agriculture where they are the first lenders. The banks in cluster two are the second-lowest lenders in the banking system, and they almost finance every activity at an average level compared to other clusters. In contrast, cluster 3 is made up of big lenders in every economic sector, except for agriculture where they are the second largest. In cluster 4, we found the lowest financing group of the economic activities, except for trade and mining financing where they are the second last. These results show that banks within the same cluster tend to finance different categories of economic activities, almost the same in spite of the bank size.

Figure 14: Cluster features

Source: Authors' calculation using data from the National Bank of Rwanda

6. Conclusion and policy recommendations

In this study, we assess the systemic risk of banks using portfolio similarity and clustering methods using data from Rwandan banking sector between 2016 and 2019. The main insight is that similarity and cluster analysis techniques help uncover the groups of banks that share the same features in assets and loans portfolio. For as much as banks have common features, they are prone to the same risk exposures, thus the failure of one bank due to one sector could fail similar banks. Therefore, this study provides additional tools to macro-prudential policy makers, especially with regard to the assessment of systemic risk.

Results suggest that the overall similarity based on loans by sector in the banking system was noticeably high at 90% in 2016 and relatively stable at 63% in the following periods. However, adjusting loans with risk-weight based on credit exposures to the real economy, the findings reveal that overall banks' similarity was somewhat unchanged in the first three years at 75% and peaked to 79% in 2019. Therefore, this points to increasing similarity in non-performing loans in some sectors.

For the year 2019, the banking sector has four clusters. In the first cluster, banks finance the economic activities moderately, except for agriculture where they are the first lenders. The banks in cluster two are the second-lowest lender in the banking system, and they almost finance every activity at an average level compared to other clusters. In contrast, the third cluster is made up of big lenders in every economic sector, except for agriculture where they are the second largest. In the fourth cluster, we found the lowest financing group of economic activities, except for trade and mining financing where they are the second last.

We found a group of five banks including large and mid-sized banks that have been similar for three (3) years and which become even more systemically important as a group, hence would deserve more scrutiny from macro-prudential policy makers, especially under certain circumstances such as shocks to the common sector they have lent to. Also, there is another outstanding cluster of three small banks that are less important individually but have been very similar in many aspects over the sample period. Even though their importance as a group is relatively small in the Rwandan banking system, this cluster should also be watched closely as its high similarity implies that a shock to assets portfolio of one bank would quickly and simultaneously spread to others in the cluster.

This study provides an additional tool for identifying systemic vulnerabilities from a different perspective. It shows that some medium-sized banks have been consistently similar in terms of the loan portfolio and associated risks in the last four years, hence they can be exposed to common risks with impactful consequence as the cluster is sizeable than banks have taken individually. This can be of interest for macro-prudential authorities because, in addition to considering bank size or centrality in interbank transactions or individual bank exposure to a given sector, dynamics in the identified cluster are equally important for systemic stability.

As a policy implication, the National Bank of Rwanda, as a regulatory and supervisory body of commercial banks, should also consider using banks' similarity and clustering tool to carry out regular monitoring of systemic risks in addition to other tools such as stress tests and market analysis. This tool can be used preferably on quarterly basis to check the individual banks that can be simultaneously affected by a common shock, and might become systemically important if taken together as a cluster. This can help detect the systemic risk early and guide authorities in taking appropriate policy measures such as prudential requirements to limit some banks' excessive exposure to a given sector(s) or to make that exposure more secure, to alleviate risks to financial system stability.

Some potential areas of future research include considering other features of banks' balance sheet especially on liabilities side, such as banks funding structure or banks liquidity, which will add more insights regarding banks similarity and implications on systemic stability. Secondly, identifying the drivers behind bank similarity could also help to understand the phenomenon.

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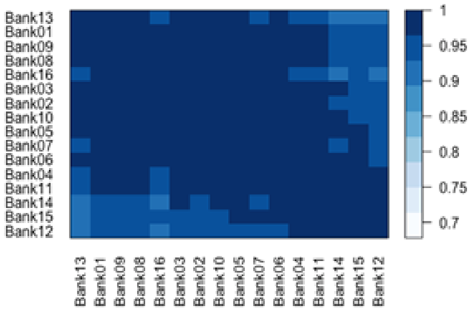
Appendix

Appendix 1: Loans based similarities between individual banks



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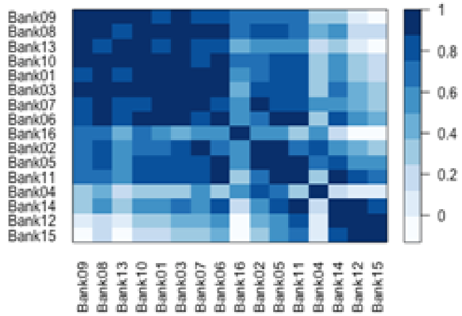

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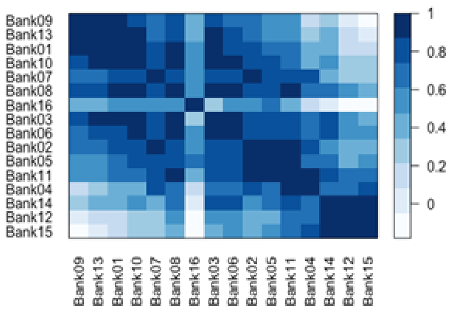

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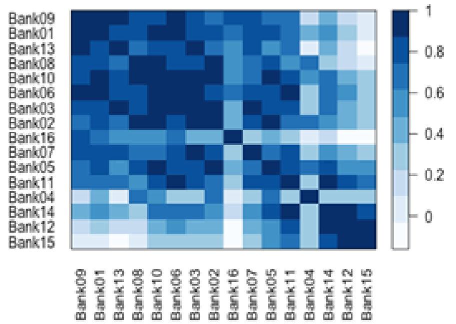
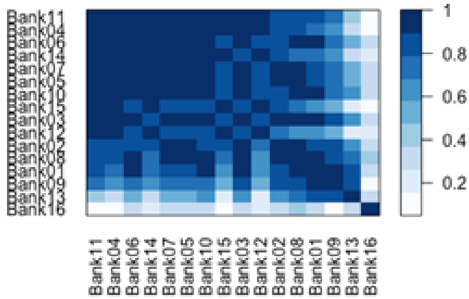


2019

Appendix 2: Risk-adjusted similarities between individual banks



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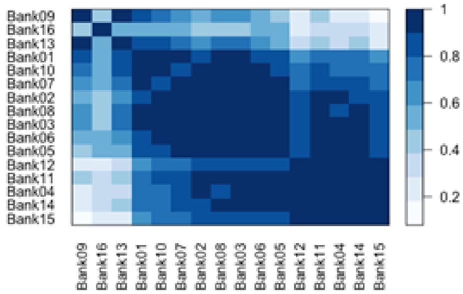

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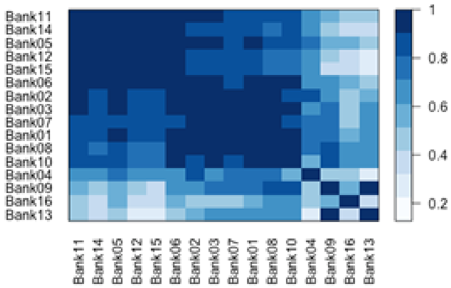

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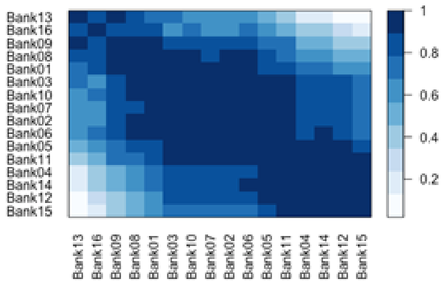
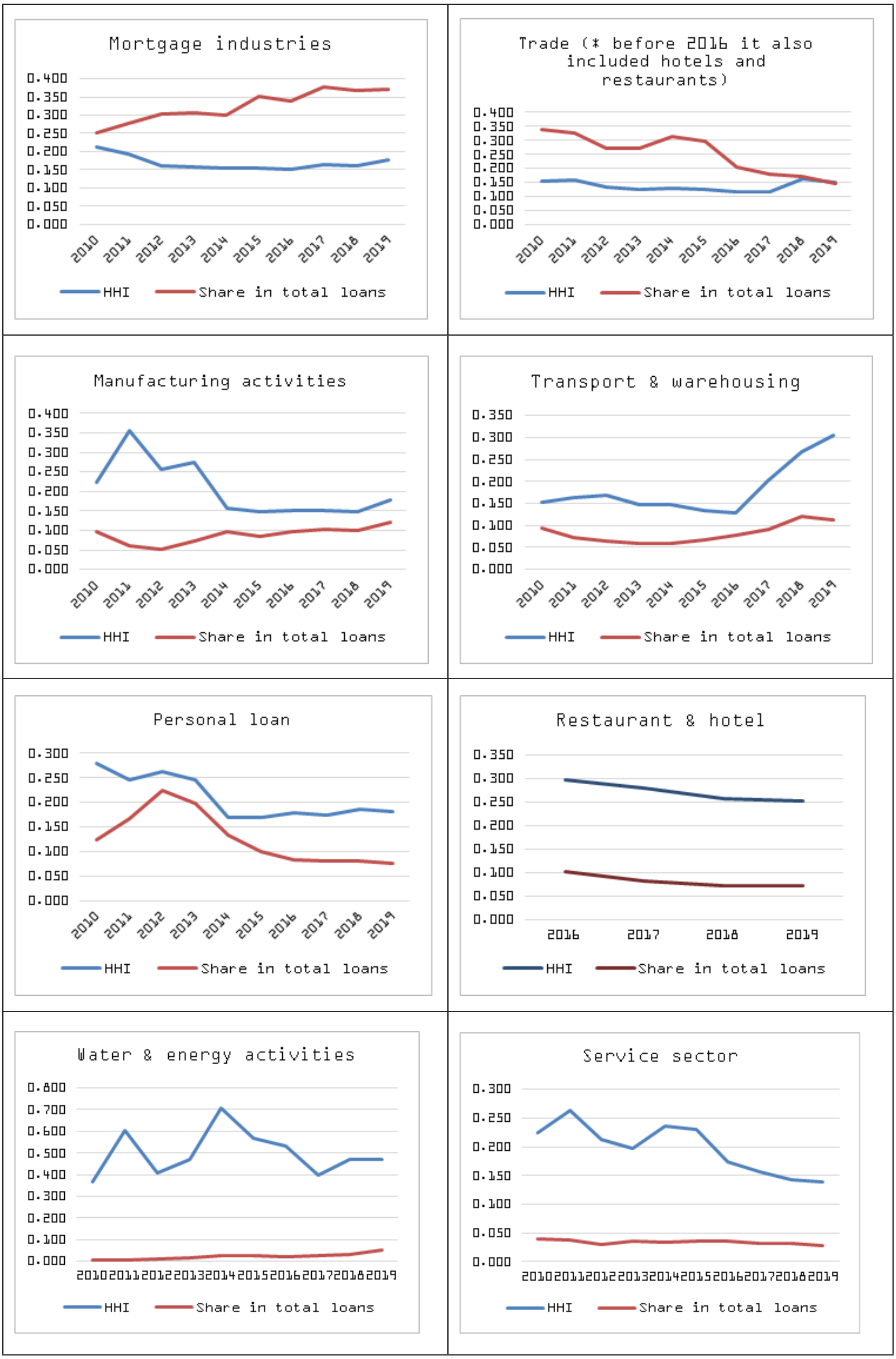
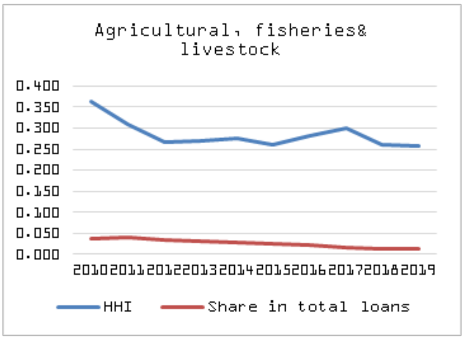
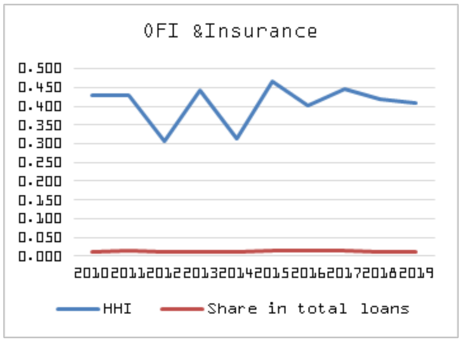


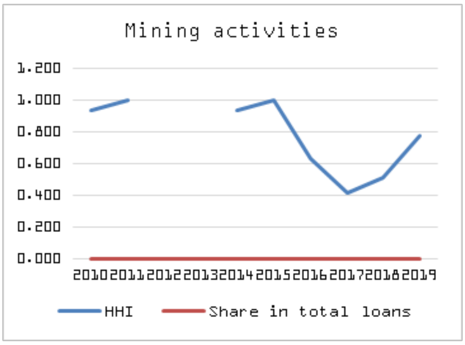
2019

Appendix 3: Evolution of loans share per sector and HHI per sector




Agricultural, fisheries& livestock
0.400
0.350
0.300
0.250
0.200
0.150
0.100
0.050
0.000
2010 2011 2012 2013 2014 2015 2016 2017 2018 2019
HHI
Share in total loans


OFI &Insurance
0.500
0.450
0.400
0.350
0.300
0.250
0.200
0.150
0.100
0.050
0.000
2010 2011 2012 2013 2014 2015 2016 2017 2018 2019
HHI
Share in total loans


Mining activities
1.200
1.000
0.800
0.600
0.400
0.200
0.000
2010 2011 2012 2013 2014 2015 2016 2017 2018 2019
HHI
Share in total loans

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