A Dynamic Economic and Monetary Union

ADEMU WORKING PAPER SERIES

The negative correlation between nonperforming loans of large and small banks

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April 2018

WP 2018/103

www.ademu-project.eu/publications/working-papers

Abstract

This paper presents a new stylized fact about bank nonperforming loans. According to data for the US, the average of the ratio of noncurrent loans to total loans for large banks presents a very high negative correlation with the same ratio for small banks. This result remains valid for different measures of bank size as well as controlling for different bank characteristics such as charter class, specialization or geographical location.

Keywords: bank size, nonperforming loans
JEL codes: G21

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Horizon 2020
The Framework Programme for Research and Innovation

Acknowledgments

This is a substantial update of a previous paper circulated with the title "The correlation of nonperforming loans between large and small banks". I would like to acknowledge the financial support from the Spanish Ministry of Economy and Competitiveness, through the Severo Ochoa Programme for Centres of Excellence in R&D (SEV-2015-0563) and through grant ECO2016-76734-P (AEI/FEDER, UE) as well as that of the Generalitat de Catalunya through Grant 2017 SGR 1571. I am also grateful for financial support from the ADEMU project, "A Dynamic Economic and Monetary Union", funded by the European Union's Horizon 2020 Program under grant agreement No 649396. Yifei Lu provided excellent research assistance. All errors are my responsibility.

The ADEMU Working Paper Series is being supported by the European Commission Horizon 2020 European Union funding for Research & Innovation, grant agreement No 649396.

1 Introduction

This short paper presents a new stylized fact about bank nonperforming loans. According to data for the US, the average of the ratio of noncurrent loans to total loans (from now on the NCL ratio) for large banks presents a very high negative correlation with the same ratio for small banks. This result remains valid for different measures of bank size as well as after controlling for different bank characteristics such as charter class, specialization or geographical location.

There are a few papers analyzing how the size of a bank affects, at the bank level, the amount of nonperforming loans. Using data for Texas banks for the period 1980-1990, Clair [1] finds that larger banks tend to have higher nonperforming loan ratios. Although size is not a significant explanatory variable, Solttila and Vihriälä [4] find that, for Finnish banks in the 80s and 90s, loan growth is one of the major determinants of nonperforming assets later on. This result is in line with the conclusions of Salas and Saurina [3] for Spanish banks although these authors in addition also find that bank size is negatively related with problematic loans. The aim of the present paper is not to look at how size affects unpaid loans but how the time series behavior of nonperforming loans in large banks correlates with that of small banks.

2 The Data

The data used in this paper is taken from the database *Statistics on Depository Institutions* provided by the Federal Deposit Insurance Corporation (FDIC) and available at www.fdic.gov. This data is obtained from the Federal Financial Institution Examination Council (FFIEC) Consolidated Report of Condition and Income (also known as *Call Reports*) and the Office of Thrift Supervision (OTS) Thrift Financial Reports submitted by all FDIC-insured depository institutions. The data set spans from the last quarter of 1992 until the fourth quarter of 2017 which represent 101 periods of data. The number of depository institutions included in the sample has been decreasing over time, due to mergers and exits, a trend well documented in the literature.[1] At the end of 1992 there were 13973 institutions reporting while at the end of 2017 this number has been reduced to 5679, less than half of the original size of the sample.

The variables of interest for this study are Total assets/liabilities (asset), Total net loans and leases (lnlsnet), and Noncurrent loans and leases to total loans and leases (nclnlsr).[2] The FDIC defines Noncurrent loans as "the sum of loans and leases 90 days or more past due, and loans and leases in nonaccrual status". Of this database, I drop banks with (i) missing values for the variables of interest, (ii) ratios of loans to assets larger than 1 or smaller than 0 and (iii) Noncurrent loan ratios equal or smaller than 0 or larger than 20 percent as I attribute these values to measurement errors. These corrections reduce the

[1] See, among others, Janicki and Prescott [2].
[2] Acronyms from the original data set are in parenthesis.

sample size by little. This way, the total number of banks included in 1992 is 13004 while in 2017 is 5073.

I use Total assets/liabilities as a measure of bank size. As documented by Janicki and Prescott [2] the distribution of bank assets is highly skewed, with a large number of small banks and a few large banks. Furthermore, concentration has increased over time. In 1992, the largest 1 percent of banks (a total of 130 banks) held around 48 percent of total assets while at he end of 2017 the top 1 percent of banks (a total of 51 banks) held 75 percent of total assets.

Below I take each bank to be an observation. Thus, averages will be taken across banks without weighting by assets or total loans. This is done because, due to the high concentration present in the banking system, weighted statistics are driven by the top distribution of banks and miss the dynamics of the vast majority of banks which is precisely what this paper is pursuing to uncover.

3 Empirical results

3.1 Whole sample

Figure 1 shows, for each quarter in the sample, the average NCL ratio for the whole distribution of banks (the grey solid line denoted as "average"). This average is computed as a simple mean (unweighted) of the Noncurrent loan ratio of each bank in the sample. The figure also includes, for each quarter, the average NCL ratio, for the largest and smallest banks by assets, with each group representing 10 percent of all banks (the series denoted as "large" and "small", respectively). Grey areas represent recessions as published by the NBER. The correlation between the average NCL ratios for small and large banks is very high, 0.93. However, we can see how NCL ratios are moving over time because the whole distribution is, itself, moving. To control for changes in the whole distribution, I subtract, for each observation, the average for the whole sample of the corresponding quarter. Figure 2 presents the averages of these differences for the largest and smallest banks. Now the two series have a strong negative correlation of -0.87.

To check whether this result is due to the particular split between large and small banks, Table 1 includes this correlation where small and large banks also represent, the bottom and top 1, 5, and 20 percent of all banks by size. The same pattern of strong negative correlation is also present in all these cases.

Furthermore, some may argue this result is due to the different impact the Great Recession may have had on nonperforming loans by small and large banks. To check this hypothesis the last two lines of Table 1 compute the same correlations for periods before and after the Great Recession. The first period covers from the fourth quarter of 1992 until the fourth quarter of 2006. The second period spans from the first quarter of 2007 until the fourth quarter of 2017. Again, the same strong negative correlation is a general feature of the data.

Table 1

Correlations of NCL ratios between small and large banks				
	Largest and smallest banks			
	1%	5%	10%	20%
Whole sample (1992-2017)	-0.48	-0.80	-0.87	-0.96
1992-2006	-0.13	-0.70	-0.82	-0.95
2007-2017	-0.54	-0.82	-0.91	-0.98

Figure 3 presents a more detailed view of the correlation pattern of non-performing loans across banks. Each line in the figure shows the time series correlation between average NCL ratios (demeaned, as before, with respect to the population mean of the corresponding quarter) of a particular measure of top banks (in the Figure either the top 1, 5, 10, 30 or 50 percent of banks) with the average NCL ratio of any possible measure of bottom banks. Obviously, for a particular group of top banks, say the top x percent, the possible grouping of bottom banks range from the bottom 1 percent to the bottom $100 - x$ percent. Furthermore, because NCL ratios are demeaned, the correlation between the top x percent of banks and the bottom $100 - x$ percent of banks is always -1. In the Figure, the lowest correlation in absolute value is the one between the top and bottom 1 percent of banks (-0.48 percent). Nevertheless, we see that, independently of how we split the sample, all correlations are negative and most of them stay between -0.70 and -1.00.

To further understand the structure of the data, Figure 4 includes a snapshot of the correlations between NCL ratios across different percentiles of the bank asset distribution. To produce this figure, for each quarter in the database I divide the distribution of banks, ordered by assets, in 20 bins each representing 5 percent of banks. For each of these bins, I compute the difference between the average NCL ratio of the group with respect to the population average of the quarter. Then I compute the correlation of these differences across bins. Figure 4 shows the correlations of 5 of these bins with respect to the other groups. This way, the thin black line labelled "p = 5" represents the correlation of the NCL ratio of the lowest 5 percent of banks by size and the average ratio of the other groups (everything as a difference of the corresponding period's population average). Obviously, this line starts at 1. We see how the correlation is strongly positive for groups close in size and very strongly negative for the top percentiles. Conversely, the thick black line labelled "p = 100" represents the corresponding correlations with respect to the top 5 percent of banks (banks in the 95 to 100 percentiles). This series is the mirror image of the one for the bottom banks with positive correlations for other groups representing large banks and negative for groups of small banks.

In fact, there is a sense of monotonicity in these correlation patterns. The figure also includes the correlations of groups "p = 25" (covering banks in the percentiles 20 to 25 of the population), "p = 50" (percentiles 45 to 50) and "p = 75" (percentiles 70 to 75) with the other groups in which the sample is divided. To identify a group, just notice where the correlation reaches a value of 1. Interestingly enough, we can see how the correlations of the middle groups in general remain between those of the extremes. That is, in general, the correlation of the group of banks "p = 25" or "p = 75" with any other group remain between that of "p = 5" or "p = 100" and that of "p = 50" with respect the same group. Computations have been done for different splits (groups of banks representing 1, 2, 10 and 20 percent of the total population) and results in terms of shape and monotonicity remain the same.

3.2 Splitting the sample

The empirical findings described above could be due to a particular distribution of banks across different bank characteristics such as charter classes, product specializations or geographical location. To check whether similar results hold for these bank characteristics, the same computations are done for a variety of subsamples. Because the number of banks decreases rapidly as the sample is divided in categories, I will show the main results for the top and bottom 5, 10 and 20 percent of the size distribution of banks of those categories with at least 100 observations per quarter.

The dimensions in which I split the sample are:

- *Specialization.* The FDIC classifies depository institutions in 9 categories according to their primary specialization in terms of asset concentration. Results are presented in Table 2. The conclusions remain valid for the classes with enough observations, namely, “Agricultural”, “Commercial”, “Mortgage”, “Other specialization < \$1 Billion” and “All other < \$1 Billion”. The four remaining classes had less than 100 observations for at lest a quarter.

Table 2

Specialization

Specialization	Observations [min-max]	Largest/smallest banks 5%	10%	20%
Agricultural	[1193-2732]	-0.04	-0.39	-0.58
Commercial	[2696-3157]	-0.53	-0.78	-0.93
Mortgage	[380-2218]	-0.25	-0.60	-0.85
Other spec. < \$1 Bill.	[195-1175]	-0.13	-0.05	-0.45
All other < \$1 Billion	[479-3200]	-0.42	-0.47	-0.42

- *Charter class.* This is a classification code assigned by the FDIC based on the institution’s charter type (commercial bank or savings institution), charter agent (state or federal), Federal Reserve membership status (Fed member, Fed nonmember) and its primary federal regulator (state chartered institutions are subject to both federal and state supervision). With this information, banks are classified in 6 categories:

    1. N = commercial bank, national (federal) charter and Fed member, supervised by the Office of the Comptroller of the Currency (OCC).

2. SM = commercial or savings bank, state charter and Fed member, supervised by the Federal Reserve.
3. NM = commercial bank, state charter and Fed nonmember, supervised by the FDIC or OCC.
4. SB = savings banks, state charter, supervised by the FDIC.
5. SA = FDIC supervised state chartered thrifts and OCC supervised federally chartered thrifts. Prior to that date, state or federally chartered savings associations supervised by the OTS.
6. OI = insured U.S. branch of a foreign chartered institution.

Table 3 presents the computations of the 5 charter-classes with more than 100 observations per quarter. Results remain valid for all of them.

Table 3

Charter-class				
	Observations	Largest/smallest banks		
Charter-class	[min-max]	5%	10%	20%
N	[777-3396]	-0.62	-0.85	-0.92
SM	[738-895]	-0.76	-0.83	-0.92
NM	[2898-6381]	-0.67	-0.83	-0.94
SB	[312-503]	-0.49	-0.73	-0.88
SA	[348-1829]	-0.30	-0.55	-0.85

- *Federal Reserve district.* The Federal Reserve District in which the institution is physically located. Table 4 shows the results. The correlation between NCL ratios of large and small banks remains negative in 9 out of the 12 district. Correlations are close to 0 for 4 of the smallest districts in terms of number of banks when considering only 5 percent of the population but gets significantly negative with larger groups.

Table 4

Federal Reserve district				
	Observations	Largest/smallest banks		
Fed district	[min-max]	5%	10%	20%
Atlanta	[608-1537]	-0.69	-0.70	-0.88
Boston	[206-523]	-0.42	-0.40	-0.57
Chicago	[861-2198]	-0.79	-0.93	-0.94
Cleveland	[278-724]	-0.48	-0.64	-0.83
Dallas	[452-1230]	-0.57	-0.85	-0.87
Kansas City	[726-1840]	-0.67	-0.67	-0.92
Minneapolis	[498-1107]	-0.44	-0.63	-0.83
New York	[196-483]	0.09	-0.05	-0.62
Philadelphia	[155-411]	-0.06	-0.31	-0.55
Richmond	[274-833]	-0.02	-0.46	-0.65
San Francisco	[272-838]	0.06	0.17	-0.47
St. Louis	[547-1280]	-0.72	-073	-0.80

4 Conclusions

This paper has presented evidence about the negative correlation between nonperforming loan ratios of large and small banks. With quarterly data covering from 1992 until 2017, this negative correlation is a feature of the data that survives controlling for bank size as well as splitting the sample in time and bank characteristics such as specialization, charter class and Federal Reserve district.

This result has several implications for the banking industry in the US. First, it shows how an aggregate worsening of loan quality can be distributed differently depending on the size of a bank. Second, because the supply of credit differs between large and small banks, the different evolution of the quality of their loans may affect aggregate loan supply. This composition effect may remain hidden if one only looks at the relation between the aggregate Nonperforming loan ratio and the aggregate loan level. Third, because loan quality is an indicator of future banking profitability, this result suggests that profitability may diverge across banks according to their size.

References

[1] Clair, R. T. (1992): "Loan Growth and Loan Quality: Some Preliminary Evidence from Texas Banks" Economic Review, Federal Reserve Bank of Dallas, Third quarter.

[2] Janicki, H. J., and E. S. Prescott (2006): "Changes in the Size Distribution of U.S. Banks: 1960—2005" Economic Quarterly 92(4), Federal Reserve Bank of Richmond.

[3] Salas, V., and J. Saurina (2002): "Credit Risk in Two Institutional Regimes: Spanish Commercial and Savings Banks" Journal of Financial Services Research 22(3), pp. 203-224.

[4] Solttila, H., and V. Vihriälä (1994): "Finnish Banks' Problem Assets: Result of Unfortunate Asset Structure or Too Rapid Growth?" Bank of Finland Discussion Paper 23/94.

Figure 1: Ratio of Noncurrent loans to Total loans

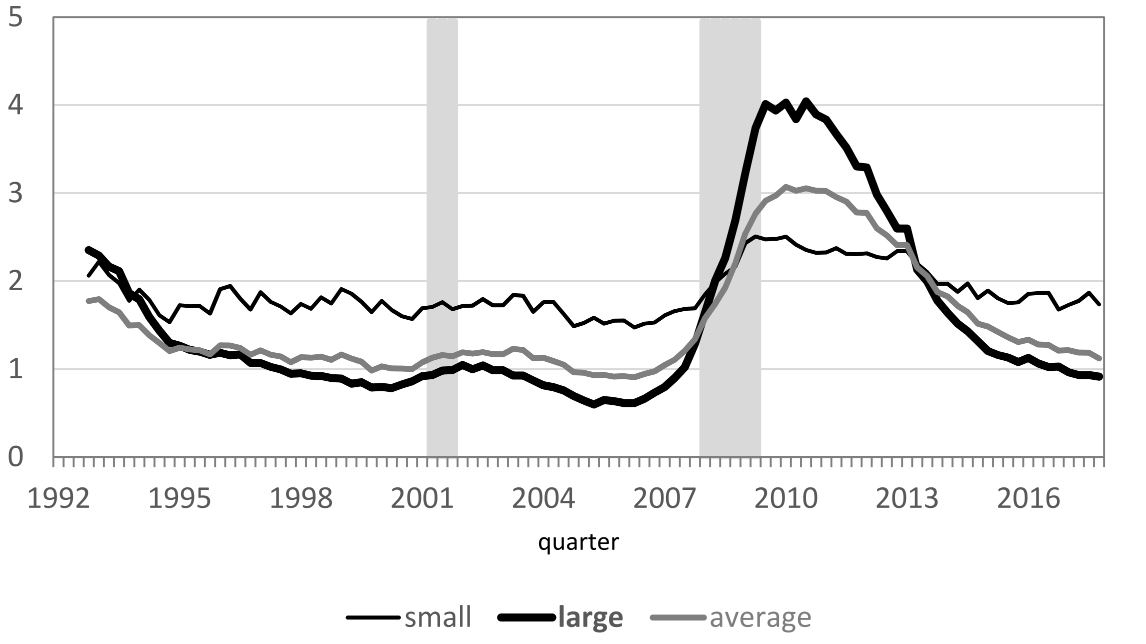
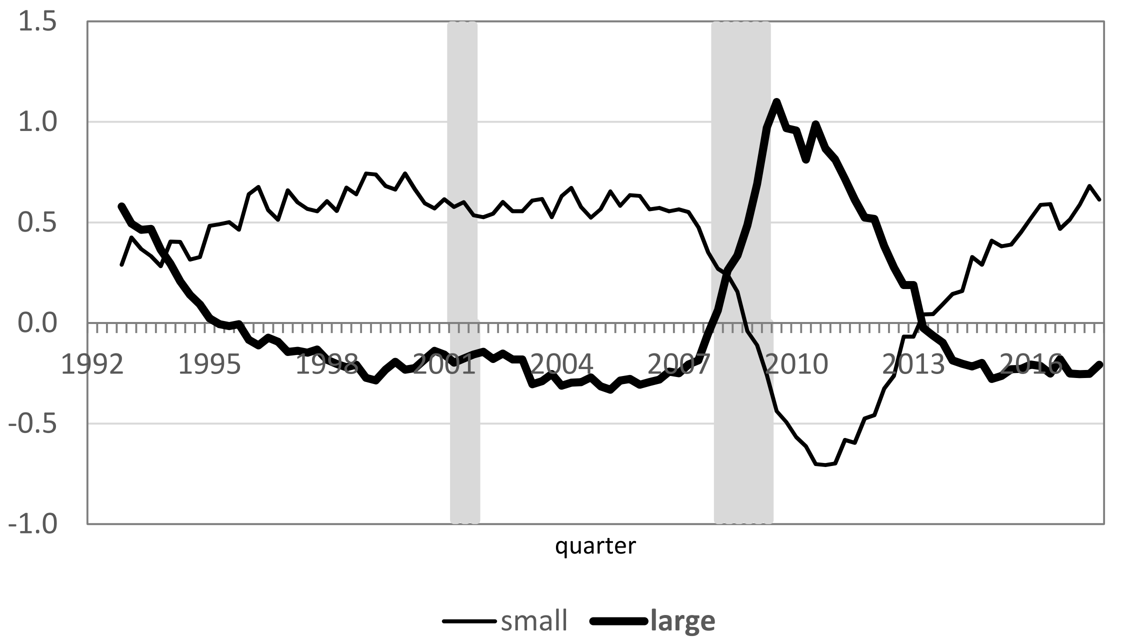


Figure 2: Differences of Noncurrent ratio to population average



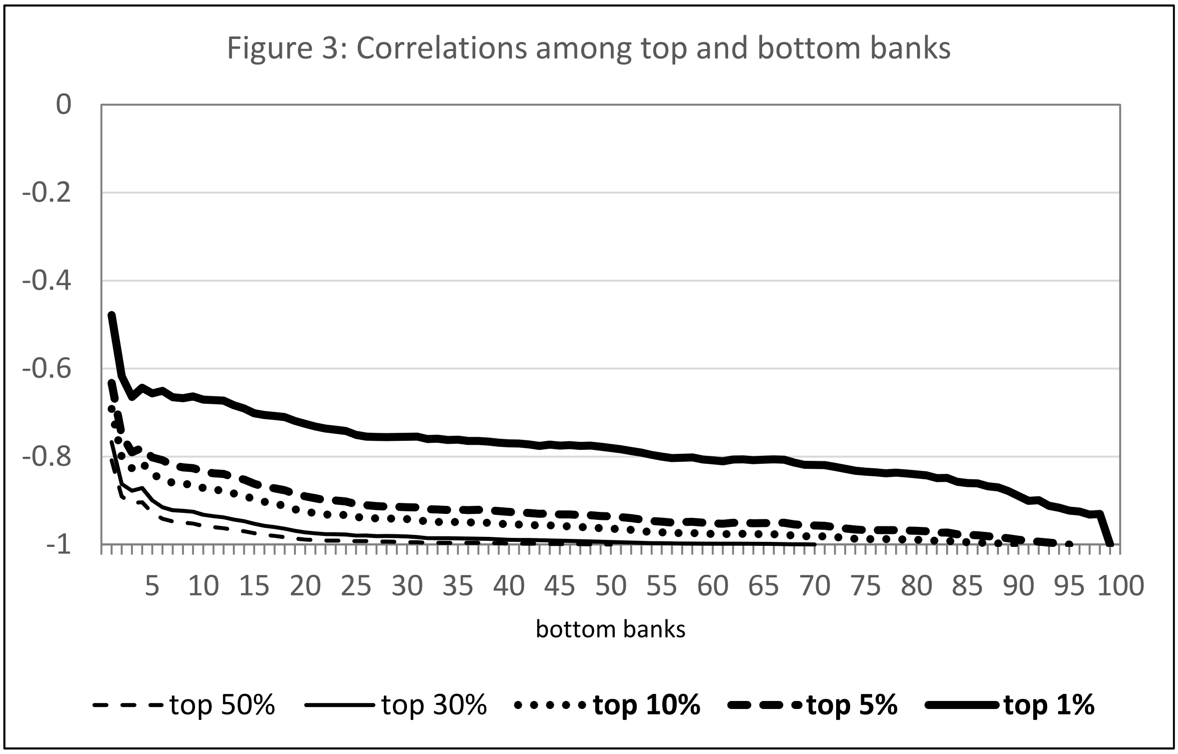


Figure 3: Correlations among top and bottom banks
0
-0.2
-0.4
-0.6
-0.8
-1
5 10 15 20 25 30 35 40 45 50 55 60 65 70 75 80 85 90 95 100
bottom banks
top 50%
top 30%
top 10%
top 5%
top 1%

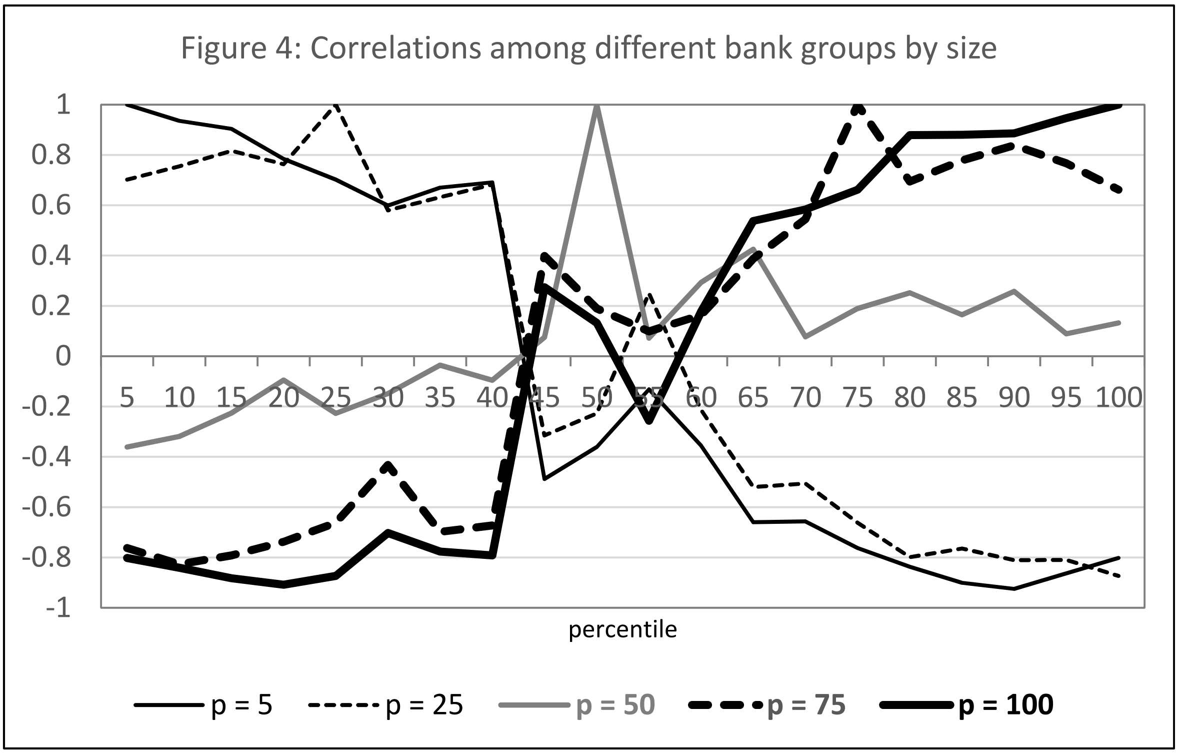


Figure 4: Correlations among different bank groups by size
1
0.8
0.6
0.4
0.2
0
-0.2
-0.4
-0.6
-0.8
-1
5 10 15 20 25 30 35 40 45 50 55 60 65 70 75 80 85 90 95 100
percentile
p = 5
p = 25
p = 50
p = 75
p = 100