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homogeneous are they?

Por: Carlos León

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Banks in Colombia: how homogeneous are they?¹

Carlos León²

Abstract

In complex systems, homogeneity (i.e. lack of diversity) has been documented as a source of fragility. Likewise, financial sector's homogeneity has been documented as a contributing factor for systemic risk. We assess homogeneity in the Colombian case by measuring how similar banks are regarding the structure of their overall financial statements, and their lending, investment, and funding portfolios. Distances among banks and an agglomerative clustering method yield the hierarchical structure of the banking system, which exhibits how banks are related to each other based on their financial structure. The Colombian banking sector displays homogeneous features, especially among the largest banks. Results enable to study to what extent the banking sector is homogeneous, and to identify banking firms that have a(n) (un)common financial structure. Yet, as we neither examine Colombian banking system complexity nor banks' soundness nor higher dimensions of diversity, conclusive inferences about systemic risk and financial stability are pending.

Keywords: clustering, banks, diversity, systemic risk, machine learning.

JEL Codes: G21, C38, L22, L25.

¹ The opinions and statements in this article are the sole responsibility of the author, and do not represent neither those of Banco de la República nor of its Board of Directors. Results alone may not to be interpreted as conclusive or comprehensive about systemic risk or financial stability. Any remaining errors are the author's own. I am grateful to Jorge Cely for his work on data extraction and processing, and to Hernando Vargas, Pamela Cardozo, Clara Machado, Freddy Cepeda, and the Financial Stability Department staff for their comments and suggestions.

² Financial Infrastructure Oversight Department, Banco de la República, Bogotá, Colombia; CentER, Tilburg University, Tilburg, The Netherlands; cleonrin@banrep.gov.co / carlosleonr@hotmail.com; Banco de la República, Carrera 7 #14-78, Bogotá, Colombia; Tel.+57 1 3430731.

1 Introduction

Complexity and homogeneity have been pinpointed as two defining but potentially problematic features of financial systems (see Haldane, 2009, Landau, 2009, Farmer et al., 2012). Financial system's complexity refers to the many, intricate, and multi-dimensional connections among numerous adaptive financial institutions (see Sornette, 2003; Haldane, 2009, Landau, 2009,). Homogeneity refers to the lack of diversity among financial institutions, presumably due to some form of *uniform diversification* (see Beale et al., 2011) or *herding* (see Sornette, 2003), which has resulted –for example- in similar balance sheets and risk management practice, common trading strategies, and correlated positions and returns (see Rebonato, 2007, Brown et al., 2009, Haldane, 2009, Haldane & May, 2011, Goodhart & Wagner, 2012). Together, complexity and homogeneity predispose financial systems to abrupt changes, even from small shocks (Haldane, 2009).

Our aim in this paper is related to homogeneity. We aim at examining similarity among Colombian banks by means of implementing agglomerative clustering techniques on a particularly granular decomposition of their financial statements (i.e. balance sheet and income statement), comprising more than 3,000 different features (i.e. accounts) for each bank in a given period. Additionally, we measure similarity in the asset and liability sides of their financial structures by examining their lending, investment, and funding portfolios, which may be deemed as the three most interesting sections of their core banking functions.

Results suggest that the Colombian banking sector displays some degree of homogeneity that varies with the portfolio under examination. They also suggest that the distance among most contributive banks tends to be rather low. The lending, investment, and funding portfolios of the two largest banks by asset size is exceptionally similar. Hence, results enable to study to what extent the banking sector is homogeneous, to identify banking firms that have a(n) (un)common financial structure, and –thus- to better examine systemic risk.³ However, conclusions related to systemic risk and financial stability are conditional on

³ Our definition of *systemic risk* follows that of several authors (e.g. Ibragimov et al., 2011, Allen et al., 2012), meaning the negative externalities of joint failures of financial institutions as a result of a common shock or a contagion process.

unexplored factors, such as Colombian banking sector complexity, banks' individual soundness, and higher dimensions of diversity.

The homogenization of financial institutions has intricate implications for the stability and the efficiency of the financial system (Wagner, 2008). Literature has highlighted the importance of assessing and monitoring homogeneity in the financial sector, especially after the global crisis that started circa 2007. For instance, as stated by Haldane and May (2011), in the run-up to crisis, and in the pursuit of diversification, banks' balance sheets and risk management became increasingly homogeneous. Likewise, as pinpointed by Caccioli et al. (2014), common asset holdings and the related spiral effects have been the primary vector of contagion in the global financial crisis. It has been shown that clustered asset structures (i.e. groups of banks holding similar asset portfolios) entail higher systemic risk when bad information about banks' future solvency arrives in the economy, whereas in unclustered structures defaults are more dispersed (Allen et al., 2012). Also, regarding the liability side of banks, by raising funds from similar sources the financial system as a whole becomes vulnerable to disruptions in funding markets (Goodhart & Wagner, 2012). All in all, as put forward by several authors (Huang et al., 2013, Zhao et al., 2013, Caccioli et al., 2014, Aymanns & George, 2015), homogeneity, either in the form of overlapping portfolios or sharing similar financial positions, constitutes one of several contagion channels –along with counterparty and liquidity roll-over risk exposures.

Accordingly, the International Monetary Fund (2007) has stated that policymakers should recognize that a diversity of market participants is more conducive to market stability; Beale et al. (2011) have suggested that regulators may wish to promote systemic stability by incentivizing a more diverse diversification among banks; Haldane and May (2011) have emphasized that a financial sector's systemic diversity objective should be given much greater prominence by the regulatory community; and Goodhart and Wagner (2012) have suggested that steps towards a safer financial system should not ignore the lack of diversity across financial institutions. Then, following Beale et al. (2011), regulators should pay attention to the average distance between banks as a measure of financial system's diversity and –thus- as a key observable feature of systemic risk. In this vein, as liquidity spirals and common shocks are more likely and intense when financial institutions share

similar portfolio positions and financial structures, monitoring similarity dynamics may help to identify systemic risk build up.

Empirical related literature, devoted to measuring and examining the homogeneity in banking systems, is not abundant and has surfaced recently. Pool et al. (2015) measure the overlapping (i.e. similarity) of mutual funds managers' stock portfolios, but they focus on studying whether such overlap may be explained by the social interaction of those managers. Fricke (2016) examines the dynamics of homogeneity for Japanese banks' loans portfolio from 1996 to 2013. Cai et al. (2017) study the similarity of banks by measuring the similarity between their syndicated loan portfolios in the United States from 1989 to 2011. Our work is closely related to that of Fricke (2016) and Cai et al. (2017), but we contribute to literature by implementing an agglomerative clustering technique to identify the groups of banks that may be regarded as particularly similar, and by using an unusually granular set of financial statements.

Some limitations are worth noticing. We limit our scope to banks because they are the most prevalent type of financial institution in related literature. As banks account for about 76 percent of all financial institutions' assets in the Colombian case, our results are fairly representative. Also, due to some limitations on the extension of the datasets available, we restrict our examination to 2016's average monthly financial statements.⁴ Moreover, although the dataset provides a particularly granular decomposition of banks' financial statements that exceeds the standard supervisory analysis, our exercise is unable to explore higher dimensions of banks' financial position, such as the identity, industry, or geographical location of lenders and borrowers, which may be key to supplement the assessment of homogeneity across banking institutions. Therefore, as we neither assess Colombian banking system complexity nor incorporate higher dimensions of diversity nor consider the soundness of banks, conclusive inferences about systemic risk and financial stability are pending. Finally, an explanatory model of homogeneity is not intended.

⁴ Datasets are available since 2015 (after the adoption of International Financial Reporting Standards). Thus, examining the dynamics of homogeneity for a small number of months (about 30) is –in our view- inadequate at the moment.

2 Complexity and homogeneity in financial systems

Complexity has been related to the existence of a system with a large number of elements that interact in a non-simple (e.g. non-linear) way, in which the whole is more than the sum of its parts (Simon, 1962). Similarly, Arthur (1999) pinpoints that all studies on complexity are systems with multiple elements adapting or reacting to the pattern these elements create.⁵

Financial systems' complexity has no single definition and is difficult to measure (Gai et al. 2011). Yet, some distinctive features of financial systems' complexity are rather evident (see Arthur, 1999, Sornette, 2003, May et al., 2008, Landau, 2009, Haldane, 2009, León et al. 2012, Farmer et al., 2012). First, the large number of financial institutions (i.e. the elements of the system). Second, financial institutions' numerous, intricate, and somewhat opaque connections across several dimensions (e.g. markets, financial products, jurisdictions), which may take many forms, such as bilateral exposures (e.g. Bank A lends Bank B), payments (e.g. Bank A transfers funds to Bank B), common exposures (e.g. both Bank A and Bank B hold a bond issued by Firm C), and ownership relations (e.g. Bank A is the holding of Bank B). Third, financial institutions react with strategy and foresight by considering outcomes that might result as a consequence of behavior they might undertake; that is, elements are adaptive. Fourth, the size of an event and its consequences may be unrelated, with modest events triggering disproportionately large changes (e.g. the US sub-prime crisis triggering the 2007-2008 global financial crisis). As highlighted by Lo (2011), the once simple and almost boring banking business (e.g. accepting deposits, paying interest, and making loans) has turned complex (e.g. spanning many markets, business, countries, and financial instruments) thanks to competition, deregulation, globalization, population growth, and technological and financial innovation.

Homogeneity has been related to the lack of diversity among the elements of a system. Contemporary financial systems' homogeneity is related to the sharp loss of diversity among financial institutions. Correspondingly, as emphasized by Goodhart and Wagner (2012), financial institutions –in particular very large ones- have become very similar to each other. From a behavioral viewpoint, herding and imitation in financial markets (see Sornette, 2003)

⁵ Yet, there are many definitions and measures of complexity, intended for different purposes. The interested reader is referred to Anderson (1999) and Mitchell (2011).

may be enduring factors behind this lack of diversity. However, there has been a recent severe loss in diversity, which has resulted from an extensive pursuit-of-return, uniform risk management tools, extreme spread of risk management “best practice”, consolidation, deregulation, disintermediation, and innovation (see Rebonato, 2007, Wagner, 2008, Haldane, 2009, Goodhart & Wagner, 2012). Reduced diversity is apparent in homogenized financial sector balance sheets and risk management practice, and in financial institutions’ similar trading strategies, and correlated positions and returns (see Rebonato, 2007, Brown et al., 2009, Haldane, 2009, Haldane & May, 2011, Goodhart & Wagner, 2012).

Beale et al. (2011) suggest that the recent lack of diversity may be driven by a *uniform diversification* process, which results in a state of the banks maximally herding together in the sense of adopting the same set of exposures by adopting common diversification strategies. In such a process, financial institutions diversify their risks and lower their own failure probability, but at the expense of increasing the failure probability of the system as a whole (see Wagner, 2008, Wagner, 2010, May & Arinaminpathy, 2010, Ibragimov et al., 2011, Haldane & May, 2011, Fricke, 2016). That is, although diversification may be good for individual institutions, it can create dangerous systemic effects, and as a result financial contagion gets worse with too much diversification (Caccioli et al., 2014). In this vein, many banks diversifying in similar ways makes joint failures more likely (Beale et al., 2011) because diversification makes the banks more similar to each other by exposing them to the same risks (Wagner, 2010). Also, when a large number of financial intermediaries choose the same investment strategy (i.e. their portfolios are very similar) the financial system as a whole becomes vulnerable to common shocks (Aymanns & George, 2015), and the lack of opposite positions can give rise to extreme price movements (Farmer et al., 2012). A stable financial system needs a diversity of views on risks that are competing with each other (Goodhart & Wagner, 2012).

The perils related to homogeneity are well known to complex systems’ literature. From a general viewpoint, Anderson (1999) highlights that partially connected systems (e.g. non-homogeneous) are less unstable as the behavior of a particular agent depends on the behavior (or state) of some subset of agents in the system.

Financial systems' systemic risk surging from homogeneity may be portrayed as a *bipartite network* (see Zhao et al., 2013, Huang et al, 2013, Caccioli et al., 2014). A bipartite network is a graph with two groups of elements, in which linkages are inter-group only. In the financial systems' base case the two groups are financial institutions and assets (or liabilities, industries, etc.), in which a link exists between a bank and an asset when the bank has the asset in its portfolio, whereas no links between banks or assets exist.⁶

In the bipartite network framework risk propagates bidirectionally between assets and banks, and may be transmitted from one bank to another bank via a shared set of assets, and from asset to asset via a common set of holders. For instance, a sharp decline in the price of an asset may force a bank into a clearance sale of its portfolio that may further push asset prices downwards, therefore affecting other banks and other assets in a spiral of sales and descending prices. Intuitively, although banks have attained maximal diversification in the completely interconnected case portrayed in panel a. of Figure 1, the spiral of sales and descending prices should be pronounced because all banks are linked by means of their common holding of assets (i.e. they are homogeneous). On the other hand, a weakly connected bipartite network (panel c.) should be immune to the aforementioned spiral effect, whereas a partially interconnected bipartite network (panel b.) should be affected in a limited manner. In this vein, as in a weakly connected system the short-run behavior of each of its components is approximately independent of the other components (Simon, 1962), avoiding financial system's portfolio homogeneity allows for an advantageous degree of independence in the system, and a lower incidence of systemic risk and financial instability.

⁶ The assumption of no links among banks and among assets may be relaxed as well. This may be convenient as banks are linked to each other because of, say, interbank lending, and because asset price dynamics tend to display dependence (e.g. correlation). None of these intra group effects are considered here, but are key for a comprehensive portrait of risk propagation.

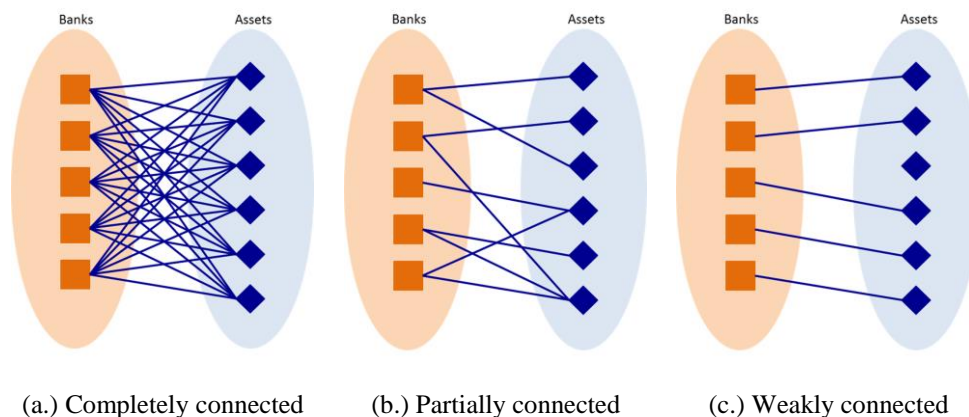


Figure 1. Bipartite networks of banks and assets. In the completely connected case (panel a.) all banks share the same set of assets (i.e. they are homogeneous because of their overlapping portfolios); thus, although all banks have a diversified portfolio, potential contagion due to a spiral of sales and descending prices is maximal. In the weakly interconnected connected case (panel c.) contagion is, by construction, at the lowest among the three cases –despite diversification is rather low.

Strogatz (2003) suggests that there is a connection between the homogeneity of elements in a system and the latter’s propensity to lock in a potentially unstable state in which all elements act in a synchronized manner. And, by means of analogy, *ceteris paribus*, the more homogeneous financial institutions are, the more prone the financial system is to instability (Strogatz, *private communication*). Likewise, Wagner (2008) and Goodhart and Wagner (2012) suggest that a more homogeneous financial system means that contagion effects are likely to be more pronounced as a failure of one institution is then more likely to occur at times when other institutions are under stress. In this vein, as highlighted by Gai et al. (2011), the financial system has become markedly more susceptible to systemic collapse because it has become more homogeneous.

Accordingly, in the spirit of Simon (1962) and Anderson (1999), systems’ fragility may be mitigated by allowing more heterogeneity among its elements. Hence, with financial stability in view, literature after the global financial crisis agrees on advising financial authorities to avoid financial institutions’ homogeneity by means of fostering financial markets’ diversity. For instance, Haldane & May (2011) assert that in rebuilding and maintaining the financial system, the systemic diversity objective should probably be given much greater prominence by the regulatory community. Likewise, to avoid the uniform diversification problem and its harmful consequences, regulators may wish to give banks

incentives to adopt differentiated strategies of diversification (Beale et al., 2011). Or, as suggested in Allen et al. (2012) and Wagner (2010), from a systemic viewpoint, it may be optimal to limit or discourage diversification.

3 Agglomerative clustering⁷

Under the assumption that the data represents features that would allow distinguishing one group from another, a clustering procedure organizes a set of data into groups of observations (i.e. clusters) that are more similar to each other than they are to observations belonging to a different group (Martínez et al., 2011). The main concern in clustering is to reveal the organization of patterns into “sensible” groups, which allows to discover similarities and differences, and to derive useful conclusions about them (Halkidi et al., 2001). As the clustering algorithm discovers by itself how the data may be organized, a clustering problem is considered an *unsupervised machine learning* problem (see Sumathi & Sivanandam, 2006).

In agglomerative clustering methods we start with m groups (one observation per group) and successively merge the two most similar groups until we are left with one group only (Martínez & Martínez, 2008).⁸ The result of agglomerative clustering methods is a hierarchical structure that represents how observations relate to each other based on their cross-section similarities. The more similar their features, the closer they are in the hierarchy. The resulting structure is constrained to be hierarchical because the groups or clusters can include one another, but they cannot intersect (Witten et al., 2011).

The hierarchical classifications produced by agglomerative clustering are represented by a two-dimensional diagram known as a *dendrogram or tree diagram*, which illustrates the successive merges made at each stage of the procedure (Everitt et al., 2011). As the resulting hierarchy contains the entire topology of the observations’ grouping, it allows unveiling how

⁷ This section is based on León et al. (2017).

⁸ Divisive clustering methods exist as well (i.e. starting with a single group containing all observations and successively splitting them until there are m groups with one observation per group), but they are less common. Other clustering methods are available as well (e.g. k-means, fuzzy clustering, model-based clustering, and spectral clustering).

the data is classified as the number of groups varies –from a single group to m groups, or viceversa.

The key in agglomerative clustering is the selection of a dissimilarity measure. Distances are used as measures of dissimilarity, in which small (high) values correspond to observations that are close (distant) to (from) each other. Let x_{iw} be the w -th feature (e.g. the w -th item in the financial statement) of the i -th observation (e.g. the i -th bank), the most commonly used measure of distance between two banks, i and j , is their Euclidean distance, d_{ij} :⁹

$$d_{ij} = \sqrt{\sum_w (x_{iw} - x_{jw})^2} \quad [1]$$

Similarity between two banks i and j as in [1] is calculated using all the features or accounts in the financial statements. The distance between two banks i and j is ultimately determined by the sum of the distances between i and j for each w -feature. If all w -accounts in the financial statements are strictly the same for two banks i and j , then $d_{ij} = 0$. Also, as a byproduct of the square of differences, $d_{ij} = d_{ji}$ (i.e. dissimilarity between two banks is symmetric). Finally, with respect to a third bank g , the distance between i and j , d_{ij} , should be lower or equal than the sum of distances d_{ig} and d_{gj} (i.e. $d_{ij} \leq d_{ig} + d_{gj}$).

If there are n banks, the pairwise dissimilarity between them is presented as a $n \times n$ square matrix, which is commonly known as an interpoint distance matrix. Let D be an interpoint distance matrix based on a Euclidean distance, D is squared and symmetrical:

⁹ Euclidean distance is the most often used for continuous data because of its simplicity and interpretability as a physical distance. Other measures of distance exist as well (see Martínez & Martínez, 2008, Everitt et al. 2011). Cai et al. (2017) chooses Euclidean distance to measure similarity between banks' syndicated loan portfolios in the United States. When examining the homogeneity in Japanese banks' loan portfolios, Fricke (2016) use several measures of distance, including the Euclidean distance; all measures are reported to be strongly correlated, and results are reported to be robust to the choice of measure.

$$D = \begin{pmatrix} 0 & d_{1,2} & \cdots & d_{1,n} \\ d_{2,1} & 0 & \cdots & d_{2,n} \\ \vdots & \vdots & \ddots & \vdots \\ d_{n,1} & d_{n,2} & \cdots & 0 \end{pmatrix} \quad [2]$$

In agglomerative clustering methods we start with m groups (one observation per group) and successively merge the two most similar groups (i.e. the less distant) until we are left with one group only. As expected, the similarity criterion for merging groups is based on distance. However, measuring the distance between groups comprising several observations is different from measuring the distance between individual observations.

The way the distance between groups or clusters is calculated is known as the linkage method. Several linkage methods are available (see Everitt et al., 2011, Martínez et al. 2011).¹⁰ The simplest method is *single linkage* (also known as *nearest neighbor* method), which uses the smallest distance between two observations pertaining to two different groups. *Complete linkage* (also known as *furthest neighbor* method) consists of using the maximum distance between two observations pertaining to two different groups. *Average linkage* uses the average distance from all observations in a group to all observations in another group. *Centroid linkage* measures the distance between clusters as the distance between the means of observations in each group (i.e. between the average observation of each cluster).

Figure 2 illustrates how these four basic linkage methods work in the case of two clusters, each one containing three observations. From left to right, the linkage methodologies are single (a.), complete (b.), average (c.), and centroid linkage (d.). The discontinuous lines illustrate how the distance is calculated in each case.

¹⁰ For a comprehensive explanation of the different linkage methods, their shortcomings and advantages, see Everitt et al. (2011) and Martínez et al. (2011).

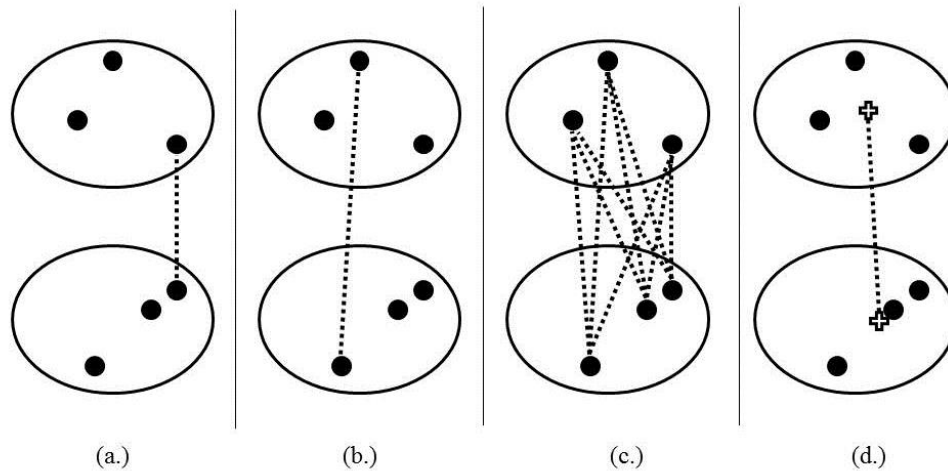


Figure 2. Single (a.), complete (b.), average (c.) and centroid linkage (d.) methods. The cross in the centroid linkage method corresponds to the average observation estimated for each cluster. Source: León et al. (2017).

Ward (1963) realized that the linkage problem could be better described with an objective function that minimizes the loss of information caused by merging two groups into a single one. Ward's choice for such objective function is the variance of distances among observations in a group (i.e. sum of squares of distances within a group); hence, it is also known as the *minimum variance method*.

Each linkage method has its own shortcomings (see Martínez et al., 2011, Everitt et al. 2011). The choice of a linkage method should pursue the validity of the clustering solution. Such validity is commonly assessed by measuring how *compact* and *separated* the clusters are. As in Halkidi et al. (2001), clustering methods should search for clusters whose members are close to each other (i.e. compact) and well-separated. A widely used clustering validity criterion is the Calinski and Harabasz (1974) clustering validity index, which is the ratio of the between-cluster distance sum of squares (i.e. separateness) to the within-cluster distance sum of squares (i.e. compactness); the larger the index the better the clustering solution.

4 The data

We use the 2016's average monthly financial statements for each bank. We focus on banks because they are the most prevalent type of financial institution in related literature, and because they are the largest contributors to financial systems' asset size (i.e. about 76 percent). Also, as there are 25 banks in the sample, working on banks instead of the entire universe of financial institutions (about 150) enables us to make a clearer visualization and analysis. The identity of banks is not disclosed.

Each financial statement in our dataset comprises 3,063 features or attributes of banks, corresponding to a six-digit filtering of statements reported to the Colombian Financial Superintendence under International Financial Reporting Standards (IFRS). These 3,063 features are continuous variables that pertain to six different categories: assets (837), liabilities (575), equity (112), operational income (442), expenses (713), and disclosure (384).

Unlike traditional (i.e. summarized) financial statements, our dataset is particularly granular. Besides, not only our datasets include granular data on assets, liabilities, equity, income and expenses, but they also comprise detailed data on banking firms' loan portfolios (e.g. classified by type of loan, days of delinquency, and type of collateral), write-downs by type of loan, and received assets –among others. Hence, it is fair to state that the dataset used to calculate the similarity among banking firms is unusually detailed and comprehensive.

Three major portfolios may be extracted from financial statements, namely the investment portfolio (145 features), lending portfolio (111) and the funding portfolio (139).¹¹ The investment portfolio and the lending portfolio pertain to the asset side of the financial statements, and they contribute to 18.62 and 67.25 percent of banks' assets, respectively. The funding portfolio pertains to the liability side, and it contributes to 86.11 percent of banks' liabilities. As not only these three portfolios account for most of assets and liabilities of

¹¹ Before transforming the features we remove those in which all banks reported figures equal to zero; this has no impact on the results (i.e. all banking firms are strictly equal with respect to those features), but may reduce computational burden and allow for a clearer visualization. After removing those blank features the number of features decrease from 3,063 to 1,327 in financial statements; from 145 to 55 in the investment portfolio; from 111 to 82 in the lending portfolio; and from 139 to 67 in the funding portfolio.

banks, but also correspond to their core banking activities, examining how similar banks are at the portfolio level is of utmost importance.

As usual, in order to avoid issues related to differences in scale or dispersion of data (see Martínez et al. 2011), the series are transformed (i.e. standardized) before calculating the distance d_{ij} as in [1]. This is done by means of subtracting their corresponding mean and dividing by their corresponding standard deviation, as in a customary z-score. After this transformation the mean and standard deviation of financial statements for each banking firm are 0 and 1, respectively. As differences in scale are avoided, the size of each banking firm is not considered as a feature. This is particularly convenient in our case because we are interested in determining how homogeneous banking firms are based on the similarity of their financial structure –not on their size.

Figure 3 exhibits a visualization for each bank (in rows) of each set of standardized features (in columns) that compose financial statements and the three selected portfolios (i.e. investment, lending, and funding). The contribution of each bank to the sum of the features is reported in the vertical axis, and it is used to rank the banks in the sample –in decreasing order. From this visualization it is apparent that there is some degree of homogeneity in the financial structure of banks for the four sets of features. However, it is also apparent that the degree of homogeneity varies across the four sets. For instance, the funding portfolio displays a hefty similarity among banks, with a clear overlapping of funding sources in the 11-15-feature range (in the horizontal axis).

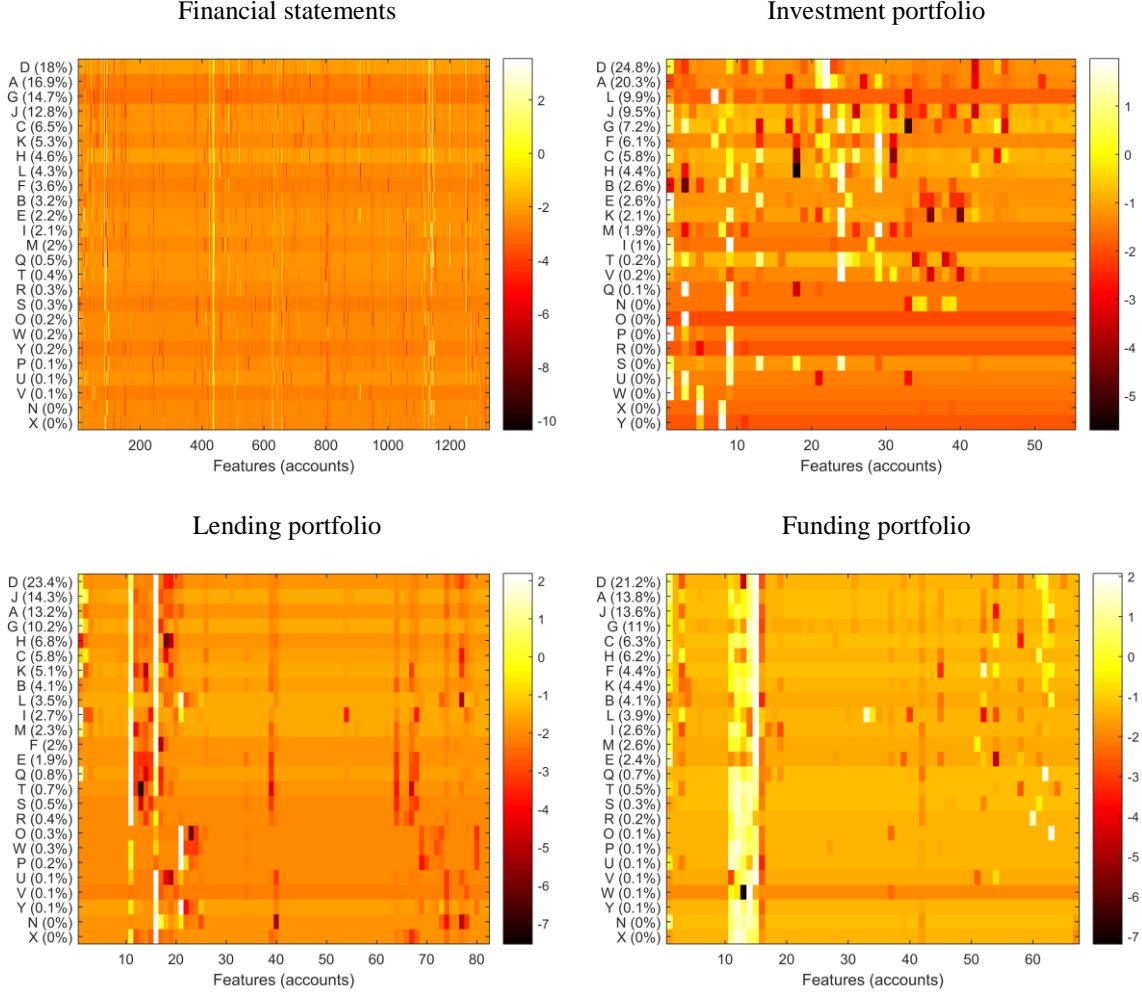


Figure 3. Features. Heatmap of each bank (in rows) of each set of standardized features (in columns) that compose financial statements and the three selected portfolios (i.e. investment, lending, and funding); the contribution of each bank to the sum of the features is reported in the vertical axis, and it is used to rank the banks in the sample –in decreasing order.

Afterwards, we build the interpoint distance matrix as in [2]. By construction, the interpoint distance matrix has a lower bound (if $i = j$, $d_{ij} = 0$) but has no obvious upper bound; hence its interpretation and comparison may be burdensome. Interestingly, as stated by Borgatti (2012), if observations are standardized there is an equivalence between Euclidean distance (d_{ij}) and correlation (r_{ij}).¹² Therefore, as correlation is easily interpreted because it is bounded to the interval $[-1, 1]$, with -1 corresponding to the most distant and

¹² As in Borgatti (2012), the Euclidean distance is a sum of squared differences, whereas correlation is an average product. If series are standardized (mean is zero, standard deviation is one), the correlation between two variables (r_{ij}) can be written in terms of the distance between them: $r_{ij} = 1 - (d_{ij})^2 / 2n$.

1 to the closest, Figure 4 exhibits a visualization of the resulting correlation matrices for the entire financial statements and the three selected portfolios (i.e. investment, lending and funding).¹³

Akin to Figure 3, the contribution of each bank to the sum of the features is reported in the vertical axis, and it is used to rank the banks in the sample –in decreasing order. It is rather apparent that those that contribute the most to the entire financial statements tend to display a lower distance (i.e. higher correlation), thus they tend to be similar; this result overlaps with Goodhart and Wagner (2012) and Fricke (2016) regarding the homogeneity of large financial institutions. It is noticeable that for the three portfolios the top contributors are alike (banks D, A, J), and they tend to display particularly high correlations among them, which may be readily interpreted as they are holding rather similar financial statements. Regarding those that contribute the less, results are mixed; yet, there are low-contributing banks that share rather common portfolios (e.g. banks O, W, and P in the lending portfolio). All in all, from visual inspection of Figure 4 it is apparent that the investment portfolio is the less homogeneous (i.e. less correlated), whereas the funding portfolio is the most homogeneous.

¹³ The interpoint distance matrices are displayed in Figure 10 (Appendix A). As expected, they conform to an inverse mapping of the correlation matrices in Figure 2.

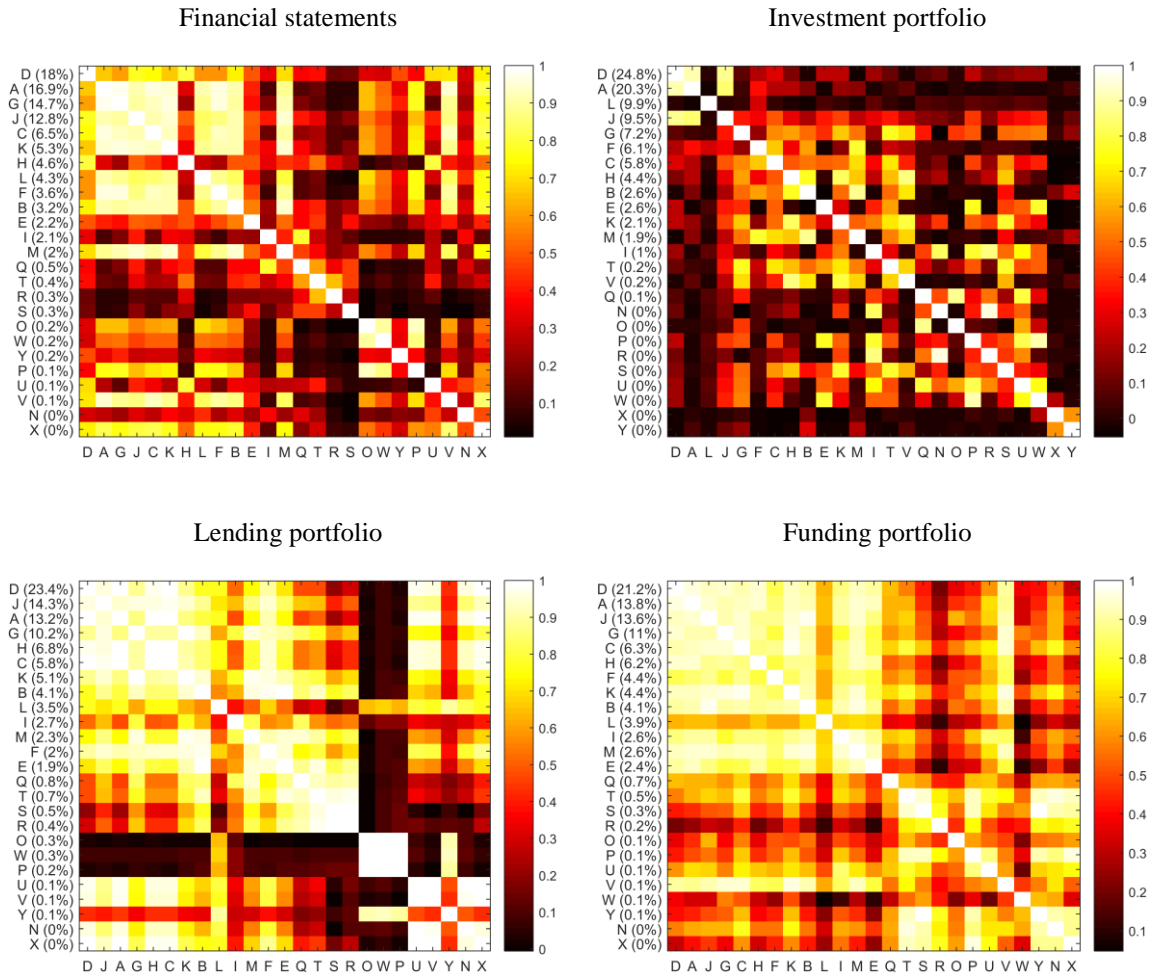


Figure 4. Correlation matrices. Distances are calculated as in [2], and transformed into the corresponding correlations (see Borgatti, 2012). The contribution of each bank to the sum of the features is reported in the vertical axis, and it is used to rank the banks in the sample –in decreasing order.

Figure 5 compares the cumulative probability distribution of correlations for the four matrices in Figure 4; Table 1 (in Appendix) exhibits the main descriptive statistics of each distribution. It is rather obvious that the investment portfolio is the one exhibiting less correlated (i.e. more distant) banks. The investment portfolio is the only one with a non-negligible number of negative correlations, but they all are not manifestly different from zero. The funding portfolio and the lending portfolio are those in which banks tend to be more correlated. For instance, the average correlation for the funding and lending portfolio are .65 and .57, respectively, whereas for the investment portfolio is .24.

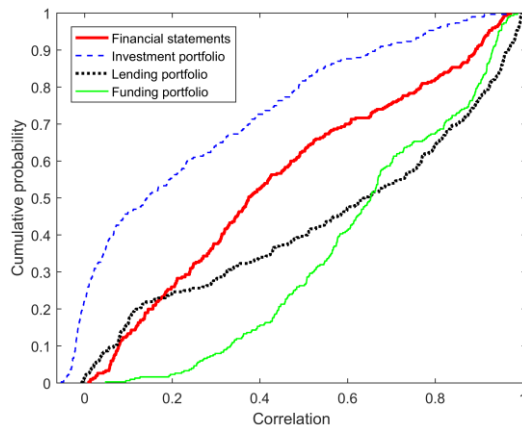


Figure 5. Cumulative probability distribution of correlations. Only the upper triangle of the matrix is considered, and the diagonal is discarded. The investment portfolio is the one exhibiting less correlated (i.e. more distant) banks, whereas the funding portfolio and the lending portfolio are those that exhibit more correlated banks. Table 1 (in Appendix) exhibits the main descriptive statistics of each distribution.

5 Main results

The hierarchical classifications produced by agglomerative clustering are represented by a *dendrogram or tree diagram*, which illustrates the successive merges made at each stage of the procedure (Everitt et al., 2011). We use horizontal dendrograms, in which the successive merge of clusters appears from right to left, with the horizontal axis representing the dissimilarity between clusters. As exhibited in Figure 11 (Appendix), Ward linkage method dominates the Calinski and Harabasz index (i.e. validity in terms of clusters' compactness and separateness); therefore we present and discuss the dendrograms corresponding to Ward linkage method only.¹⁴ As correlation is easier to interpret, we discuss similarity and clusters in terms of correlations (r_{ij}) reported in Figure 4.

Figure 6 exhibits the dendrogram corresponding to the similarity of financial statements. Two main clusters are evident. The two most similar banks by the structure of their balance sheets are G and A ($r_{GA} = .97$), which contribute to about 32 percent of the sum of features (i.e. they are the second and fourth by contribution). Banks G and A are similar to bank F as well ($r_{GF} = .95$; $r_{AF} = .96$). The largest bank by contribution (D) does

¹⁴ Several unrelated empirical studies tend to favor Ward's linkage method (see Milligan & Cooper, 1987, Ferreira & Hitchcock, 2009, Everitt et al., 2011, Hossen et al., 2015).

not resemble bank G, A or F, but it is similar to bank H ($r_{DH} = .81$). Consistent with Figure 4, it is evident that a subset of banks tend to be rather similar: banks A, G, F, C, V, L, B, J, K, M, contributing with about 70 percent of the sum of features, displays low Euclidean distances, corresponding to correlations surpassing .80. In terms of size, these ten banks account for about 63 percent of banking firms’ assets. Therefore, as the overall financial structure of a representative set of banks is fairly similar, it may be argued that a large part of the banking sector is exposed to similar shocks from an overall financial structure perspective. Although the largest bank by asset size (D) is not that similar to those in that ten-bank cluster, the average correlation with that set is about .68.

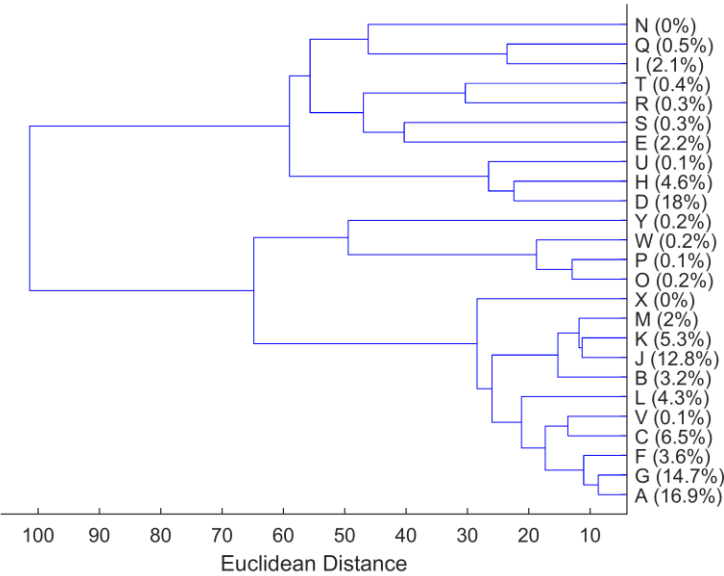


Figure 6. Financial statements dendrogram. The successive merge of clusters appears from right to left, with the horizontal axis representing the dissimilarity between clusters. Ward linkage method is used. The contribution of each bank to the sum of the features is reported in the vertical axis, and it is used to rank the banks in the sample –in decreasing order.

Figure 7 exhibits the dendrogram corresponding to the similarity of investment portfolios. Two main clusters are evident: one with ten banks contributing with about 31 percent of investment portfolios’ total value, the other with 15 banks contributing with the remaining 69 percent. The two most similar banks by the structure of their investment portfolios are R and N ($r_{RN} = .97$), but their contribution to the sum of features (i.e. size of the investment portfolio) is nil. However, the second two most similar banks are D and A

($r_{DA} = .91$), and they contribute with about 45 percent to the sum of features. Bank J is also similar to D and A ($r_{DJ} = .88$; $r_{AJ} = .85$), with all three banks contributing with about 55 percent of the sum of features. Therefore, despite most banks' investment portfolios are not very similar (i.e. average correlation is .24), the overlapping of three rather contributive banks (D, A, J) is noteworthy.

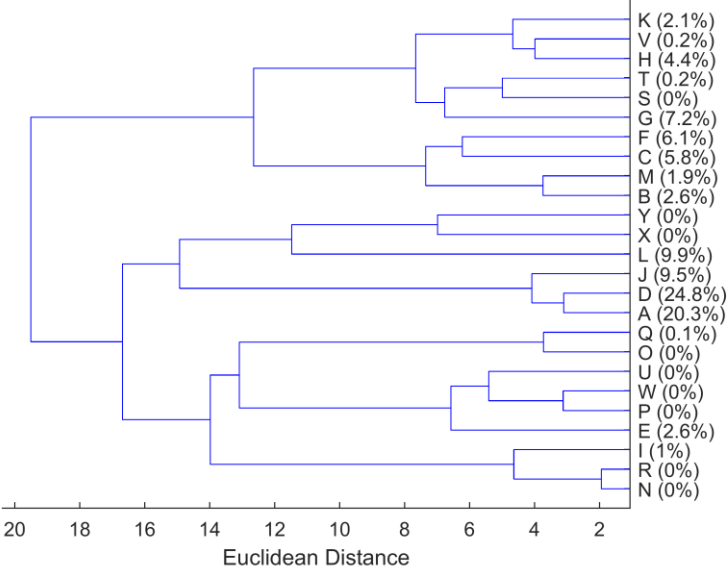


Figure 7. Investment portfolio dendrogram. The successive merge of clusters appears from right to left, with the horizontal axis representing the dissimilarity between clusters. Ward linkage method is used. The contribution of each bank to the sum of the features is reported in the vertical axis, and it is used to rank the banks in the sample –in decreasing order.

Figure 8 exhibits the dendrogram corresponding to the similarity of lending portfolios. Two main clusters are evident: one with five banks contributing with about five percent of lending portfolios' total value, the other with 20 banks contributing with the remaining 95 percent. There are several pairs of banks that share an almost identical lending portfolio structure, namely H and C, V and U, W and P, E and B, D and A, K and G, and S and R, all exhibiting correlations about .99. Although most of those pairs do not contribute manifestly to the sum of the features in the lending portfolio, the pair corresponding to D and A contribute with about 37 percent, whereas K and G contribute with about 15 percent. Moreover, the cluster of banks composed by C, H, A, D, X, J, N, U, V exhibits quite similar portfolios, with a mean correlation of .96, with a .86 minimum and .99 maximum. As this

cluster contributes with about 64 percent of the sum of features of the lending portfolio, it is fair to say that there is a significant overlap in the lending portfolio of banking firms. Also, it is fair to say that largest banks tend to have an almost identical lending portfolio.

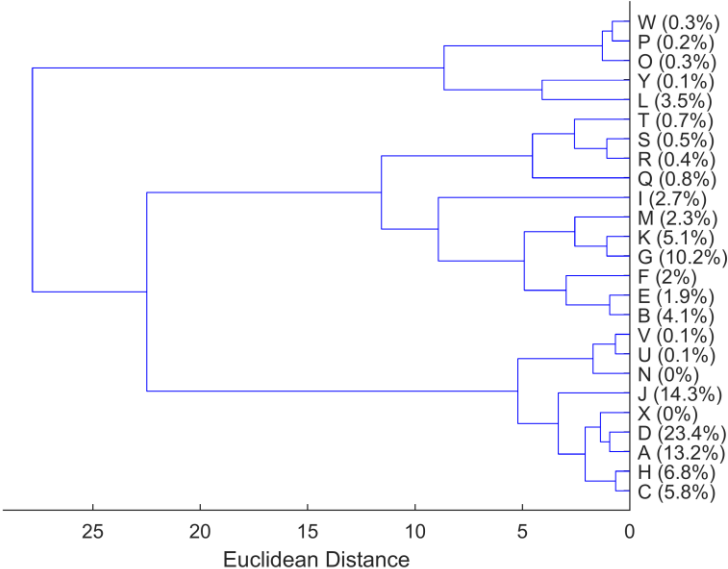


Figure 8. Lending portfolio dendrogram. The successive merge of clusters appears from right to left, with the horizontal axis representing the dissimilarity between clusters. Ward linkage method is used. The contribution of each bank to the sum of the features is reported in the vertical axis, and it is used to rank the banks in the sample –in decreasing order.

Figure 9 exhibits the dendrogram corresponding to the similarity of funding portfolios. Two main clusters are evident: one with fourteen banks contributing with about 97 percent of funding portfolios’ total value, the other with eleven banks contributing with the remaining 3 percent. In the first of these clusters there are some pairs of banks that share an almost identical funding portfolio structure, namely K and C ($r_{KC} = .98$), J and B ($r_{JB} = .97$), and D and A ($r_{DA} = .96$). Banks in this first cluster (i.e. A, D, H, E, B, J, I, M, F, C, K, V, G, L) exhibit quite similar funding portfolios, with a mean correlation of .87, with a .62 minimum and .98 maximum. Thus, as is the case with the lending portfolio, it is fair to say that there is a significant overlap in the funding portfolio of banking firms as well.

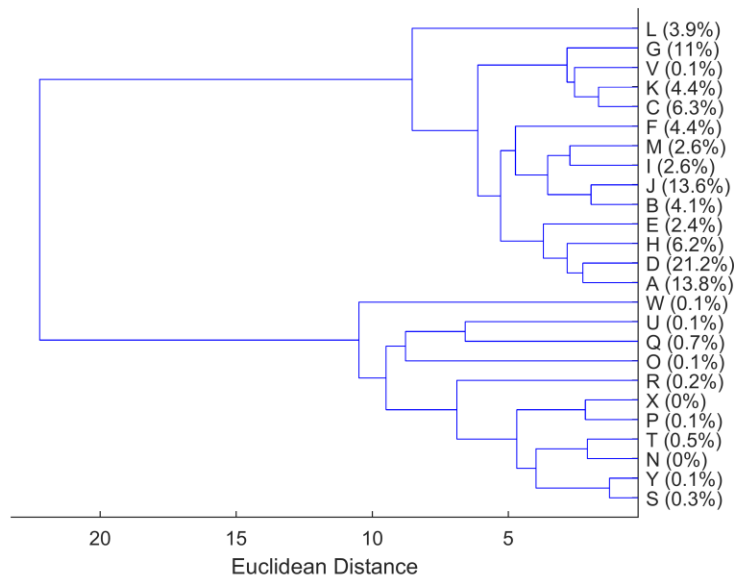


Figure 9. Funding portfolio dendrogram. The successive merge of clusters appears from right to left, with the horizontal axis representing the dissimilarity between clusters. Ward linkage method is used. The contribution of each bank to the sum of the features is reported in the vertical axis, and it is used to rank the banks in the sample –in decreasing order.

All in all, it is rather evident that Colombian banks’ financial structure displays some degree of similarity, which reveals that they are homogeneous to some extent. The structure of financial statements and of the three portfolios (i.e. lending, investment, funding) exhibit strong correlations that reveal how similar banks are in cross section. Furthermore, the clusters attained by means of grouping by similarity show that banks contributing the most to financial statements or to each portfolio tend to cluster together (i.e. to be similar). This exposes that there is an important degree of homogeneity in the Colombian banking sector, in which most contributive banks share a rather common financial structure; this overlaps with findings by Fricke (2016), who reports that in the Japanese case the largest banks have become more similar over time. Under specific circumstances, such homogeneity may become problematic as it corresponds to a state of banks potentially herding together and being exposed to common shocks by the adoption of a similar set of positions. On the other hand, non-contributive banks displaying different financial structures suggest that their size may determine their ability or willingness to follow the prevalent financial structure.

Regarding how similarity diverges between financial statements and the three portfolios here considered, it is remarkable that the lending portfolio and the funding portfolio exhibit the most homogeneous structures. This suggests that the core banking function, namely the intermediation of funds, tends to follow a common structure; yet, as the datasets are not granular enough to, say, discriminate between the lenders and borrowers of funds, there are numerous sources of heterogeneity yet to be accounted for. It is also remarkable that a pair of banks, D and A, are consistently the most similar in the investment, lending and funding portfolios; the average correlation between these two banks in the three portfolios is about .91. As D and A are the two largest banks by asset size (i.e. about 38 percent of assets, 23 and 15 percent, respectively), their high similarity is not to be overlooked.

6 Final remarks

Literature agrees on the perils arising from financial institutions' homogeneity (see Wagner, 2008, Haldane, 2009, Haldane & May, 2011, Beale et al., 2011, Allen et al., 2012, Goodhart & Wagner, 2012, Caccioli et al., 2014). Homogeneity, in the form of overlapping portfolios or similar financial positions, by providing a vector of contagion, has the potential of making a complex financial system vulnerable to joint failures (i.e. systemic risk) and prone to financial instability.

Accordingly, there is an ongoing discussion regarding how financial authorities should counter financial institutions' homogeneity (e.g. encouraging diversity, increasing capital requirements, restricting activities), namely for preserving financial stability and overall welfare (see Wagner, 2008, Ibragimov et al, 2011, Beale et al., 2011). Hence, the aim of financial authorities' intervention should be to weaken the connectedness of financial systems by making financial institutions less similar (i.e. more independent); this, in turn, should contribute to a lower incidence of systemic risk and financial instability. Thus, financial authorities face several challenges related to homogeneity, such as enhancing information, developing suitable measurements, and designing the corresponding set of

policies. These challenges add to those related to reducing the complexity of financial systems and preserving financial institutions' soundness.

Our work contributes to related literature by measuring homogeneity based on an unusually granular decomposition of Colombian banks' financial statements. Not only empirical works that measure homogeneity are scarce, but techniques to identify groups of banks that are similar by their financial structure are absent from related literature –to the best of our knowledge. In this vein, our work presents a novel application of unsupervised machine learning techniques to the examination of otherwise unexploited large and granular financial datasets. Also, our work adds to traditional approaches that pursue cross-section examination of banks, with the convenience of mitigating selection bias by working on raw data instead of using a set of arbitrarily selected financial ratios –that may discard useful information.

Results suggest that the Colombian banking sector displays some degree of homogeneity. The distance among largest banks tends to be rather low; the lending, investment, and funding portfolios of the two largest banks by asset size are particularly homogeneous. That is, akin to results reported by Fricke (2016), evidence suggests that largest banks tend to be more similar to each other. It is notable that homogeneity varies depending on the portfolio under examination: somewhat surprising, the investment portfolio is the less homogeneous, whereas the lending and funding are the most homogeneous.

The empirical outcomes here reported should shed some light on the homogeneity of the Colombian banking sector. However, as homogeneity is one among many factors contributing to systemic risk, inferences are to be made with caution. It is inadequate to draw conclusions about systemic risk based solely on how homogeneous the banking system is. The contribution of homogeneity to systemic risk and financial instability in the Colombian case is conditional on unexplored factors, such as banking sector's complexity and soundness, along with higher dimensions of diversity that are unavailable in financial statements.

Some paths of future work are worth stating. First, as datasets are available since 2015 only, a proper dynamic examination of homogeneity is pending –as in Fricke (2016). Second,

as financial statements do not allow for further exploring, say, the identity, industry, or geographical location of lenders, borrowers or issuers, it is obvious that there are some other dimensions of similarity awaiting to be considered; using other types of detailed reports gathered by financial authorities or financial market infrastructures is a promising avenue of research. Third, taking into account the relevance of non-banking financial institutions (e.g. pension funds, broker-dealers), it may be convenient not to limit the examination of homogeneity to banking institutions. Fourth, as homogeneity is an additional contagion channel to counterparty and liquidity risk, aggregating them into a comprehensive measure of contagion risk is a pending challenge. Fifth, despite literature focuses on the perils arising from similarity, monitoring and examining why some banks diverge manifestly from others may be valuable for financial authorities too. Finally, an explanatory model for the determinants of similarity among banks, with traditional (e.g. leverage, profitability, size, credit risk rating) and non-traditional variables (e.g. belonging to a conglomerate, relationships), may reveal some interesting features of the banking sector.

7 References

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8 Appendix.

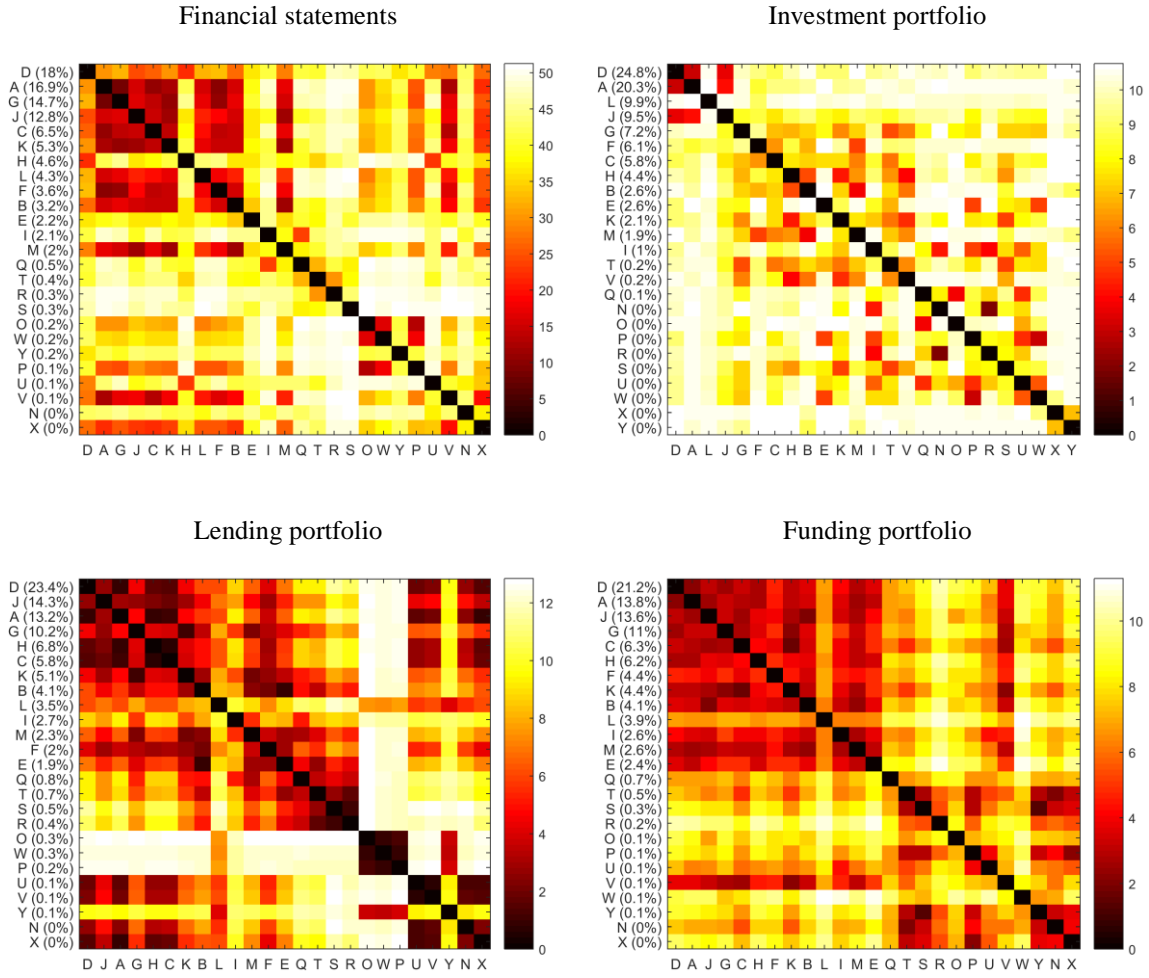


Figure 10. Interpoint distance matrices. Distances are calculated as in [2]. The contribution of each bank to the sum of the features is reported in the vertical axis, and it is used to rank the banks in the sample –in decreasing order.

	Financial statements	Investment portfolio	Lending portfolio	Funding portfolio
Minimum	.01	-.05	-.06	.00
Mean	.44	.24	.57	.65
Median	.37	.14	.64	.65
Maximum	.97	.97	.99	.99

Table 1. Descriptive statistics of correlations. Only the upper triangle of the matrix is considered, and the diagonal is discarded.

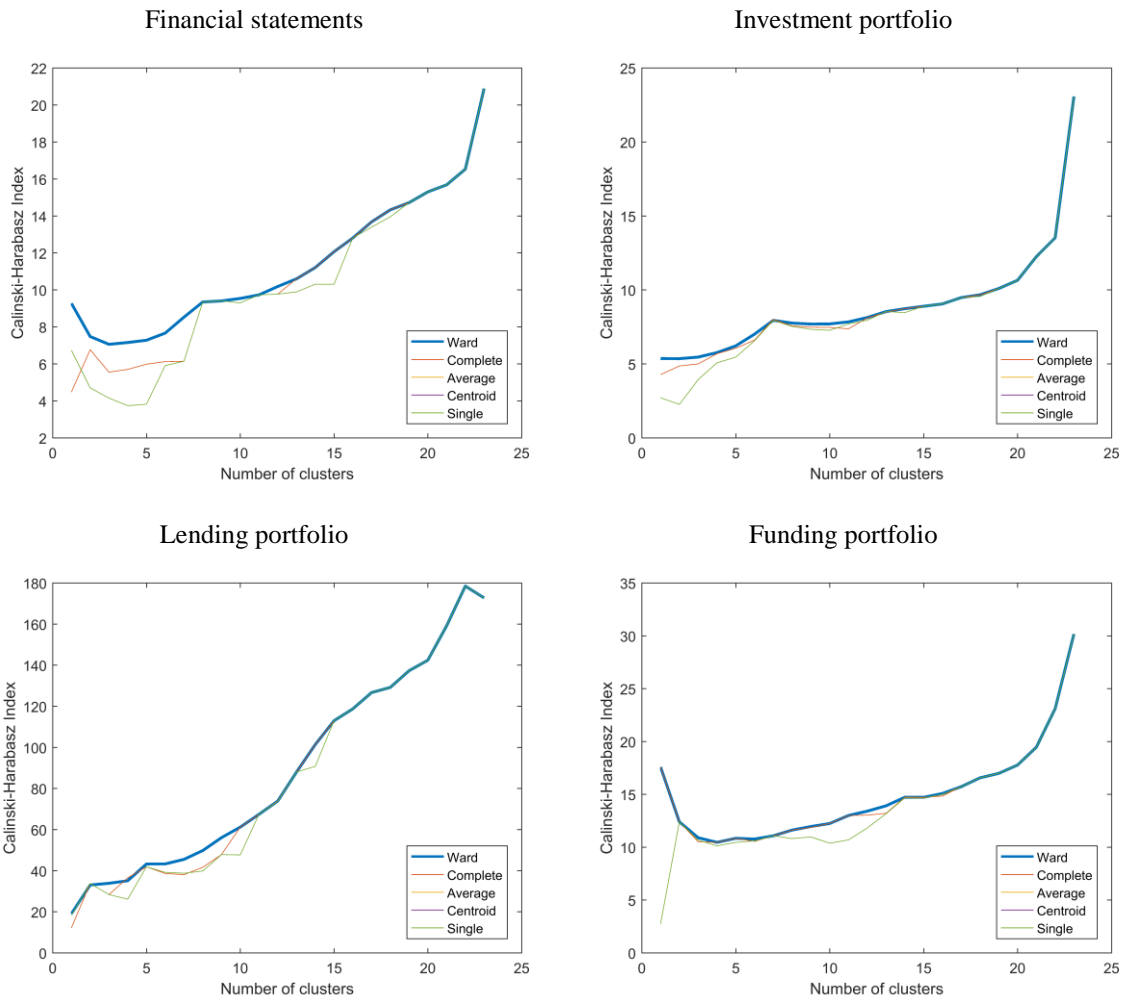


Figure 11. Calinski-Harabasz index (Calinski & Harabasz, 1974). Calculated as the ratio of the between-cluster distance sum of squares (i.e. separateness) to the within-cluster distance sum of squares (i.e. compactness); the larger the index the better the clustering solution.

