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José Alejandro Fernández Fernández
Corresponding author
ESERP University,
Madrid,
Spain
alejandr0fernandez@hotmail.com

Virginia Bejarano Vázquez
UNED University,
Madrid,
Spain
vbejarano@cee.uned.es

Juan Antonio Vicente Virseda
UNED University,
Madrid,
Spain
javicente@cee.uned.es

The US Banking System: Does the Size of the Institution Matter to Its Economic-Financial Situation?

Summary: This paper analyzes the relationship between the size of the entities in the US banking system and their economic-financial situation. The objective of this study is to group different economic and financial variables of the entities together into factors that characterize the US banking system and identify how the factors vary according to the size of the entities. To do this, we start from the values taken by 32 economic-financial and regulatory ratios, obtained directly from the Federal Deposit Insurance Corporation (FDIC), for a period between the first quarter of 1990 and the penultimate of 2016. With this data it is performed a factorial analysis that allows synthesizing the 32 variables in 7 factors and, at the same time, obtaining relationships between these variables and the size and between themselves. Finally, through a neural network, the previous factors are hierarchized according to the influence that the size of the entities exerts on them. Among the conclusions reached, it should be noted that the loan structure is the factor that best classifies the size. It also determines the existence of a negative "profitability-solvency" relationship with larger entities, (Assets > \$250 B.) and smaller ones (Assets < \$100 M.), as well as demonstrating the existence of moral hazard and the need for regulation that limits said risk (because the largest entities are the least solvent and assume the most risks).

Keywords: Neural network, Factor analysis, Size, Moral hazard, Systemic risk solvency.

JEL: G20, G21, M41.

The introduction, in Basel III (Bank for International Settlements 2010), of capital restrictions on larger institutions which pose a systemic risk to the financial system, brought into relief the importance of this variable when measuring this risk. This paper analyzes the possible influence of size on the more or less stringent application of certain regulatory measures also aimed at other variables such as risk, capitalization, liquidity, profitability, efficiency and portfolio impairment, which in turn would be impacted by it. In particular, by using factor analysis together with a neural network, an analysis is conducted of the behavior of all the indicated variables in the US banking system over the period from the first quarter of 1990 until the third quarter of 2016.

This work contributes to the existing literature in which the relationship of the size of banking entities with their economic-financial variables is studied. This takes on a holistic view through ratios of the entities' financial statements, combining two techniques not used in this type of study, thus carrying a number of advantages. The use of factor analysis allows for reduction of the dimension of the variables used, as well as defining the structure of the data. This is how the structure of the US banking system is defined.

One of the differences of this work compared with other studies is that some inputs and outputs are not established. This is achieved by using an unsupervised machine-learning technique, such as factor analysis. With this, we are able to characterize how the factors obtained behave against the size of the entities in two ways. Firstly, discriminating according to the established size groups as the factors behave. Secondly, temporarily over the years of study, we analyze how the factors behave according to the size groups. This analysis will allow us to study important aspects such as moral hazard, systemic risk and other characteristics that define the factors obtained.

Another contribution of the work is the identification of the factors that determine the size according to its degree of importance, using the neural network technique.

First in Section 1, the study of art is carried out. In Section 2, the data and variables used are defined and in Section 3 the methodology and analysis of the results are presented, both of the factorial analysis and the neural network. Then, we present the conclusions.

1. Review of Existing Literature

The last financial crisis (2008) reignited the existing debate in banking regulation circles about the moral hazard borne by financial systems caused by the more risky conduct observed among larger institutions, which may have gone beyond acceptable limits. Back in 1994, John H. Boyd and Mark Gertler (1994) highlighted how one of the primary objectives of the first Basel Accords (1988) was indeed to scale down excessive risk-taking by large banks. These may have judged that there existed an implicit support by Governments that, fearing possible collapses, were willing to bear the possibly too high a cost, of rescuing banks to avoid such failures. In this same line of reasoning, Dean Baker and Travis McArthur (2009) calculated a parameter, defined and referred to by them as the "subsidy differential" which large banks benefitted from compared with small ones. They found evidence of the existence of this implicit state support, which is instrumental in the application of lower interest rates for larger banks by the markets compared with those for small institutions by assigning a lower risk premium to the former. This interesting relationship is examined in this paper through factor analysis. Tigran Poghosyan, Charlotte Wergerb, and Jakob de Haan (2016), taking the "Fitch" financial corporation ratings as the tool for their analysis, observed and concluded that, on the one hand, such ratings were contingent on the size of the bank and, on the other, that there was an implicit State support for larger institutions. These studies confirm the importance of size in reducing the perception of risk by the market and rating agencies. The implicit support from a state can cause changes in the balance sheet structure of each entity, depending on the size and generated systemic risks in the largest entities, such as an increase in leverage. We cover all of these aspects in our work.

Among the works that report the influence of the size of systemic risk, Simone Varotto and Lei Zhao (2014) stand out. These authors conclude that size is a fundamental explanatory factor in increasing said risk. In contrast to other authors, they developed new tools aimed at measuring this risk among smaller institutions. Luc Laeven, Lev Ratnovsli, and Hui Tong (2016) meanwhile concluded that the size-systemic risk ratio is directly proportional.

Among the studies combining the aforementioned variables (size-moral hazard-systemic risk), Asli Demirgüç-Kunt and Harry Huizinga (2011) found – in contrast to the conclusions of Baker and McArthur (2009) – that in principle, moral hazard is moderated in systemic banks due to the properly functioning discipline of the markets, which have the capacity to impose greater financing costs on them. However, the risk-performance ratio is weaker in systemically important banks, in larger countries, owing to the State's implicit willingness to shore up the banks in systemic risk situations. In sum, these authors found that the moral hazard is more acute in countries with a greater capacity to save their banks, such is the case in the US, the subject of analysis in this paper. In our work we will analyze these relationships, differentiating the entities according to various sizes and in conjunction with the structural characteristics of the banking system that are defined according to the factors obtained.

In relation to the limitation of the negative externalities which larger entities can cause, there is literature for and against its regulation. Ata Can Bertay, Demirgüç-Kunt, and Huizinga (2013) observe a predominance of wholesale and short-term financing with higher leverage ratios in larger entities. They conclude that, on average, funding costs are inversely proportional to the size of the bank, which leads them to show support for regulatory action as a method of reducing systemic risk. Francesco Vallascas and Kevin Keasey (2012) also concluded that limits on bank size have a positive influence on the reduction of a systemic risk. Conversely, a previous study by Jean Dermine and Dirk Schoenmaker (2010) was not in favor of restricting bank size due to the diminished risk diversification this may lead to. Finally, Chun-Nan Chen et al. (2011) observed that with larger banks and greater investment diversification the "specific risk" was reduced but at the expense of increasing the systemic risk, concluding that measures for minimizing moral hazard should be applied in a way that does not hamper institutions' risk diversity.

Regarding market concentration, Edgar A. Ghossoub and Robert R. Reed (2015) demonstrated, through a theoretical model of imperfect competition among banks, that the European Union tends towards a greater banking concentration, reaching an optimum level, according to the authors, with a large number of large banks and a small number of smaller institutions. They also conclude that in a more concentrated market, institutions have higher liquidity ratios and are less likely to grant loans, which was likely a consequence of the timeframe they analyzed. And finally, they believe the impact of monetary policy on the regional economy is very weak when there is a predominance of large entities and *vice-versa*; the influence on the monetary policy measures is smaller for smaller institutions.

Profitability is another aspect studied at work and is one of the factors defined with efficiency. With regard to profitability, Choudhry T. Shehzad, de Haan, and Bert Scholtens (2013) concluded that profitability and the bank growth variable bear no relation to the size. However, in OECD countries with higher *per capita* incomes, the largest banks grow more slowly and are more profitable than small banks. Virginie

Terraza (2015) has found evidence of a positive relationship between efficiency and bank profitability, capital and profitability and finally, between liquidity risk and bank size. This is due, the author posits, to larger banks having fewer demand deposits, thus requiring fewer liquid reserves than smaller banks.

As for the quality of the assets and the amount of leverage, aspects that are the object of study, in the study, Tianxi Wang (2013) explains that bank expansion coupled with little variation in market share leads to a lowering of the quality of its assets, although he concludes that larger banks are better at surviving the competition.

Our study is also related to the literature that evaluates bank concentration, using a study variable of size and different ratios that we use in our work, that determine solvency or liquidity. Hubert P. Janicki and Edward S. Prescott (2006) mathematically describe the process of bank concentration in the United States, especially after 1980 in the wake of the deregulation process initiated by Reagan, which allowed banks to make riskier investments. De Haan and Poghosyand (2011) also found in the US an inverse relationship between size and yield volatility, and directly between the latter and the degree of concentration in the market. Joseph N. Heiney (2011), also in the United States, showed how one of the effects of the coming into force of the Riegle-Neal Act in 1994, was a reduction in the number of smaller banks. David Carter, James McNulty, and James Verbrugge (2004) conclude that the smaller US banks make better decisions with regard to choosing which loans to grant. According to Hirofumi Uchida, Gregory F. Udell, and Wako Watanabe (2006), this is because smaller banks have an advantage when processing information before granting a loan because of their regional specialization that provides them with better client knowledge.

Among the studies attempting to identify which variables are the most representative for measuring the size of the institutions, the most notable is that undertaken by Jan Schildbach (2017), who concludes that "assets" is the variable most often used by academics and regulators. Based on these conclusions, this study has chosen this variable for this purpose. One alternative is "overall exposure", proposed by Basel III (Bank for International Settlements 2011), for the purpose of calculating the leverage ratio. This variable is not included in this study due to the difficulty in obtaining the necessary data.

2. Data and Variables Used

To analyze the US banking system under the terms set out in the introduction to this study, a number of ratios have been selected which are defined by the Federal Deposit Insurance Corporation (hereinafter FDIC)[1] (see Table 1). Their values have been obtained from the quarterly financial statements of all the institutions forming part of the US banking system[2], for the period between the first quarter of 1990 up until the third quarter of 2016. The institutions have been grouped according to size, measured in terms of the amount of total Assets, into the five groups below (in billions of dollars):

[1] Independent US Federal Agent, equivalent to the Spanish Deposit Guarantee Fund, whose mission is to guarantee deposits up to $100,000 in member commercial banks.
[2] Credit unions are not included in the FDIC.

1) Assets > 250 billion;
2) Assets \$10 Billion - \$250 Billion;
3) Assets \$1 Billion - \$10 Billion;
4) Assets \$100 Million - \$1 Billion; and
5) Assets < \$100 Million.

Table 1 shows the selected ratios and their definition. Table A1 in the Appendix contains the tables with the descriptive statistics.

Table 1 Selected Ratios

Name	Definition
Assets > 5 years as a percent of total assets	Loans and debt securities maturing > 5 years Total assets
Average assets per employee (\$ millions)	Total assets No. employees (average)
Commercial real estate loans as a percentage of total assets	Loans for the purchase of commercial real estate Total assets
Core capital (leverage) ratio (pca)	Capital requirement Asset exposure
Cost of funding earning assets	Cost of interest paid Loans and investments earning interest and dividends
Efficiency ratio	Operating income General expenses (business)
Equity capital to assets	Equity Total assets
Insured deposits as a percent of total deposits	Deposits insured by the FDIC Total deposits
Loss allowance to noncurrent loans and leases (coverage ratio)	Impairment Loans and leases in “non asset” status + 90 days or more past due date
Loss allowance to loans and leases	Impairment Total loans and leases
Loss provision, percentage of net operating revenue	Impairment provision Operating margin
Loss provisions, percentage of net charge-offs	Impairment provision Total loans and leases charged off and recovered a posteriori
Net interest margin	Receivable interests and dividends - interests paid Average productive assets
Net charge-offs to loans and leases	Total loan & lease charge-offs - recovered a posteriori Total loans & leases
Net loans and leases to total assets	Net loans & leases Total assets
Net operating revenue as percentage of average assets	Operating margin Total assets
Noncurrent assets plus other real estate owned to assets	Long-term investments + real estate investments Total assets
Noncurrent loans and leases as a percent of tier 1 capital plus reserves	Loans & leases 90 days or more past due date and in “non-asset” status Capital tier 1 + Reserves
Non interest expense as percentage as average assets	Non-interest payment expenses Total assets
Non interest income as percentage of average asset	Non-interest payment income Total assets
Percent of loans and leases 30-89 days past due	Loans & leases 30 to 89 days past due date Total loans
Percent of loans and leases noncurrent	Loans & leases 90 days or more past due date and in “non-asset” status Total loans

Pretax return on assets	Profit/(loss) before income tax / Total assets
Pretax return on equity	Profit/(loss) before income tax / Equity
Return on assets	Profit/(loss) for the period / Total assets
Return on equity	Profit/(loss) for the period / Equity
Retail loans as a percent of total loans	Retail loans / Total loans
Risk-weighted assets to total assets	Risk-weighted assets / Total assets
Tier 1 risk-based capital ratio (pca)	Capital tier 1 / Risk-weighted assets
Total deposits as a percentage of total assets	Total deposits / Total assets
Total risk-based capital ratio (pca)	Total capital requirement / Risk-weighted assets*
Yield on earning assets	Interests + dividends + commissions / Total assets

Notes: * Calculated according to the currency control bureau.

Source: Compiled by authors based on the FDIC Quarterly Banking Profile.

3. Empirical Results

The Principal Component Analysis (PCA) is a statistical technique for the synthesis of information or reduction of the dimension (number of variables).

Given n observations of p variables, $m < p$ any variables that are linear combinations of the original p and are uncorrelated, will be searched, collecting most of the information or variability of the data.

We consider a series of variables $(x_1, x_2, \dots x_p)$ on a group of objects or individuals from which, we calculate a new set of variables $(y_1, y_2, \dots y_p)$. We correlate them with one another, working out which variances progressively decrease. Each y_j (where $j = 1, \dots, p$) is a linear combination of the original $x_1, x_2, \dots x_p$, that is:

$$y_j = a_{j1}x_1 + a_{j2}x_2 + \dots + a_{jP}x_p = a'_j x, \quad (1)$$

where $a'_j = (a_{j1}, a_{j2}, \dots, a_{jp})$ and $x = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_p \end{bmatrix}$

The objective is to maximize the sum of the variances of $y_1 = a'_1 x$, $y_2 = a'_2 x$,…, $y_p = a'_p x$ where a_1, a_2,…, $a_p$are the vectors that define the plane. The objective function will therefore be:

$$L(a_1, a_2, \dots, a_p) = a'_1 \sigma a_1 + a'_2 \sigma a_2 - \lambda_1(a'_1 a_1 - 1) - \lambda_2(a'_2 a_2 - 1). \quad (2)$$

Imposing the following restrictions:

$$a'_i a_i = 1, a'_i a_j = 0.$$

Therefore, factor analysis, as we know, seeks to uncover the factors that explain most of the common variance. Specifically, new "fictitious variables" are calculated, which, despite being unobservable, are a linear combination with the real ones and can reveal most of the information about these real variables.

Table 2 KMO and Bartlett's Test

KMO and Bartlett's test		
Kaiser-Meyer-Olkin measure of sampling adequacy		0.727
	Approx. Chi-square	50418.068
Bartlett's test of sphericity	GL	496
	Sig.	0.000

Source: Compiled by authors.

Table 2 shows the KMO statistics (Henry F. Kaiser 1974) and the Bartlett sphericity test, (Maurice Bartlett 1950), where the KMO indicates an acceptable adjustment of the figures to the factor model. The sphericity test is acceptable since it has a high Chi-square value (or low determinant on the correlation matrix), indicating that there are high correlations between the variables.

In relation to the communalities obtained by the factor model, it is observed that the variables are generally explained adequately by the model, with an average communality of 0.923. Additionally, 27 of the 32 original variables have communalities of above 90% (see Table A1 in the Appendix).

The explanation of the variance and the percentage represented by each of the factors can be consulted in Table A2 (Appendix). Seven have eigenvalues greater than one. It was decided to extract these seven factors, since they explain 92.28% of the variance.

To simplify the factor structure, the factor axes are rotated to bring them closer to the original variables and to force the variables to become defined, preferably in a latent dimension over others, thus facilitating the interpretation of the factor matrix, since a greater differentiation is obtained between factors, resulting in more defined profiles. Following the rotation, the number of factors, the total percentage of variance explained by the original model and the variables communality are maintained. Only the composition of the factors is varied by changing the factorial coefficients of each variable in each factor. This also alters the proportion of variability explained by each factor (see Table A2 in the Appendix).

Among the various existing procedures available, the Varimax (Kaiser 1958) method was used to simplify the factorial structure, maximizing the variance of the factorial coefficients to the square of each factor.

Table 3 Matrix of Rotated Components

Matrix of rotated components	Component						
	1	2	3	4	5	6	7
(1) Risk-weighted assets to total assets	-0.921						
(2) Total deposits as a % of total assets	0.907						
(3) Tier 1 risk-based capital ratio (pca)	0.890						
(4) Insured deposits as a percent of total deposits	0.859				0.401		
(5) Total risk-based capital ratio (pca)	0.845						
(6) Non interest income as % average assets	-0.789						
(7) Core capital (leverage) ratio (pca)	0.720			-0.506			
(8) Net interest margin	0.597						0.492
(9) Return on equity		0.917					
(10) Return on assets		0.905					
(11) Pretax return on assets		0.900					
(12) Pretax return on equity		0.886					
(13) Loss provision, % of net operating revenue		-0.768	0.412				
(14) Noncurrent assets plus other real estate owned to assets			0.906				
(15) Percent of loans and leases noncurrent			0.898				
(16) Noncurrent loans and leases as a percent of tier 1 capital plus reserves			0.877				
(17) Loss allowance to loans and leases			0.798				
(18) Loss allowance to noncurrent loans and leases (coverage ratio)			-0.681				
(19) Net charge-offs to loans and leases		-0.431	0.661				
(20) Loss provisions, % of net charge-offs		-0.486	-0.514				
(21) Yield on earning assets				0.940			
(22) Cost of earning funding assets				0.938			
(23) Assets and 5 years as a percent of total assets (call reporters only)				-0.756			
(24) Equity capital to assets	0.481			-0.752			
(25) Average assets per employee ($ millions)	-0.476			-0.707			
(26) Percent of loans and leases 30-89 days past due		-0.431		0.572			
(27) Net loans and leases to total assets					0.921		
(28) Commercial real estate loans as a % of total assets					0.852		
(29) Retail loans as a percent of total loans						0.864	
(30) Efficiency ratio	0.541					-0.705	
(31) Non interest expense as % as average assets							0.759
(32) Net operating revenue as % of average assets		0.429				0.445	0.706
Extraction method: principal component analysis. Rotation method: varimax with kaiser normalization.							
a. Rotation converged in 9 iterations.							

Source: Compiled by authors.

Table 3 represents the matrix of rotated components, representing the factorial structure. When comparing the relative saturation of each factor a change in the percentage of explained variance is observed, where the greater the change the greater the success in the rotation (see last three columns of Table A2 in the Appendix). In our case the percentage variation falls in the first, second factor and negligibly in the third factor, but that of the fourth to seventh factor increases, which implies a success of the Varimax rotation.

3.1 Interpretation of the Factors

Factor 1 Solvency. This factor, which groups the ratios (1) to (8), as defined by the FDIC (see Table 3), is called "solvency" because it groups those which, in one way or another, have this measurement capacity. Ratio (1) has the highest degree of saturation with factor although in the negative, as a result of the negative incidence of the weighting due to the risk to the institution's solvency. Ratio (4) has an "average" correlation with solvency, indicating that the proportion of insured deposits over total deposits is a good measure of solvency, although less so than ratios (1) to (3). Finally, (8) has the weakest relationship of all of them, even though the net interest margin should, in principle, increase together with an institution's solvency. Having access to cheaper sources of funding – such as insured deposits – (8) also increases, since it allows for more profitable – and riskier – investments, which depending on how they evolve, may result in diminished solvency.

Factor 2 Profitability. This factor is obtained from the FDIC ratios (9) to (13) (see Table 3), which offer a measurement of the economic or financial profitability of an institution. It explains the name of this factor with which all the ratios have high degree of saturation (around 0.9), reflecting their capacity as instruments for measuring the profitability of an institution. Ratio (13), despite its negative correlation, has the lowest saturation and consequently the lowest explanatory power in relation to the operating margin, in contrast with ratio (9) whose explanatory power is the strongest. We must also remember that (32) has a high communality with the factor, illustrating the connection indicated above (operating margin). The fact that ratio (26) has a negative communality indicates, as can be observed in factor 4, that the existence of a high percentage of 30-90 days past due dates implies higher funding costs.

Factor 3 Asset impairment. This groups together the ratios defined by the FDIC that directly or indirectly measure an institution's impairment provision policy. They have been obtained from the ratios (13) to (20) (see Table 3), with (15) having a high communality despite this being an indirect measurement of impairment. This contrasts with the lower explanatory power of the coverage ratio (18), perhaps on account of the accounting rules requiring the total or partial charge-off of the asset or its impairment be recorded, even though it explains the negative correlation of (19) in factor 2 and the positive one in factor 3, confirming our hypothesis. Ratio (20), with a negative communality of 0.514, reveals its lower explanatory power for impairment.

Factor 4 Funding costs. The groups the ratios (21) to (26) (see Table 3), which, according to the FDIC definition, can explicitly or implicitly measure the financing effort, measured in terms of costs borne by the sources of funding. Of all the ratios included, it is striking that (25) saturates here, maybe due to a higher volume of assets per employee implying greater funding requirements, and thereby, greater costs. Conversely, the lower the number of employees per asset, the lower the costs, which will have a favorable impact on the net interest margin, thus for certain asset interest earnings a higher liability interest payment can be permitted. However, (23) having a negative saturation with the factor indicates that those institutions with longer-term investments have lower funding costs. To sum up, the performance of this factor leads us to conclude that when an institution's investment capacity increases, it must make higher risk investments, which will have a negative impact on the cost of external funding, raising its cost, since the market will demand a higher risk premium in exchange for lending to the institution.

Factor 5 Loan structure. This factor groups ratios (27) and (28). Table 3 clearly shows that the degree of saturation of both ratios is high, which means that we can state that these two ratios have sufficient explanatory power to describe an institution's business model.

Factor 6 Inefficiency This factor groups ratios (29) and (30). The last one, the efficiency ratio, naturally has a negative correlation with the factor. The results generated allow us to conclude that institutions whose business structure focuses mainly on retail banking are less efficient.

Factor 7 Income structure. Of all the ratios selected, only these last two – (31) and (32) – have saturation with this factor (see Table 5). It is notable that (31) saturates with this factor and (32) is interesting because it also saturates with inefficiency and profitability. It can therefore be stated that these two ratios have sufficient explanatory power to describe an institution's business model.

Table A3 in the Appendix contains the factor averages generated through factor analysis, discriminating them according to institution size into the five groups mentioned above. By analyzing the resulting values we can formulate conclusions about the extent to which size influences the behavior of each of the factors. Figure A1 in the Appendix shows the above interdependencies, and lastly, Graphs 1 to 7 in Figure A2 in the Appendix describe the behavior of the seven factors over the study's target period – first quarter of 1990 through to the third quarter of 2016 – for all bank sizes.

The results (see Table A3 and Figures A1 and A2 in the Appendix) clearly show how the solvency factor increases in line with a decrease in size of the institutions, beginning with a factor average of -0.975 (Assets > \$250 Billion) and ending with a factor of 1.33 for the smallest institutions (Assets < \$100 Million). That size has a negative correlation with solvency suggests the presence of moral hazard, meaning that the biggest institutions take on bigger risks knowing they can rely on State support. The significant improvement in the solvency of large banks (Assets > \$250 Billion) after the third quarter of 2008 is worth noting. This may be connected to the accountancy requirement to partially or completely charge-off impaired assets.

Size does not have a significant impact on the behavior of the profitability factor, although a considerable drop in the profitability of medium sized institutions (Assets \$1-250 Billion) is recorded in the third quarter of 2008.

The asset impairment factor remains more or less stable for all bank sizes during times of stability. However two cycles of depression were observed which impacted larger institutions more strongly, evidencing the more conservative risk-taking by smaller ones, possibly because of better information processing procedures prior to granting a loan.

Regarding funding costs, a gradual decline of this factor was noted among all groups of institutions. At the same time, a widening of the differences (dispersion) between the groups of institutions was recorded over the period analyzed. In any case, funding costs are lower for larger banks (less solvent), pointing to the possible presence of moral hazard. What was also recorded, was the rise in this cost at the end of 2007 and its gradual fall after 2009 for all institutions.

Regarding the loan structure factor, three groups of institutions are identified according to their performance. First, the medium sized banks (Assets \$100 Million - \$10 Billion) granted more loans as from 2002. The larger institutions (Assets > \$250 Billion), in the second group, generally acted in a linear fashion over the entire period of study. The other institutions fluctuated around an average value.

The pattern of the inefficiency factor revealed how over the period analyzed, whereas the two larger size groups started off as the most efficient and finished as the most inefficient, with a peak of inefficiency in the first quarter of 2009 and 2010 respectively, the other groups of institutions' performance was the converse, with a slight improvement in their efficiency over the course of the period studied.

The income structure results reveal how, in times of crisis, the larger banks generated income from activities not forming part of traditional banking, whereas the income structure of smaller banks remained more stable over the period.

3.2 Neural Network

A neural network is a simplified model that emulates the way the human brain processes information. The reason for its tremendous utility lies in its ability to organize an internal representation of knowledge in the hidden layers of neurons, in order to learn the relationship between a set of input and output data. A neural network has the ability to virtually learn any type of relationship, as long as it can be approximated in terms of a continuous function. The development of the network consists of an operational phase and a learning phase.

In the Operational Stage, an input pattern X_p: $x_{p1}, \ldots, x_{pi}, \ldots x_{pN}$ is presented, then transmitted to the network through the weights wji from the input layer to the hidden layer. The neurons in this layer transform the signals through the activation function providing an output value. This value is transmitted in turn through the weights w_{jij} to the output layer, where after applying the activation function, we obtain an output value (y_{pk}).

In the learning stage, the objective is to minimize the discrepancy or error between the output of the network and the real value presented by the user. The function to be minimized for each pattern p is given in the following expression:

$$E_p = \frac{1}{2}\sum_{k=1}^{M}\left(d_{pk} - y_{pk}\right)^2, \tag{3}$$

where d_{pk} is the output presented by the network of neuron k before the presentation of the pattern p. The general measure of error is the sum of all errors for all patterns:

$$E = \sum_{p=1}^{P} E_p. \tag{4}$$

The fundamental objective of the analysis with the neural network is to minimize the square of the errors between the real value and that of the output variable.

Based on the results generated by the factor analysis, which showed that the factors can be clearly differentiated according to size, a Perceptron Neural Network was constructed, with size as the dependent variable, in order to forecast the likelihood of an institution belonging to one of the five size groups represented (see Table A4 in the Appendix).

Table 4 Overview of the Model

Overview of the model		
Training	Cross entropy error	7.206
	Percentage of incorrect predictions	0.5%
	Stopping rule used	1 consecutive step (s) without a decrease in error a
	Training time	0:00:00.06
Testing	Cross entropy error	6.723
	Percentage of incorrect predictions	0.7%
Dependent variable: size		
a. Error calculations are based on the test sample.		

Source: Compiled by authors.

In Table 5 the diagonal cells of the joint classification of the cases are the correct forecasts, while the cells outside the diagonal are the incorrect forecasts. Since the percentage correctly forecasted is above 99% in both the training and testing samples, we can confidently state that there was a high degree of successful forecasting.

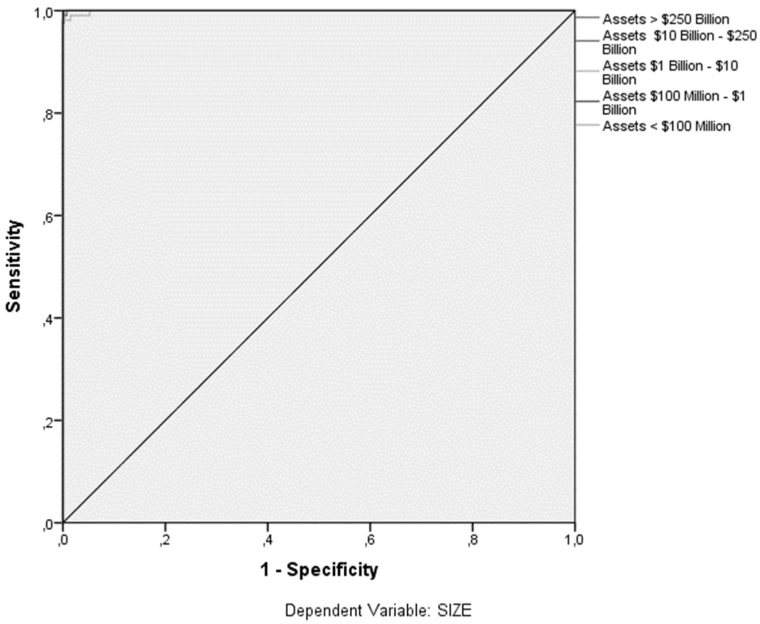
Table 5 Classification

Classification							
		Predicted					
Sample	Observed	Assets > $250 B.	Assets $10 B. - $250 B.	Assets $1 B.- $10 B.	Assets $100 M. - $1 B.	Assets < $100 M.	% Correct
Training	Assets > $250 B.	57	1	0	0	0	98.3%
	Assets $10 B. - $250 B.	0	78	0	0	0	100.0%
	Assets $100 M. - $1 B.	0	0	74	0	0	100.0%
	Assets $100 M. - $1 B.	0	0	1	78	0	98.7%
	Assets < $100 M.	0	0	0	0	78	100.0%
	Overall percent	15.5%	21.5%	20.4%	21.3%	21.3%	99.5%
Testing	Assets > $250 B.	23	0	0	0	0	100.0%
	Assets $10 B. - $250 B.	1	28	0	0	0	96.6%
	Assets $100 M. - $1 B.	0	0	33	0	0	100.0%
	Assets $100 M. - $1 B.	0	0	0	28	0	100.0%
	Assets < $100 M.	0	0	0	0	29	100.0%
	Overall percentage	16.9%	19.7%	23.2%	19.7%	20.4%	99.3%
Dependent variable: size							

Source: Compiled by authors.

The Receiver Operating Characteristic (ROC) curve represents on a single graph the sensibility (true positives) and 1-specificity (false positives) for all the groups. It rises because an increase in sensibility is only achieved by decreasing the specificity. It is more exact when the ROC curve goes from left to right and travels upward (see Figure

1) because both the sensitivity (no false negatives) and the specificity (no false positives) are high. Briefly, the area below the ROC curve represents the quality of the classification of the neural network, from which we can deduce that it is highly accurate.



Source: Compiled by authors.

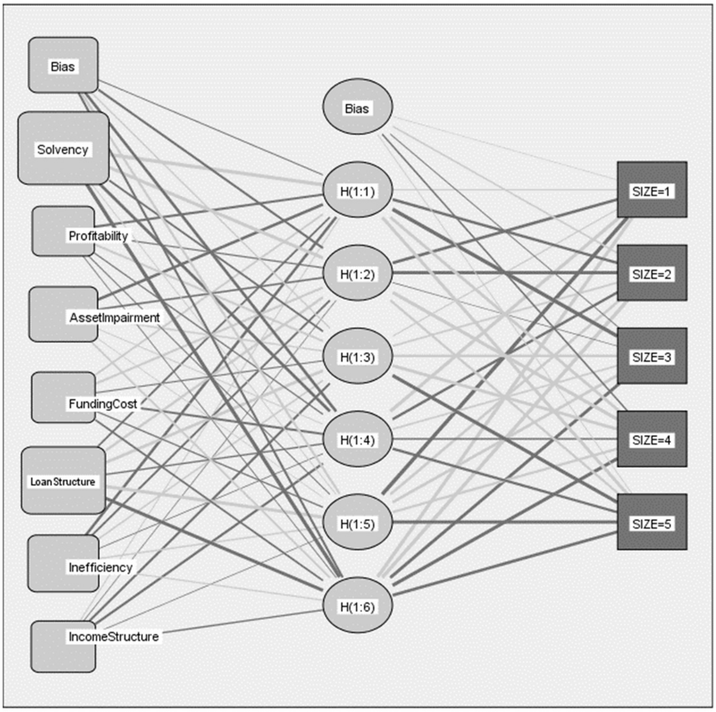
Figure 1 ROC Curve

Table 6 Area Below ROC Curve

Size	Area
Assets > $250 B.	1.000
Assets $10 B. - $250 B.	1.000
Assets $1 B.- $10 B.	1.000
Assets $100 M. - $1 B.	1.000
Assets < $100 M.	1.000

Source: Compiled by authors.

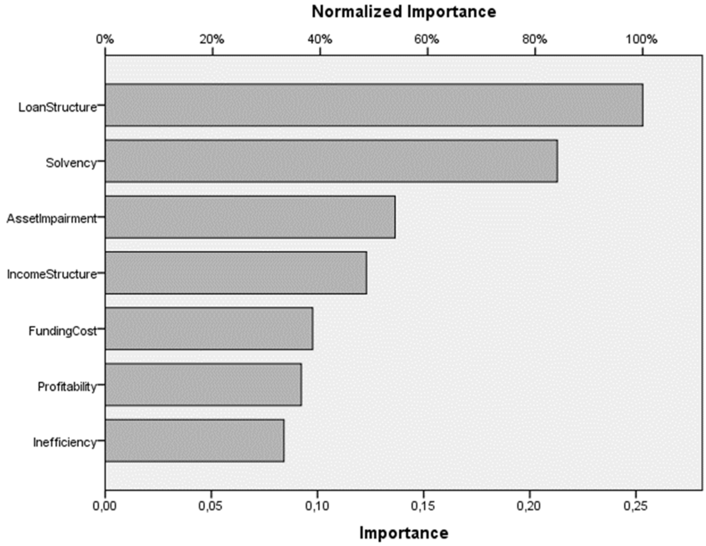
Figure 2 represents, in the input layer, the predictors – or factors in our case – in the hidden layer, non-observable nodes and the output layer, which contains the answers, the variables according to size. Table A6 in the Appendix shows the synaptic weights of the network, the estimates of the coefficients showing the relationship between the units of one layer and the units in the following layer.



Source: Compiled by authors.

Figure 2 Network Diagram

When designing the neural network, we are attempting to ascertain whether it is possible, when we know the value of the factors (independent variables), to classify the size of an institution. Figure 3, which represents the weight of the independent variables, enables us to conclude that the factor “loan structure” is the most important for the classification of institutions into groups by size, followed by “solvency”, and to a lesser extent, by “asset impairment”. Although the rest of the factors have less of an influence, the results allow us to conclude that there is a systemic pattern for all the factors in every institution size.



Source: Compiled by authors.

Figure 3 Importance of the Independent Variables

4. Conclusions

Applying factor analysis to the 32 economic-financial and regulatory variables (ratios) selected has enabled us to reduce them down to seven factors, which, by means of a neural network, have been differentiated, according to size, into five groups of institutions. This has allowed us to draw the following conclusions.

That **Solvency** has a negative correlation with the size suggests the existence of moral hazard, indicating that larger institutions take on bigger risks, assuming they have implicit State support. This contrasts with more solvent banks with a lower moral hazard and, depending on size and their exposure, a lower systemic risk. To conclude, although several authors are in favor of the existence of large institutions, which allow for a greater risk diversification, and that they trust in market discipline to minimize moral hazard, the results generated through this study suggest a need for banking regulation to take into account the moral hazard posed by large institutions. This should take the form of limiting the negative externalities they cause through their excessive risk-taking and from the market's belief in the State's implicit support.

Regarding **Profitability**, we observe that the operating margin has a reduced explanatory power for an institution's profitability, which is also undermined by the existence of a high percentage of 30-90 day loans, which is associated with the greater explanatory power of the funding cost factor. The trend in this factor in relation to size, reveals that the most profitable institutions are mid-sized ones, followed by the larger ones, while smaller banks are less profitable, although on the other hand, they are the most solvent. To summarize, the results reveal the existence of a clear negative correlation between profitability and solvency at the two extremes, i.e. for the large banks (Assets > $250 B) and for the smaller ones (Assets < $100M).

Regarding **Asset Impairment**, the reduced explanatory power of the coverage ratio as a measurement of this factor is striking. This could be explained by the accounting regulations requiring the complete or partial charge-off of assets, together with their corresponding provisions. The growth in the importance of this factor according to size is evidence that the smaller banks have fewer impaired assets, which may be explained by their policy of lower risk-taking, based on a better client portfolio selection through improved information processing prior to granting loans.

The pattern of the **Funding Costs** factor, combined with the institution's size, leads us to conclude that when the institution's investment capacity increases, it tends to make higher risk investments, which will have a negative impact on the cost of external funding (an increase) and also on its solvency, since the market demands a higher risk premium in exchange for lending to the institution.

In terms of **Inefficiency,** we can observe how the institutions whose business is focused on retail banking are the least efficient, followed by the larger entities, whereas the most efficient institutions are the medium-sized ones. So overall, all differences considered, a similar behavior is observed with regard to profitability and inefficiency, with both the smaller and larger institutions being less efficient and profitable than the mid-sized banks, which tend to perform better.

The neural network enabled us to conclude the systemic behavior of all the factors in all institution sizes, with "loan structure" being the factor which best enables us to classify the size of the institution, followed by the "solvency" factor and then by "asset impairment".

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Appendix

Table A1 Communalities (Extraction Method: Principal Component Analysis)

Communalities	Initial	Extraction
Return on assets	1.000	0.954
Pretax return on assets	1.000	0.975
Return on equity	1.000	0.970
Pretax return on equity	1.000	0.979
Yield on earning assets	1.000	0.946
Cost of earning funding assets	1.000	0.924
Net interest margin	1.000	0.920
Non interest income as % average assets	1.000	0.927
Net operating revenue as % of average assets	1.000	0.975
Non interest expense as % as average assets	1.000	0.914
Efficiency ratio	1.000	0.941
Loss provision, % of net operating revenue	1.000	0.958
Net charge-offs to loans and leases	1.000	0.931
Loss provisions, % of net charge-offs	1.000	0.699
Percent of loans and leases 30-89 days past due	1.000	0.910
Percent of loans and leases noncurrent	1.000	0.944
Noncurrent assets plus other real estate owned to assets	1.000	0.968
Loss allowance to noncurrent loans and leases (coverage ratio)	1.000	0.833
Noncurrent loans & leases as a percent of tier 1 capital plus reserves	1.000	0.951
Loss allowance to loans & leases	1.000	0.860
Equity capital to assets	1.000	0.922
Core capital (leverage) ratio (pca)	1.000	0.956
Tier 1 risk-based capital ratio (pca)	1.000	0.982
Total risk-based capital ratio (pca)	1.000	0.969
Commercial real estate loans as a % of total assets	1.000	0.940
Risk-weighted assets to total assets	1.000	0.912
Net loans & leases to total assets	1.000	0.955
Total deposits as a % of total assets	1.000	0.929
Retail loans as a percent of total loans	1.000	0.866
Insured deposits as a percent of total deposits	1.000	0.947
Assets > 5 years as a percent of total assets	1.000	0.759
Average assets per employee ($ millions)	1.000	0.913

Source: Compiled by authors.

Table A2 Explained Variances

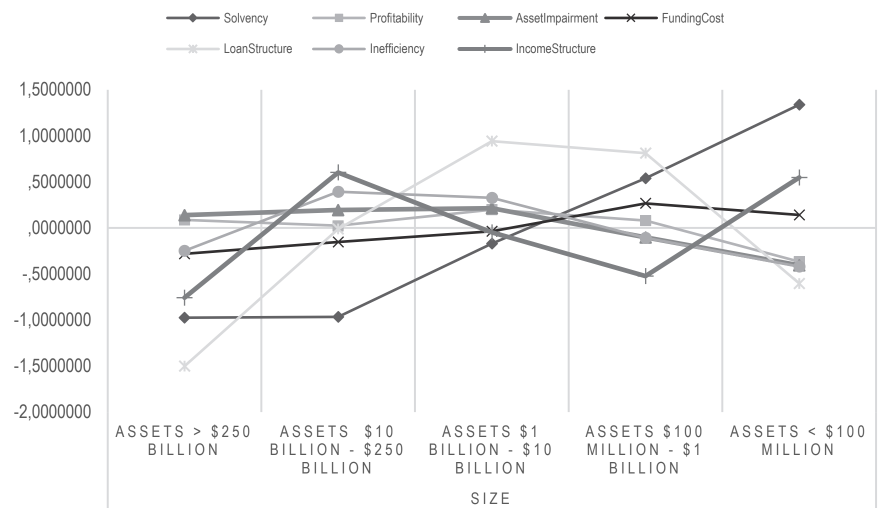
Total explained variance (extraction method: principal component analysis)									
	Initial eigenvalues			Sums of extraction of squared loads			Sums of rotation of squared loads		
Component	Total	% variance	% accumulated	Total	% variance	% accumulated	Total	% variance	% accumulated
1	8.469	26.465	26.465	8.469	26.465	26.465	7.113	22.228	22.228
2	8.187	25.585	52.049	8.187	25.585	52.049	5.493	17.166	39.394
3	5.149	16.092	68.141	5.149	16.092	68.141	5.126	16.018	55.412
4	2.617	8.177	76.318	2.617	8.177	76.318	4.941	15.441	70.852
5	2.192	6.852	83.170	2.192	6.852	83.170	2.465	7.703	78.555
6	1.596	4.988	88.158	1.596	4.988	88.158	2.283	7.134	85.690
7	1.318	4.120	92.277	1.318	4.120	92.277	2.108	6.588	92.277

Source: Compiled by authors.

Table A3 Factor Averages According to Size

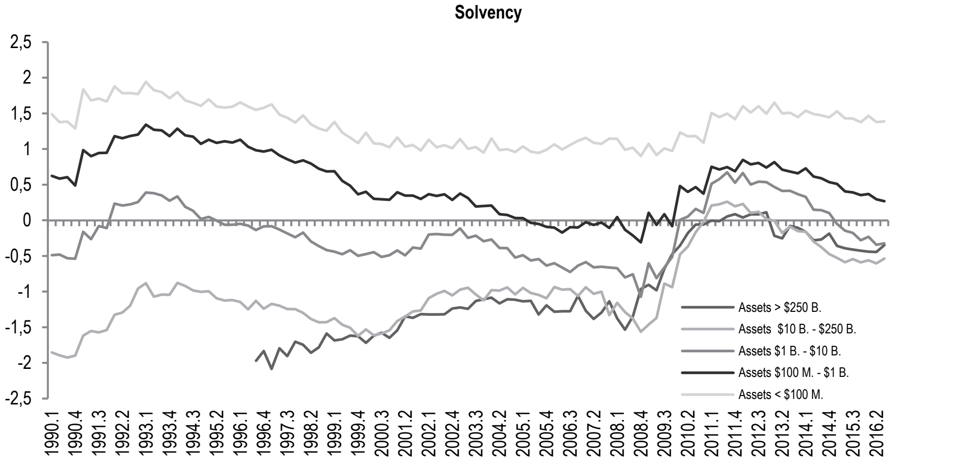
	Size				
Factor averages according to size	Assets > $250 B.	Assets $10 B. - $250 B.	Assets $1 B.- $10 B.	Assets $100 M. - $1 B.	Assets < $100 M.
	Average	Average	Average	Average	Average
Solvency	-0.97505	-0.96667	-0.17105	0.53836	1.33748
Profitability	0.08617	0.02317	0.19783	0.07951	-0.36576
Asset impairment	0.13735	0.19308	0.21324	-0.10417	-0.40613
Funding costs	-0.28227	-0.15401	-0.03784	0.26589	0.13964
Loan structure	-1.50118	-0.01250	0.94242	0.81062	-0.60413
Efficiency	-0.24921	0.39220	0.32531	-0.10891	-0.41995
Income structure	-0.75783	0.60181	-0.04994	-0.52446	0.54627

Source: Compiled by authors.



Source: Compiled by authors.

Figure A1 Factor Analysis Factors According to Size


Solvency
2,5
2
1,5
1
0,5
0
-0,5
-1
-1,5
-2
-2,5
Assets > $250 B.
Assets $10 B. - $250 B.
Assets $1 B. - $10 B.
Assets $100 M. - $1 B.
Assets < $100 M.
1990.1
1990.4
1991.3
1992.2
1993.1
1993.4
1994.3
1995.2
1996.1
1996.4
1997.3
1998.2
1999.1
1999.4
2000.3
2001.2
2002.1
2002.4
2003.3
2004.2
2005.1
2005.4
2006.3
2007.2
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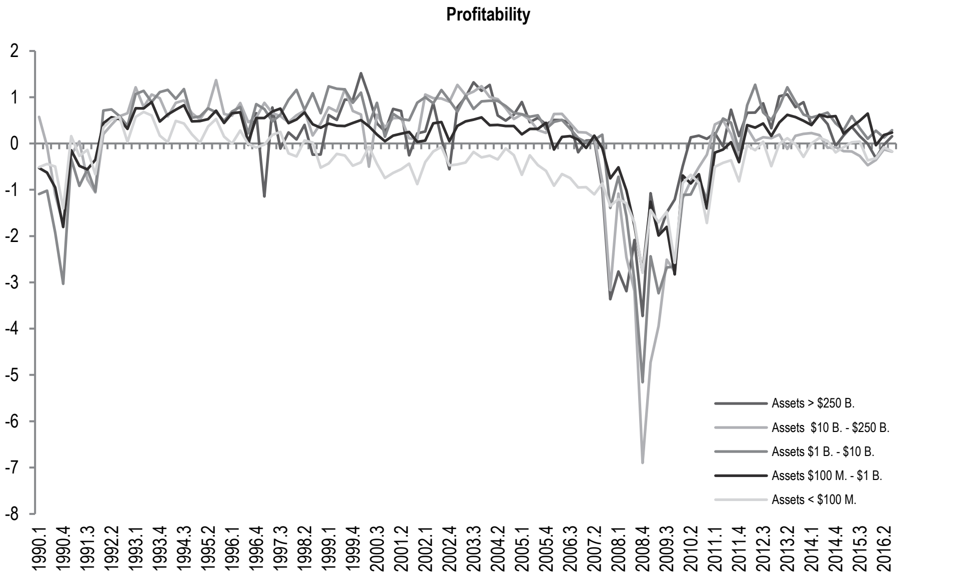
2010.2
2011.1
2011.4
2012.3
2013.2
2014.1
2014.4
2015.3
2016.2


Profitability
2
1
0
-1
-2
-3
-4
-5
-6
-7
-8
Assets > $250 B.
Assets $10 B. - $250 B.
Assets $1 B. - $10 B.
Assets $100 M. - $1 B.
Assets < $100 M.
1990.1
1990.4
1991.3
1992.2
1993.1
1993.4
1994.3
1995.2
1996.1
1996.4
1997.3
1998.2
1999.1
1999.4
2000.3
2001.2
2002.1
2002.4
2003.3
2004.2
2005.1
2005.4
2006.3
2007.2
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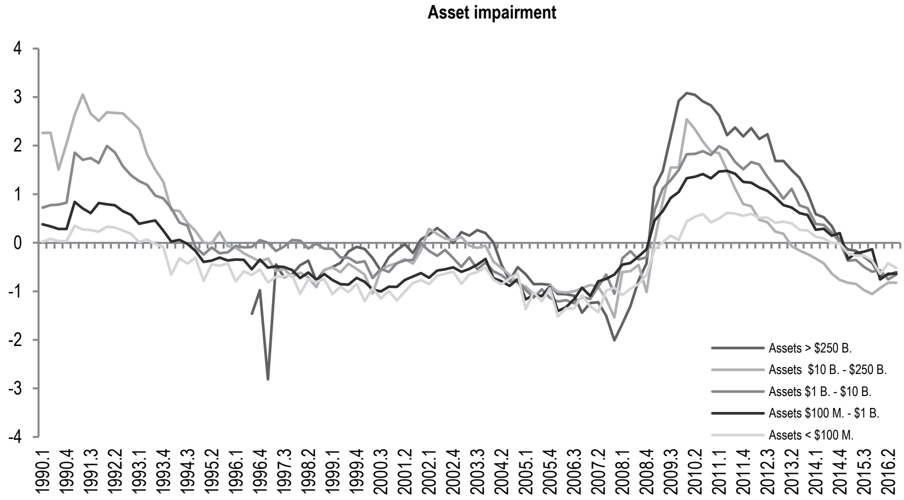
2014.4
2015.3
2016.2


Asset impairment
4
3
2
1
0
-1
-2
-3
-4
Assets > $250 B.
Assets $10 B. - $250 B.
Assets $1 B. - $10 B.
Assets $100 M. - $1 B.
Assets < $100 M.
1990.1
1990.4
1991.3
1992.2
1993.1
1993.4
1994.3
1995.2
1996.1
1996.4
1997.3
1998.2
1999.1
1999.4
2000.3
2001.2
2002.1
2002.4
2003.3
2004.2
2005.1
2005.4
2006.3
2007.2
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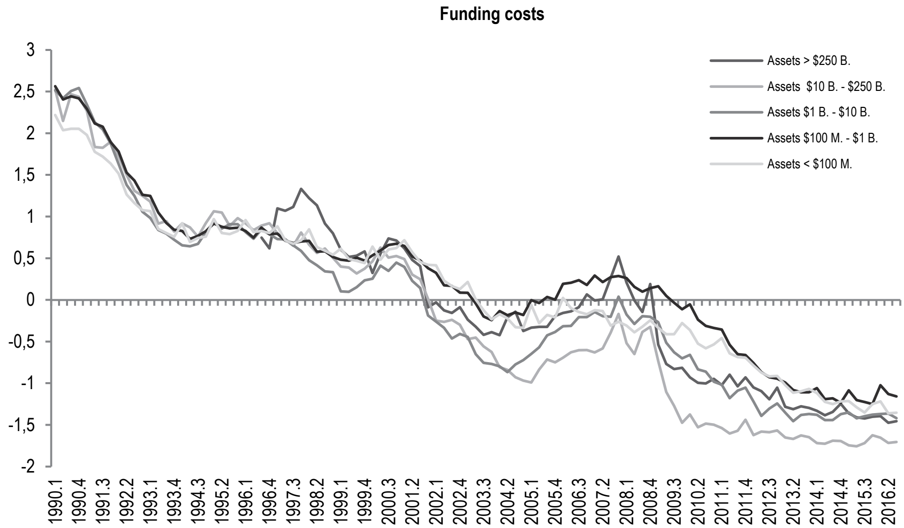
2014.4
2015.3
2016.2


Funding costs
3
2,5
2
1,5
1
0,5
0
-0,5
-1
-1,5
-2
Assets > $250 B.
Assets $10 B. - $250 B.
Assets $1 B. - $10 B.
Assets $100 M. - $1 B.
Assets < $100 M.
1990.1
1990.4
1991.3
1992.2
1993.1
1993.4
1994.3
1995.2
1996.1
1996.4
1997.3
1998.2
1999.1
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2002.1
2002.4
2003.3
2004.2
2005.1
2005.4
2006.3
2007.2
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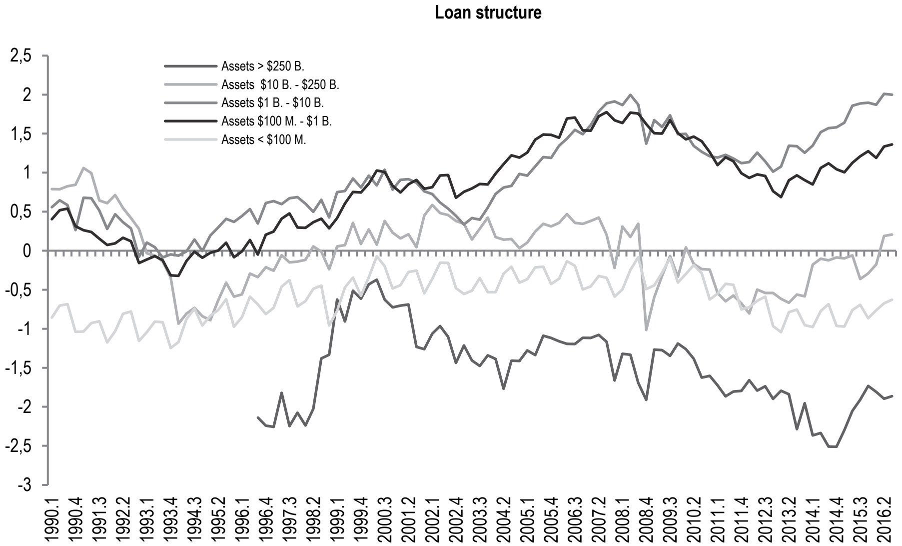
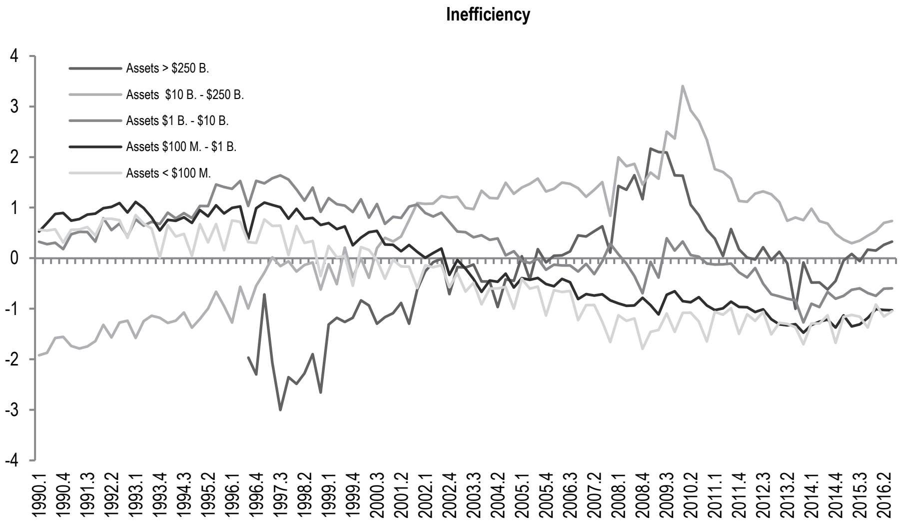
2014.4
2015.3
2016.2


Loan structure
Assets > $250 B.
Assets $10 B. - $250 B.
Assets $1 B. - $10 B.
Assets $100 M. - $1 B.
Assets < $100 M.


Inefficiency
Assets > $250 B.
Assets $10 B. - $250 B.
Assets $1 B. - $10 B.
Assets $100 M. - $1 B.
Assets < $100 M.

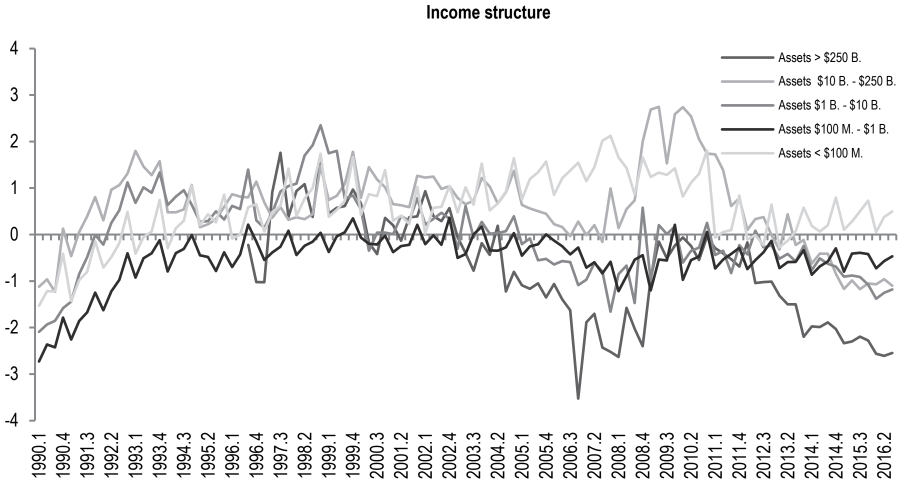


Figure A2 Factor Behavior by Year

Table A4 Summary of Cases Processed and of the Model

		N	Percentage
Sample	Training	367	72.1%
	Testing	142	27.9%
Valid		509	100.0%
Excluded		0	
Total		509	

Source: Compiled by authors.

Table A5 Ratios According to Size

	Size				
	Assets > $250 B.	**Assets $10 B. - $250 B.**	**Assets $1 B.- $10 B.**	**Assets $100 M. - $1 B.**	**Assets < $100 M.**
	Mean	**Mean**	**Mean**	**Mean**	**Mean**
Return on assets	0.009239	0.009513	0.009596	0.009087	0.008279
Pretax return on assets	0.013560	0.014747	0.014486	0.012883	0.011221
Return on equity	0.111417	0.103548	0.099266	0.092960	0.074816
Pretax return on equity	0.164666	0.160482	0.150859	0.132586	0.102033
Yield on earning assets	0.053132	0.066251	0.066996	0.067683	0.067888
Cost of earning funding assets	0.021690	0.029255	0.027838	0.027369	0.026274
Net interest margin	0.031442	0.036996	0.039159	0.040314	0.041614
Non interest income as % average assets	0.020852	0.021806	0.016574	0.011685	0.011556
Net operating revenue as % of average assets	0.046939	0.053935	0.052048	0.048770	0.049773
Non interest expense as % as average assets	0.029513	0.032514	0.032164	0.032522	0.036116
Efficiency ratio	0.616301	0.579117	0.601377	0.661400	0.723803
Loss provision, % of net operating revenue	0.097879	0.131475	0.119480	0.080430	0.057365
Net charge-offs to loans and leases	0.008757	0.011462	0.007947	0.004643	0.003637
Loss provisions, % of net charge-offs	0.971666	1.012835	1.158674	1.304440	1.394776
Percent of loans and leases 30-89 days past due	0.011408	0.011698	0.011980	0.012867	0.016224
Percent of loans and leases noncurrent	0.026141	0.019859	0.018841	0.015684	0.014938
Noncurrent assets plus other real estate owned to assets	0.013819	0.014391	0.015897	0.014426	0.012641
Loss allowance to noncurrent loans and leases (coverage ratio)	1.041066	1.250531	1.203413	1.156227	1.085767
Noncurrent loans & leases as a percent of tier 1 capital plus reserves	0.155721	0.140511	0.127570	0.100274	0.074980
Loss allowance to loans & leases	0.019969	0.020673	0.017300	0.014559	0.014832
Equity capital to assets	0.085847	0.096628	0.098267	0.098239	0.113467
Core capital (leverage) ratio (pca)	0.069871	0.080206	0.088062	0.094495	0.111376
Tier 1 risk-based capital ratio (pca)	0.093603	0.101975	0.123316	0.140152	0.176806
Total risk-based capital ratio (pca)	0.124039	0.127758	0.138531	0.151738	0.187760
Commercial real estate loans as a % of total assets	,051306	,107023	0.208520	0.227223	0.141849
Risk-weighted assets to total assets	,728795	,768276	0.696736	0.664694	0.622547
Net loans & leases to total assets	,493213	,599244	0.635359	0.637103	0.584270
Total deposits as a % of total assets	,661136	,658685	0.724451	0.821113	0.847456
Retail loans as a percent of total loans	,456808	,493255	0.467729	0.452494	0.442914
Insured deposits as a percent of total deposits	0.387084	0.589277	0.740562	0.816785	0.870464
Assets > 5 years as a percent of total assets	0.203144	0.193878	0.236753	0.217730	0.183764
Average assets per employee ($ millions)	6.226213	5.591890	4.117159	3.168047	2.654642

Source: Compiled by authors.

Table A6 Synaptic Weights

Predictor		Predicted								
		Hidden layer 1				Output layer				
		H(1:1)	H(1:2)	H(1:3)	H(1:4)	Size = 1	Size = 2	Size = 3	Size = 4	Size = 5
Input layer	(Bias)	-,774	-,457	-1.454	-0.368					
	Solvency	-3.632	4.758	-1.590	0.140					
	Profitability	0.070	-0.921	0.338	0.848					
	Asset impairment	0.437	-1.873	1.411	1.952					
	Funding costs	-1.059	0.792	0.953	2.063					
	Loan structure	-3.239	-,584	-2.216	4.046					
	Efficiency	-0.550	-1.865	-1.068	-0.398					
	Income structure	0.273	-0.097	-2.086	0.643					
Hidden layer 1	(Bias)					-0.951	1.429	0.438	0.335	-0.797
	H(1:1)					2.505	3.602	-3.536	-0.695	-1.573
	H(1:2)					-0.589	-2.381	-3.764	2.934	4.062
	H(1:3)					3.888	-1.068	0.105	-2.093	-0.764
	H(1:4)					-3.501	1.679	2.189	3.538	-3.435

Source: Compiled by authors.