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Abstract

It is a common place that during financial crises, like the one started in 2007, authorities provide substantial financial support to some problem banks, whilst at the same time let several others to go bankrupt. Is this happening because some particular banks are considered important and big enough to save, whereas some others are perceived as being 'Too-Small-To-Survive'? Is the size of banks the fundamental factor that makes authorities to treat them differently, or it is also that some banks perform poorly and are not capable of withstanding some considerable shocks whatsoever? Our study provides concrete answers to these questions thus filling part of the void in the existing literature. A short- and a long-run positive relationship between size and performance is documented regardless of the level of bank soundness (healthy *vs.* failed and assisted banks) under scrutiny. Importantly, we pose and lend support to the 'Too-Small-To-Survive' hypothesis according to which the impact of bank performance on failure probability strongly depends on size. Evidence shows that authorities tend not to save banks whose size is below some specific threshold.

Keywords: CAMEL ratings; financial crisis; bank size; 'Too-Small-To-Survive' banks
JEL classification: C23; D02; G01; G21

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1. Introduction

In September 2007, Northern Rock, one of the most significant retail and commercial banking institutions in UK and a substantial mortgage lender, after being largely affected by the problems in credit markets triggered by the U.S. subprime crisis, sought for a liquidity support facility with the purpose to replace money market funding. Due to the systemic importance of Northern Rock and in order to prevent the negative effects that its failure might have had on the entire system, Bank of England took the decision to extend a loan facility to the distressed institution. By January 2008, Northern Rock had borrowed more than $25 billion from the Bank of England. A month later and after the inability of Northern Rock to find a commercial buyer that would commit to repay taxpayers' money, the bank was eventually nationalised by the British government.

The financial aid provided to Northern Rock has been officially recorded as the first bank bailout after the eruption of the subprime mortgage crisis in August 2007. This was the prelude of a series of far-reaching and urgent rescue efforts that occurred in the global financial services industry during the late 2000s financial crisis. Indeed, in October 2008, the U.S. federal government launched the $700 billion Troubled Asset Relief Program (TARP) to offer emergency financial support to corporate firms but, most importantly, to banking institutions which were teetering on the edge of failure. Not surprisingly, the vast majority of the largest U.S. banks together with a number of smaller counterparts almost immediately agreed to participate in TARP. In Europe, a series of bailouts of some widely-known banking organisations also took place after the beginning of the crisis. The Swiss UBS, the three major Icelandic commercial banks (Glitnir, Kaupthing, and Landsbanki), the Danish Ebh Bank and the Roskilde Bank, the Dexia and the Fortis from Benelux countries are just some of the bailed out European banking companies. Apparently the key purpose of all the aforementioned rescue efforts was for national authorities to avert the sudden collapse of troubled institutions. But even more importantly, bank bailout policies were aiming at maintaining the stability of the system and containing systemic risk in financial markets.

Nevertheless, as it is almost always the case, every coin has two sides. On 28 September 2007, NetBank, a savings-and-loan bank located in the State of Georgia in U.S., was shut down by the federal regulatory authorities mainly due to excessive mortgage defaults. The Federal Deposit Insurance Corporation (FDIC) took receivership of the failed bank and all insured deposit accounts (of up to $100,000) were transferred to an assuming institution. NetBank thus became the first banking firm to fail due to the mortgage market problems. Some days later, on 4 October 2007, Miami Valley Bank was also hit by the credit crunch and shut down by the U.S. authorities. The collapse of Miami Valley Bank was followed by those of Douglas National Bank and Hume Bank in early 2008. Importantly, the number of U.S. bank failures increased rapidly from 2008 onwards. In total, for the period starting from early September 2007 and extending to the early days of 2013, there have been recorded 468 bank collapses in U.S. and the FDIC has been appointed receiver of all those bankrupt institutions. The losses from these failures in U.S. have been estimated to exceed the amount of $90 billion. By the same token, a number of banks in Europe and elsewhere were either failed, or nationalised during the crisis thus inflicting substantial losses on European governments and tax payers.

According to the above discussion, the U.S. federal authorities as well as the European and other national authorities worldwide have provided substantial financial support to several -mostly large- banking organisations whilst, at the same time, have let many others to go bankrupt, the vast majority of them being small banks. This non-uniform policy raises a series of important questions: are some particular institutions considered important and big enough to save -or alternatively 'Too-Big-To-Fail' (TBTF)- by the authorities in the sense that a collapse of any of them is very likely to trigger contagious defaults in the entire banking network, whereas some others are perceived as being 'Too-Small-To-Survive' (TSTS) in that their failure has no material impact on their counterparts, let alone on the system as a whole? Are, indeed, the size and the systemic importance of financial institutions the fundamental factors that make the authorities to treat them differently, or it is that the collapsed banks lag behind in terms of performance? To put it differently, is it that the authorities are reluctant to help some of the problem banks to stay afloat because they consider them as being TSTS, or these banks are (also) of so poor performance that are not capable of withstanding any serious shocks whatsoever? And, further, is there any particular threshold size below which a bank is very likely to fail in case of a banking crisis or in times of a financial turmoil? In other words, what is the threshold size (if any) below which a banking firm is viewed as being TSTS by regulatory authorities?

In this paper, we focus on the U.S. banking industry and make an attempt to provide concrete answers to all the aforementioned questions, which have never been examined in the burgeoning crisis literature. In fact, a large part of this literature is focused on Systemically Important

Financial Institutions (SIFIs) trying to explain their relevance in the propagation of the latest financial crisis. Hence, more research is clearly needed on the operation of small banking firms and their role in the functioning and the stability of the banking system. With this in mind, we collect data for the entire population of U.S. commercial and savings banks and categorise the sample banks in four distinct size groups: small, medium, large, and extra-large banks. We further construct three groups of banking institutions with respect to their soundness: healthy, failed, and assisted institutions via TARP. We, then, employ two different yet interrelated econometric models to test for any alterations in the overall performance and risk-taking behaviour amongst the different bank groups taking into account the above-mentioned size classification. A third model which defines a threshold size below which a banking firm is viewed as not being resilient to shocks is employed in our analysis to examine the validity of our TSTS hypothesis.

Our empirical analysis shows that size is a key determinant of performance and risk-taking behaviour of banks. More specifically, we demonstrate that smaller banks perform poorly compared to their larger counterparts and take higher risk. We report positive linear and non-linear effects of size on bank performance and risk-taking, where the non-linear effects are found to be stronger. Along the same lines, we show that when banks grow in size, this has a further positive impact on their performance and risk profile. Overall, a long-run positive relationship between size and performance is documented regardless of the level of bank soundness (healthy *vs.* failed and assisted banks) under examination. We further show that the decision of supervisory and regulatory authorities to let a bank fail seems to be influenced by the bank's absolute size and whether this falls below some particular threshold level. Indeed, we lend support to our TSTS hypothesis according to which the impact of bank performance on failure probability strongly depends on bank size.

The structure of the paper is as follows. Section 2 reviews the role of bank size in the literature. The aim of this Section is not to provide an extensive review of the past and current literature; rather, its key purpose is to present how size is intertwined with the operation of banks, discuss the relevance of bank size in the crisis literature, and indicate the literature gaps that our study aims to fill. Section 3 presents in detail the data set and the variables which are employed in the empirical analysis. The econometric models are sketched out in Section 4, where the estimation results are also discussed. Section 5 is devoted to robustness checks, whereas Section 6 concludes.

2. The importance of size in the banking literature

In September 1984, the Office of the Comptroller of the Currency (OCC) in U.S. made, for the first time, a public distinction between systemically and non-systemically important banking institutions. It announced that the biggest eleven from a total of approximately 14,000 banks that were in operation at that time were considered as TBTF and as such they would be offered full deposit insurance, whereas all the other banks would remain only partially covered. After that announcement, numerous studies have turned to investigate the operation of large, systemically important financial organisations. Some of the most prominent examples in this early TBTF literature are those of O'Hara and Shaw (1990), Boyd and Runkle (1993), Demsetz and Strahan (1997), and Galloway et al. (1997).

A significant part of the current banking literature which has been sparked by the emergence of the recent financial crisis has also focused its interest on the relevance of TBTF banks in the propagation of the crisis and its subsequent dissemination throughout the global economy. For instance, Huang et al. (2009) construct a framework for measuring and stress testing the systemic risk of 12 U.S. major commercial and investment banks; Adrian and Shin (2010) examine the procyclicality in leverage of the 5 biggest U.S. investment banks before the outbreak of crisis; Papanikolaou and Wolff (2013) focus on 20 U.S. systemically important Bank Holding Companies (BHCs) to study how modern banking that gave birth to the off-balance-sheet leverage activities affected the risk profile of these banks as well as the level of systemic risk before and after the onset of the crisis; lastly, Patro et al. (2013) uses the 22 largest commercial and investment banks in U.S. to analyse the relevance of stock return correlations in assessing the level of systemic risk.

Size has been introduced in the extant banking literature not only in absolute terms, but also in relative terms. There are indeed several studies that discuss the substantial differences which exist between the business operation and the performance of large banking firms with those of their smaller peers. For instance, size has been found to be amongst the key factors in the decision of a bank to follow some specific business model. Focusing on the U.S. banking market and distinguishing banks in different size clusters, DeYoung et al. (2004) claim that the deregulation process and the technological changes of the ’80s and the ’90s gave birth to two main bank size groups. The first group consists of big banks, whose operation is characterised by the use of ‘hard’ information, impersonal relationships with their customers, low unit costs, and standardised loans. The second group contains small banks, which collect and make use of ‘soft’ information, develop more personal relations with their customers, face higher unit costs, offer non-standardised loans, and provide the bulk of financing to small business firms.

In line with DeYoung et al. (2004), Carter and McNulty (2005) document an inverse relationship between the size of banking firms and the net return on small business lending, suggesting that smaller banks perform better than larger banks in the relevant loan market. On the other hand, larger banks are found to have an advantage in credit card lending, a market characterised by impersonal relationships and standardised loans. In a similar vein, Berger et al. (2005) find that small banks have a comparative advantage in making loans based on ‘soft’ information. This happens because of the different sets of incentives in the organisational structures of small and large banks.

Large banking organisations are generally found to be engaged in a very broad range of activities -other than traditional banking activities like loan granting and deposit taking- compared to their smaller peers. The study of Rime and Stiroh (2003) show that big banks are indeed very prone to the so-called ‘universal activities’ in contrast to small and mid-sized institutions, which are less diversified and resemble single-line businesses. These activities, which are mainly market-based, are explicitly defined by the Gramm-Leach-Bliley Act of 1999 in the U.S. banking market, and include -among others- securities dealing and underwriting, insurance underwriting, financial and investment advisory services, merchant banking, and issuing or selling securitised interests in bank-eligible assets.

As seen from the above discussion, size is found to be a crucial determinant of banks’ overall performance in the relevant literature. Banks of different sizes follow diverse business models, which are related to various levels of risk, increased or reduced earnings, higher or lower failure probabilities and so forth. Notwithstanding the fact that this sort of variations in the operation of banks has been well-documented in the extant literature, the burgeoning crisis literature, within which our study falls, does not appear to have paid the necessary attention to them. Rather, crisis literature is greatly concerned with the relevance of large and systemically important financial institutions in the emergence and the spread of the crisis. Accordingly, in the current paper, we make an attempt to fill this void by examining the performance of banks of different sizes in the recent crisis from various perspectives. Most importantly, we shed more light on the role of small banking institutions and the weight they carry for the system.

3. The data set

3.1. Description

The bank balance sheet data we employ in our empirical analysis are of quarterly frequency and extend from the beginning of 2002 to the end of 2012. We do not examine the years before 2002 for two main reasons. First, the two international financial crises which erupted in East Asia and in Russia at the end of the '90s combined with the Long Term Capital Management (LTCM) crisis of 1998 both had a destabilising impact on the U.S. banking system. Second, no considerable regulatory or other similar reforms occurred in the U.S. banking market after 2002, meaning that the operation of banks remained largely unaffected by exogenous factors throughout the examined period. In fact, the latest legislative activity in the U.S. that largely influenced the operation of the entire banking sector was the Gramm-Leach-Bliley Act of 1999, which opened up the local market allowing commercial and investment banks, and securities firms and insurance companies to merge their activities. If any further reforms had taken place in the banking regulatory environment after 2002, it would be very likely to have biased our results; indeed, it is well established in the relevant literature that regulation strongly affects industry structure and alters the behaviour of banks in terms of performance and risk-taking (see, for example, Brissimis et al., 2008).[1]

The bank data we employ in our empirical analysis have been hand-collected from the website of the Federal Reserve Bank of Chicago and that of the Federal Financial Institutions Examination Council (FFIEC). We begin with a total of 8,905 U.S. commercial and savings banking institutions that filed a Report on Condition and Income (widely known as Call Report) in the first quarter of 2002, that is, in 2002q1. Due to failures, mergers and acquisitions (M&As) that took place during the sample period but, mainly, after the onset of the crisis in mid-2007, the total number of active commercial and savings banks in the U.S. was reduced to 7,581 in

[1] It has to be mentioned at this point that the U.S. government enacted the Sarbanes-Oxley Act in mid-2002 with the purpose to set new or enhanced disclosure standards for all U.S. public company boards including those of banking firms. However, that Act had a partial effect on the operation of the banking industry as it only targeted the listed banks; further, it was introduced in the very beginning of our sample period implying that its overall impact is (most likely) reflected in our data.

2012q4. It is important to mention here that we do not consider any savings associations (*i.e.*, thrifts) in our analysis as they file a different regulatory report (the Thrift Financial Report) compared to the Call Report filed by commercial and savings banks. In addition, *de novo* banks, defined as banks less than five years old, are dropped from our sample because the operating behaviour and the characteristics of this sort of banks have been found to be substantially different from those of banks in operation for longer periods of time.[2] Moreover, banks which belong to the 1% and 99% percentiles of the size distribution are not considered in our sample. After checking the data for reporting errors and other inconsistencies (missing, negative or zero values), we obtain an unbalanced panel of 340,076 observations corresponding to N = 7,729 banks.

3.2. Classification of banks on the basis of their soundness

We identify all the U.S. commercial and savings banks which either failed or received financial assistance during the recent financial meltdown. To begin with, failed banks are defined as the insured institutions that have been closed requiring disbursements by FDIC. For the period starting in early September 2007 and extending to the end of December 2012, there have been recorded 468 bank collapses in U.S. and FDIC has been appointed receiver of all the bankrupt institutions. From this number, a total of 450 refer to failures of commercial and savings banking institutions, whereas the rest 18 failures concern thrifts which, as already noted, are not included in our sample.[3] To give the broad picture of the extent of bank failures in the recent crisis, we mention that only 25 banking institutions went bankrupt in the U.S. from 2000 to the beginning of the crisis. All the relevant information on bank failures is collected from the FDIC website.

We would like to clarify that the set of failed banks we construct does not contain Lehmann Brothers which also declared bankruptcy during the crisis and, more specifically, in September 2008. The reason for this exclusion is twofold: first, Lehmann Brothers was an investment bank and as such it was neither supervised from, nor insured by FDIC; and, second, this has been the biggest bank failure in the history of U.S. and is thus treated as an outlier in our study and is omitted from our data sample. For similar reasons, Bear Sterns & Company, American

[2] For further analysis on this issue, see, e.g., DeYoung and Hasan (1998), and DeYoung (2003).

[3] The names of the banks, the distribution of banks across the U.S. states and cities, the date that every failed institution ceased to exist as a privately-held going concern entity, the estimated assets and deposits of each institution at the time of failure, and the cost of every individual failure for FDIC are all available upon request.

International Group (AIG), Federal National Mortgage Association (Fannie Mae), and Federal Home Loan Mortgage Corporation (Freddie Mac) are also excluded from our sample.

Turning now to the assisted institutions of our sample, these refer to the banks which received some funding via TARP. The relevant list of TARP recipients is obtained from the U.S. Department of Treasury. We use this list to trace all commercial and savings banks which participated in TARP either directly, or through their parent (holding) firms. However, neither Bank Holding Companies nor Financial Holding Companies that received money from TARP are taken into consideration in our analysis, as this is not undertaken at a holding company level. In total, we are capable of tracing 824 TARP-funded banking firms in the U.S.[4]

Together with the above-described sets of failed and assisted banking companies, we also construct a third one which plays the role of the control sample in our econometric analysis and consists of all the healthy U.S. commercial and savings banks. Healthy institutions are those that neither failed nor received a financial aid during the crisis. From a statistical perspective, the sets of failed and rescued banks as described above do not intersect with each other in the sense that none of the sample banks that received financial assistance did later fail. Apparently this also holds true for the set of healthy banks and those of failed and bailed out banks.

3.3. Size classification of banks

As earlier discussed, our sample consists of the whole range of banks in terms of size. In Section 2, we took a literature-based approach to show how size influences the decisions of bank owners and managers regarding the activities, the performance and the risk-taking profile of banks. To control for the effects of size on the different business models that our sample banks have adopted and which have a considerable impact on their overall performance, we follow Berger and Bouwman (2013) and split our sample into four separate size clusters denoted by the lower-case letter k. We define small banks as those banks with total assets up to \$1 billion ($k = 1$); this definition of small banks conforms to the usual notion of community banks in U.S. We further define medium-sized banks with total assets between \$1 billion and \$3 billion ($k = 2$), large banks with total assets from \$3 billion to \$10 billion ($k = 3$), and extra-large banks as all those institutions with more than \$10 billion in total assets ($k = 4$).

[4] The detailed list of these banks is also available upon request.

Table 1
Size classification of banks. This table presents the four separate size groups into which the sample of banks is divided.

Size cluster (*k*)	Bank size	Bank Total Assets
1	Small banks	Up to $1 billion
2	Medium banks	Between $1 billion and $3 billion
3	Large banks	Between $3 billion and $10 billion
4	Extra-large banks	More than $10 billion

3.4. Sample characteristics

We can now proceed to discuss the characteristics of the sample banks on the basis of the above-described classifications. Although there are several thousands of banking firms in the U.S. market, the banks with total assets that account for more than $10 billion constitute only the 0.7% of the entire bank population; yet, on average, they hold more than 60% of total bank assets. On the other hand, the institutions with less than $1billion of assets account for 78% of banks, but all banks in this size category only hold about 12% of total assets. Large and extra-large banks hold together a market share which is equal to 76% of the entire U.S. banking industry.

To continue, small bank failures account for 83% of total failures during the crisis, while the rescues of large and extra-large banks account for 93% of total rescues. An exception of an extra-large bank with more than $300 billion of assets which was not saved by the authorities and declared insolvent was that of Washington Mutual Bank. This Bank was the sixth largest U.S. commercial bank when it failed in September 2008; Bank of America, JP Morgan Chase, Wachovia Bank, Citibank, and Wells Fargo Bank were those five institutions with more assets than Washington Mutual Bank. In fact, no other commercial or savings banking organisation with more than $100 billion of total assets went bankrupt during the crisis. On the other hand, the smallest failed bank held approximately $10 million of assets.

As regards the business models followed by the sample banks, business lending accounts for the substantial majority of loans for large and, especially, for extra-large banks. In contrast, small and medium-sized banks have been mainly involved with housing loans. In addition, extra-large banks obtain more than 67% of their purchased funds from abroad. Moreover, the relative use of core deposits (checkable, savings, and time deposits) shrinks with bank size, while the relative use of money market instruments like, for instance, derivatives and securitised assets, increases with size. These explain why the Net Interest Margin (NIM) measured as the difference between

Total interest income and Total interest expense divided by the interest-bearing assets is lower for large and extra-large banks. Correspondingly, non-interest income and non-interest expense are found to be lower for both small and medium-sized banks.

Based on the geographical characteristics of our data set, we note that extra-large as well as large banking firms are headquartered and located in terms of branching activity near salt water, that is, near the East and West Coasts of the U.S. On the other hand, small and medium-sized banks tend to concentrate their activity in the mainland and, more specifically, in states like Iowa, Nebraska, and Utah. As regards the distribution of failures, the states of Arizona, California, Georgia, and Nevada are amongst those with the highest number of bankruptcies. Most of the Northeastern and Southeastern states (excluding California) had either no or a few bank failures, whereas the Western U.S. states, which experienced a relatively larger decline in economic performance as measured by the GDP growth rate and the unemployment rate, had the highest bank failure rates. The converse holds true for bank bailouts: the vast majority of banking institutions that received some financial aid via TARP are headquartered in the eastern part of U.S.

3.5. CAMEL ratings

The bank performance variable we employ in our empirical analysis relies on the CAMEL rating system, which is utilised by the U.S. regulatory authorities to monitor the conditions in the banking industry. The Uniform Financial Rating System, informally known as CAMEL, was introduced by the U.S. authorities in November 1979 to conduct on-site examinations of bank safety and soundness. CAMEL is a vector of five different measures capturing Capital adequacy, Asset quality, Management expertise, Earnings strength, and Liquidity. In 1996, CAMEL evolved into CAMELS, with the addition of a sixth component ('S') that summarises the Sensitivity to market risk. U.S. regulators resort to CAMELS every 12 to 18 months; they assign a score on a scale of 1 (best) to 5 (worst) for each of the six CAMELS components. The six components are thereafter combined to generate a composite rating for each bank. Banks with composite ratings of 1 or 2 raise few, if any, supervisory concerns; on the other hand, banks with ratings of 3, 4, or 5 present moderate to extreme degrees of supervisory concern.

We construct a set of financial variables that largely resemble the components of the original CAMEL system. The 'Sensitivity to market risk' component is not considered in our analysis, because the majority of our sample banks are not significantly engaged in market activity. As earlier discussed, it is mainly the large banking organisations which are heavily involved with market-based products and services and are therefore influenced by market interest rate risk. We use the equity-to-assets ratio as an indicator of bank capital strength (*CAP1*); asset quality is captured by the provisions for credit losses divided by total loans and leases (*CREDLOSS1*); the quality of bank management is proxied by total operating income as a fraction of income generating assets (*MNGEXP1*), which is a typical measure of operating efficiency in the banking literature (see, e.g., Lane et al., 1986); the return on assets (*ROA*) is applied as a measure of earnings strength, whereas the ratio of cash & cash equivalents and federal funds sold and securities purchased under agreements to repurchase to total assets reflects the degree of bank liquidity (*LQDT1*). To develop the five ratios, we use bank balance sheet data collected from Call Reports. Appendix A summarises the *CAMEL* components and their data sources.

The two tables that follow report the results of simple univariate analyses of mean differences between the failed (Table 2a) and the rescued (Table 2b) sample banks with the healthy institutions. In these tables, we present the means and standard deviations of the five *CAMEL* components and calculate the differences in their means.

Table 2a
Univariate analysis. This table reports the results of a simple univariate analysis of mean differences between failed and healthy banks for all five *CAMEL* components. The description of each component together with the relevant data sources are provided in Appendix A. The values of a *t*-test which captures the statistical differences in the means of failed and healthy banks are reported in the last column of the table.

	Failed banks		**Healthy banks**			
	(*N*=438)		**(*N*=6,488)**		**Mean Difference**	***t*-stat**
Variables	**Mean**	**Stdev**	**Mean**	**Stdev**		
CAP1	0.081	0.751	0.117	0.152	-0.036	-7.89***
CREDLOSS1	0.029	0.619	0.008	0.241	0.021	8.10***
MNGEXP1	0.008	0.126	0.012	0.061	-0.004	-1.84**
ROA	0.007	0.260	0.015	0.201	-0.008	-4.69***
LQDT1	0.013	0.024	0.027	0.014	-0.014	-1.89**

***, **, * correspond to 1%, 5%, and 10% level of significance respectively for a two-tailed test

Table 2b
Univariate analysis. This table reports the results of a simple univariate analysis of mean differences between bailed out and healthy banks for all five *CAMEL* components. The description of each component together with the relevant data sources are provided in Appendix A. The values of a *t*-test which captures the statistical differences in the means of failed and healthy banks are reported in the last column of the table.

	Bailed out banks		**Healthy banks**			
	(*N*=803)		**(*N*=6,488)**		**Mean Difference**	***t*-stat**
Variables	**Mean**	**Stdev**	**Mean**	**Stdev**		
CAP1	0.090	0.751	0.117	0.152	-0.027	-6.94***
CREDLOSS1	0.009	0.310	0.008	0.241	0.001	1.29
MNGEXP1	0.014	0.297	0.012	0.061	0.002	1.50
ROA	0.011	0.391	0.015	0.201	-0.004	-1.91**
LQDT1	0.022	0.034	0.027	0.014	-0.005	-1.72*

***, **, * correspond to 1%, 5%, and 10% level of significance respectively for a two-tailed test

We start by discussing the results in Table 2a. We document that, during the sample period, the mean differences are highly significant for all the examined variables. For instance, the capital ratio (*CAP1*) is 8.1% and 11.7% for failed and for healthy banking firms respectively and the difference in means between the two groups of banks (which is equal to 3.6%) is statistically significant at the 1% level. We also report that the provisions for credit losses (*CREDLOSS1*) are higher for failed banks by 2.1% and that this difference is again statistically important at the 1% level. Markedly, the signs of the reported differences of *CAMEL* components are all the anticipated ones. That is, failed banks have significantly lower capital buffers, the loans and leases of these banks are riskier compared to those of their healthy counterparts, their managerial performance (*MNGEXP1*) is significantly worse, their profitability (*ROA*) is inferior, and, lastly, institutions that declared default hold less liquid assets in their portfolios (*LQDT1*).

Table 2b reports the results of the univariate analysis for the explanatory variables between the banks that received financial assistance via TARP and the banks which stayed afloat during the crisis and up to the very end of 2012. As we can see, it is only the differences in means for the capital ratio (*CAP1*) and for profitability (*ROA*) which are statistically significant at the 1% level: the reported mean differences are equal to 2.7% and 0.4%, respectively. Additionally, the difference in means between the two examined groups of banks is statistically significant at 10%

for the liquidity variable (*LQDT1*), whereas the mean differences for the other two *CAMEL* components -that is, *CREDLOSS1* and *MNGEXP1*- are not significant at any conventional confidence level.

4. The regression analysis

4.1. The performance-risk-size nexus in banking

Our first step is to explore the bank performance-risk-size nexus controlling for the impact of geographical characteristics. As earlier shown, this sort of characteristics is strongly related with the overall bank performance and the level of bank soundness. The model we initially employ in our empirical analysis relies on a data set which consists of the universe of 7,729 U.S. commercial and savings banks and extends from 2002q1 to 2012q4. The model specification is as follows:

$$\overline{CAMEL}_{ijk} = a_j d_j^{state} + b_k d_k^{size} + \varepsilon_{ijk} \tag{1}$$

where d_j^{state} is a dummy for the U.S. state *j* (*j* = 1, 2, …, 50); d_k^{size} is a dummy for the size class *k* (*k* = 1, 2, 3, 4); a_j is a state-specific intercept; and $b_k$is a slope coefficient that depends only on size class and is assumed to be identical across the U.S. states. The index *i* stands for the number of sample banks: *i* = 1, 2, 3, …., *N*. For each bank *i*, we average *CAMEL* ratings over the sample period. The reason of doing this is twofold: first, *CAMEL* ratings are based on accounting and not on market value measures. Accounting data, however, are intentionally smoothed meaning that bank managers have some short-run discretion when they report gains and losses. By time-averaging *CAMEL* scores, the degree of discrepancy between the accounting and market measures tends to decline. Second, as previously mentioned, several banks drop out of the sample over time due to failures and also due to M&As. Omitting these banks from the regression analysis is likely to bias our estimates. Again, this problem is addressed by averaging *CAMEL* for each banking organisation over its lifetime. It is important to mention at this point that, as earlier discussed, a lower composite *CAMEL* rating indicates superior performance. Therefore, *CAMEL* is introduced with a negative sign in eq. 1 to avoid any confusion in the interpretation of the regression results.

The null hypothesis we test is that bank size is not important for performance and risk-taking:

H_0: the slope coefficients on bank size are equal to zero for every size class

If H_0 is true, then the state dummies capture all -or at least most- of the explanatory power of the model.

As shown in Table 3 below, we normalise the coefficient on the *Medium* dummy variable. In the same context, one of the state dummies included in eq. 1 is also normalised to zero. According to the regression results, we can easily reject H_0, which implies that, as expected, size is an important determinant of the performance and the risk-taking behaviour of banks. Crucially, the coefficients on size dummies increase monotonically moving up from the smallest size class to the largest size class. An analysis of this result indicates that, by and large, smaller banks show an inferior performance relative to their larger counterparts. We can thus postulate that small-sized banking enterprises may not be in a position to fully and productively exploit the technological developments and operate under increased scale and scope economies. Admittedly, the technological advances of the recent decades, combined with the changes in the business models of large banking institutions and the growth of non-bank financial services providers, have made it more difficult for smaller banks to attract new customers, or even to retain the existing ones. In fact, small, community banking firms have lost business to larger financial institutions with relatively low cost structures in the years preceding the crisis.

To continue, smaller banks may not have the capacity to efficiently diversify the different types of risk they face. For instance, community banks typically carry a relatively high degree of credit risk for three main reasons. First, they tend to have fewer loan customers and this makes them more vulnerable to loan defaults thus increasing their idiosyncratic risk. Second, the activities of the majority of community banks in U.S. are geographically concentrated to a considerable extent. Although by lending to firms and households located in the same geographical region community banks can develop long-term relationships that can contribute to the better screening and monitoring of their borrowers, a high degree of geographical concentration implies that borrowers are influenced by the same (more or less) economic and financial conditions. By contrast, large banking organisations with branches spread over a wide geographic area can reap the benefits of this diversification as economic environments are hardly perfectly correlated. Accordingly, the level of market risk tends to be higher for smaller banking companies like community banks. And, third, community banks compete with larger banks which have greater opportunities to diversify risk through the broad scale and the variety of the products they offer.

To sum up, we document that the smaller a bank is, the lower its performance and the riskier its portfolio. Importantly, we do not report any considerable changes in our findings if, instead of the coefficient on the *Medium* dummy variable, we normalise the coefficients on any of the other three size dummies.

Table 3
Bank performance-risk-size nexus: regression results. This table presents the estimated coefficients of the bank size dummy variable for all four size categories *k* (*i.e.*, *Small*, *Medium*, *Large*, and *Extra-large*) based on eq. 1. The dependent variable is bank performance (*CAMEL*), which is composed of bank capital strength (*CAP1*), asset quality (*CREDLOSS1*), the quality of bank management (*MNGEXP1*), earnings strength (*ROA*), and bank liquidity (*LQDT1*). A description of each variable and the relevant data sources are included in Appendix A. White robust standard errors are used to correct for heteroskedasticity in the residuals.

	Size Coeff. Value (b_k)	***t*-stat**
Bank size (k)		
Small	0.21	2.04***
Medium	0.00	
Large	0.54	1.91**
Extra-large	0.73	2.32***
Obs (N)	7,729	
R^2	0.11	
F-statistics	13.43	

***, **, * correspond to 1%, 5%, and 10% level of significance respectively for a two-tailed distribution

Since a clear link has been established between size, performance, and risk-taking in the operation of the U.S. banking industry, we can now proceed to further scrutinise the examined relationship. To this purpose, we follow Boyd and Runkle (1993) and De Nicoló (2000) and construct a model which is consistent with the notion of long-run equilibrium:

$$CAMEL_{it} = a_0 + a_1 SIZE_{it-1} + \alpha_2 SIZESQ_{it-1} + \alpha_3 SIZEGR_{it-1} + \alpha_4 SYSTSIZE_{it-1} \\ + \alpha_5 HHI_t + \alpha_6 MA_{it} + \alpha_7 CR1_t + \alpha_8 GDP_t + \varepsilon_{it} \tag{2}$$

The dependent variable of eq. 2 is again given by the *CAMEL* scores of the sample institutions, with the exception that this time *CAMEL* is not averaged out over the sample period. Moreover, like we did in eq. 1, we also introduce *CAMEL* with a negative sign in eq. 2 to avoid any misinterpretation of the empirical results. Regarding the right-hand side variables, we make a clear distinction between a bank's absolute size (*SIZE*) and its systemic size (*SYSTSIZE*). *SIZE* is measured by the natural logarithm of the book value of total assets. The measurement of *SYSTSIZE* relies on the relevant definition found in the 'Wall Street Reform and Consumer Protection Act' (the Dodd-Frank Act). This Act, which passed in July 2010, aims to prohibit consolidations in the banking industry which result in banks with total liabilities exceeding 10 percent of the aggregate consolidated liabilities of all the firms in the industry. In other words, one of the main purposes of the Dodd-Frank Act is to prevent the emergence of oversized banking organisations. Hence, *SYSTSIZE* is measured by each sample bank's liabilities-to-GDP ratio (see Bertay et al. 2013). To account for possible nonlinearities, we include the squared term of *SIZE*, *i.e. SIZESQ*. We also control for differences in the growth rate of banks' size by incorporating the term *SIZEGR* in our model. The sum of the coefficients on *SIZE*, *SIZESQ*, and *SIZEGR* gives us the net effect of a permanent change in bank size on *CAMEL*. In other words, it captures the notion of long-run equilibrium.

Following the relevant literature (see Leary, 2009 and Buch et al., 2013), all four size variables in eq. 2 are lagged by one quarter to address possible endogeneity and simultaneity concerns between *CAMEL* and bank size. Admittedly, selecting the number of lags to be smaller than the correct one may distort the size of the estimation tests. On the other hand, selecting orders greater than the correct one is likely to result in a significant loss of explanatory power. Therefore, the lag structure of our size variables is determined by two of the most popular model selection criteria, namely the Akaike Information Criterion and the Schwarz-Bayesian Information Criterion.

We measure the degree of market concentration with the Herfindahl-Hirschman Index (*HHI*) using bank total deposits as the input variable. *HHI* is calculated as the sum of squares of the market share of each bank included in our sample:

$$HHI_t = \sum_{i=1}^{N} (market\ share)_{iq}^2 \tag{3}$$

Eq. (3) relies on the market share of bank i in quarter q where *N* is the total number of banks in the examined U.S. market. The index ranges from 0 to 10,000, where zero indicates a market with an infinite number of banks and 10,000 shows a market with just a single banking firm. *HHI* is a static measure in the sense that it estimates market concentration at some particular point in time q.

Additionally, we control for the possible impact of M&As by introducing a dummy variable in our model (*MA*), which is equal to unity in the quarter q that bank i was involved in some M&A transaction. For example, if a transaction occurred on, say, April 15 2008, then this transaction is recorded in the second quarter of 2008, meaning that the binary variable *MA* takes the value of one in 2008q2. To construct *MA*, we resort to the relevant information provided by the FFIEC. We also introduce a crisis dummy (*CR1*) to capture the impact of the crisis on the operation of banks. *CR1* is set equal to 1 in 2007q3 and thereafter, since August of 2007 is generally accepted as the start date of the crisis. Specifically, that was the time when the TED spread, that is, the difference between the yield on three-month London Interbank Offered Rate (LIBOR) and the yield on three-month U.S.Treasury bills which is an indicator of credit risk, widened to almost 200 basis points relative to a historically stable range of 10-50 basis points. Several recent studies in the banking literature have adopted the third quarter of 2007 as the starting point of the crisis in their empirical analyses (see, e.g., Cornett et al., 2011). The variations in the macroeconomic conditions amongst U.S. states are captured by the GDP output gap (*GDP*), which is obtained from the Bureau of Economic Analysis of the U.S. Department of Commerce. All variables we use in eq. 2 and the sources utilised to construct them are summarised in Appendix A.

Table 4 reports the Pearson correlations among the dependent and the explanatory variables of eq. 2. As expected, the correlations between *SIZE* and *SIZESQ* are almost equal to unity. However, the correlation coefficients between other pairs of independent variables are in all cases below 0.65, which suggests that multicollinearity is not likely to be a problem. Nevertheless, since collinearity may exist between more than two independent variables, we proceed to regress each of the independent variables of eq. 2 on all the other independent variables and then calculate the remaining terms, which are given by the so-called Variance-Inflation Factors (VIFs). More concretely, VIFs represent a scaled version of the multiple-correlation coefficients between one variable and the remainder of the independent variables. All VIFs are found to be far below the cutoff value of 10.00, which signifies the absence of serious multicollinearity that can distort our results.[5] For the explanatory variables which are significantly correlated with the dependent variable of our model, the reported correlations are in the expected directions. To give an example, a significantly positive correlation between *CAMEL* and *GDP* is reported, showing that banks perform better under favourable economic conditions. More importantly, we observe that *CAMEL* is significantly correlated with all four size variables of eq.2 (*i.e.*, *SIZE*, *SIZESQ*, *SIZEGR*, *SYSTSIZE*), and this evidence provides support for and further motivates our analysis.[6]

[5] See Gujarati (1995) for a discussion of 'rule-of-thumb' methods of detecting multicollinearity. Gujarati suggests that a VIF in excess of 10.00 would indicate a high degree of collinearity.
[6] The results of Pearson correlation analysis are confirmed by the use of Spearman correlation rank tests.

Table 4
Correlation matrix. This table contains the Pearson correlations between the dependent and the independent variables of eq. 2. *P*-values are reported below the correlation coefficients. All variables and the sources utilised to construct them are included in Appendix A.

	CAMEL	*SIZE*	*SIZESQ*	*SIZEGR*	*SYSTSIZE*	*HHI*	*MA*	*CR1*	*GDP*
CAMEL	1.00								
SIZE	0.65***	1.00							
	0.00								
SIZESQ	0.64***	0.99***	1.00						
	0.00	0.00							
SIZEGR	0.51**	0.58***	0.52***	1.00					
	0.04	0.00	0.00						
SYSTSIZE	-0.57***	-0.22**	-0.24**	-0.10*	1.00				
	0.00	0.04	0.04	0.07					
HHI	0.45**	0.31*	0.30*	0.17*	-0.14	1.00			
	0.02	0.08	0.08	0.09	0.17				
MA	0.12**	0.25*	0.26*	0.37**	-0.09	0.14**	1.00		
	0.04	0.06	0.07	0.04	0.26	0.03			
CR1	-0.39**	-0.41*	-0.42*	-0.63**	0.42**	-0.24*	-0.15	1.00	
	0.02	0.05	0.05	0.04	0.04	0.06	0.11		
GDP	0.32***	0.53**	0.52**	0.24**	-0.33*	0.29*	0.22	-0.18	1.00
	0.00	0.04	0.04	0.06	0.06	0.08	0.12	0.24	

***, **, * correspond to 1%, 5%, and 10% level of significance respectively for a two-tailed distribution

To estimate eq. 2, we rely on the set of the above-described variables which are observable over time. Nonetheless, there might exist some unobserved variables which are likely to have an impact on the examined relationship and are not incorporated in our model. Omitted variables in general can be either constant over time, or time-dependent. Regardless of their time dimension, omitted variables are difficult, or sometimes impossible to be measured and be controlled for. If we search to find instrumental variables, or proxies, for the likely omitted variables, a series of rather strong assumptions which are hardly met in practice has to be made. Moreover, it is necessary to know how to correctly model each omitted variable's influence on the dependent variable of the regression equation as well as the relationship that holds between the instruments and the possible omitted variables. Most importantly, it is very problematic to identify the specific variables which have been omitted from the regression model and are correlated with the main model variables thus producing flawed estimates.

We choose to introduce individual (bank-specific) fixed effects in our regression analysis to account for the influence of any time-invariant omitted variables. Fixed effects can indirectly control for these variables as they focus on within-bank variation. Suppose we have the following model in which *Z* stands for the vector of correlated time-invariant omitted variables:

$$Y_{it} = \alpha_i + \beta' X_{it} + \gamma' Z_{it} + \varepsilon_{it} \tag{4}$$

We compute the time group means and express eq. 4 in the form of averages:

$$\overline{Y_\iota} = \overline{\alpha_\iota} + \beta' \overline{X_\iota} + \gamma' \overline{Z_\iota} + \overline{\varepsilon_\iota} \tag{5}$$

If we subtract eq. 5 from eq. 4 we obtain:

$$Y_{it} - \overline{Y_\iota} = (\alpha_i - \overline{\alpha_\iota}) + \beta'(X_{it} - \overline{X_\iota}) + \gamma'(Z_{it} - \overline{Z_\iota}) + (\varepsilon_{it} - \overline{\varepsilon_\iota}) \tag{6}$$

And because $Z_{it} = \overline{Z_\iota}$, eq. 6 is reduced to:

$$Y_{it} - \overline{Y_\iota} = \beta'(X_{it} - \overline{X_\iota}) + (\varepsilon_{it} - \overline{\varepsilon_\iota}) \tag{7}$$

Since there is no variation in Z over the time frame of the regression, the vector of omitted variables drops out of the model as shown in eq. 7.

The fixed-effects model is more appropriate when differences across banks are deemed to be substantial, time-invariant, and correlated with the explanatory variables. The random-effects model, on the other hand, is appropriate when correlated omitted variables are not an issue to be considered. Given the potential for omitted variables bias and the importance of bank-specific effects in our model specification, we anticipate the fixed-effects approach to be the most appropriate one. Indeed, we can easily reject the use of random effects on the basis of the Hausman (1978) test. At standard levels of statistical significance (*i.e*., 1% and 5%), we reject the null hypothesis that the differences in coefficients obtained from the two estimation methods are not significant. Accordingly, the fixed-effects model is our preferred estimator.

So far we have discussed how we address the problem of omitted variables which remain constant over time. However, as noted earlier, there is also the possibility of the estimated model parameters to suffer from bias which emerges from time-varying omitted variables. To correct for bias caused by such unobserved time-variant systematic factors (like, e.g., the level of interest rates) which may have an impact on the behaviour of banks over time, we include a vector of time fixed effects. Time fixed effects therefore capture the unobserved and the non-measurable time-varying characteristics of the likely omitted variables as well as of the variables included in eq. 2. In addition, we control for the differences in the banking environments amongst U.S. states, by incorporating state fixed effects in our regression.

We run three different regressions, one for each level of banking soundness, that is, one for the healthy institutions, another one for the failed ones, and a third one for the bailed out banks which received assistance via TARP during the crisis. The regression results are presented in the Table 5 below.

Table 5

Bank performance-risk-size nexus: regression results. This table presents the estimation results of eq.2. The dependent variable is bank performance (*CAMEL)* which is composed of bank capital strength (*CAP1*), asset quality (*CREDLOSS1*), the quality of bank management (*MNGEXP1*), earnings strength (*ROA*), and bank liquidity (*LQDT1*). The main explanatory variables are: bank size (*SIZE*), bank size squared (*SIZESQ*), the growth of bank size (*SIZEGR*), and systemic bank size (*SYSTSIZE*). All four size variables are lagged by one quarter to address possible endogeneity and simultaneity concerns between performance and size. The set of control variables includes banking market concentration (*HHI*), a dummy variable (*MA*) which accounts for M&A transactions, a crisis dummy variable (*CR1*), and the level of economic growth (*GDP*). A description of each variable and the relevant data sources are included in Appendix A. Individual bank fixed effects, time fixed effects, and state fixed effects are incorporated in the regression model. Heteroskedasticity-robust *t*-statistics are reported next to coefficient estimates.

	Healthy Banks		**Failed banks**		**Bailed out banks**	
Variables	Coef value	*t*-stat	Coef value	*t*-stat	Coef value	*t*-stat
constant	0.95	1.21	0.56	1.03	1.07	1.59*
SIZE	0.82	1.87**	0.24	1.88**	1.12	1.91**
SIZESQ	2.21	1.94**	1.69	1.86**	2.55	2.05***
SIZEGR	3.40	2.41***	2.22	2.49***	4.73	3.11***
SYSTSIZE	-1.15	-1.31	-1.07	-1.09	-2.15	-1.93**
HHI	1.39	2.47***	1.87	1.92**	0.97	1.88**
MA	0.67	1.86**	0.75	1.97***	1.02	2.09***
CR1	-1.87	-3.89***	-4.76	-4.98***	-2.71	-3.44***
GDP	2.98	3.45***	3.46	1.91**	3.02	2.90***
Obs (N)	6,488		438		803	
R^2	0.19		0.22		0.18	
Individual fixed effects	Yes		Yes		Yes	
Time fixed effects	Yes		Yes		Yes	
State fixed effects	Yes		Yes		Yes	

***, **, * correspond to 1%, 5%, and 10% level of significance respectively for a two-tailed distribution

We observe that *SIZE* and *SIZESQ* enter with positive signs in all three regressions and that are both highly significant. That is, we report positive linear and nonlinear effects of size on bank performance for the three examined groups of banks. In fact, the nonlinear effects are found to be stronger compared to the linear effects, suggesting that the interrelationship between performance, risk, and size is highly nonlinear. We also document that when a bank grows in size, this has a further positive impact on its overall performance. This is to say, small banking firms lag behind in terms of performance, a result which has been earlier discussed in detail. In fact, bailed out banks are found to have stronger incentives to increase their asset size compared to the healthy and failed banks as shown by the higher coefficient value of *SIZEGR* on *CAMEL* for the group of TARP institutions. The combination of the latter two findings provides evidence that banks follow a TBTF management strategy. Taking as granted that the systemic importance of a financial company is closely linked to its size, we claim that a bank has the tendency to become larger not only because this will potentially lead to the improvement of its performance, but also because an implicit bailout guarantee is in place by the authorities in case of a financial debacle. On the whole, the net effect of bank size on performance and risk as reflected in the sum of the coefficients on *SIZE*, *SIZESQ*, and *SIZEGR* is clearly positive regardless of the level of bank soundness under scrutiny. This reveals a long-run relationship between size and performance.

As regards systemic size, this is found to be negatively associated with bank performance, albeit the coefficient on *SYSTSIZE* is statistically significant only for the assisted institutions. The explanation we provide relies on the rationale that a change in the absolute size of a bank entails a change in its systemic size. As described above, banks have strong incentives to become larger as this, *inter alia*, has a positive impact on their overall performance. Nevertheless, when a bank achieves a TBTF status in the sense that its failure is expected to have destabilising consequences on the entire system, this exerts a reverse effect on its performance. Managers seem to be aware that even if their banks perform relatively poorly after becoming systemically important, authorities will rescue these banks if needed. This sort of bank management strategy forces the system to consider large-scale bailouts like it has been the case in the recent crisis.

Market concentration is found to positively affect the performance of banks, where the impact is lower for TARP recipients and higher for failed banks. We also report an improvement in the performance of banks due to M&As, showing that banks can expand their market shares and can better exploit economies of scale and scope via mergers. As a result, they can earn higher rents, boost their profits, and improve their overall performance. This result remains unchanged across the three different banking groups we examine. The combination of the aforementioned findings illustrates that a more concentrated banking industry consists of entities of greater performance and safer portfolios of assets. This implies that market concentration through M&As can be beneficial for the stability of the system. Two main arguments have been put forward in support of the view that concentration reduces fragility thus strengthening the stability of the system. First, Porter (1979) showed that concentrated banking systems might enhance market power and boost bank profits. High profits provide a buffer against adverse shocks and increase the charter value of banks thereby lowering the incentives for bank owners and managers to take excessive risk; this, in turn, reduces banking sector fragility. Second, it is broadly argued in the literature that it is easier to monitor a restricted number of banks in a concentrated banking market than to monitor a large number of banks in a dispersed market. Subsequently, bank supervision is more effective and fragility less pronounced in concentrated banking systems.

As expected, the impact of the late 2000s financial crisis captured by the binary variable *CR1* on bank performance is clearly negative. This holds true especially for the failed and rescued institutions; healthy banks are found to have been affected to a lesser extent from the crisis. It is widely accepted that economic performance has a considerable effect on the demand and supply of banking services. More precisely, high levels of banking activity are generally related to favourable economic conditions like price stability and economic development. In this context, the macroeconomic environment is largely considered to have an impact on the overall performance of banks. Indeed, economic growth (*GDP*) is documented as having a positive influence on *CAMEL*, meaning that recession has a negative impact on bank performance which confirms the previous result about the effect of the crisis on the banking system.

4.2. The 'Too-Small-To-Survive' threshold size

We can now proceed to investigate whether and to what extent size plays a role in determining the effects of bank performance on bank failure probability. Put differently, we wish to establish a threshold size which links bank performance to the likelihood of bank failure with the purpose to test our TSTS hypothesis. To this aim, we resort to Hansen's (1999) threshold estimation technique which presupposes the use of a balanced data set. For this reason, we construct a balanced sample that consists of 5,231 failed and healthy U.S. commercial and savings banks. The variables we employ in our analysis are the same with those used in eq. 2 (their description can be found in Appendix A). The likelihood of bank failure in eq. 8 below is denoted by $\Pr(FAIL)_{it}$; IF is an indicator function that takes the value of 1 if the argument is true, and 0 otherwise. Our model (eq. 8) allows us to investigate whether, and if so, at what level of bank size there is a statistically significant change in the coefficient of *CAMEL* and how this affects the bank failure likelihood.

$$\Pr(FAIL)_{it} = a_0 + a_1 CAMEL_{it} IF(SIZE_{it} < Threshold) + \alpha_2 CAMEL_{it} IF(SIZE_{it} > Threshold) + \alpha_3 HHI_t + \alpha_4 MA_{it} + \alpha_5 CR1_t + \alpha_6 GDP_t + \varepsilon_{it} \quad (8)$$

Table 6
The TSTS threshold size: regression results. This table presents the estimation results of eq. 8. The dependent variable is the probability of bank failure. The main explanatory variables include bank size (*SIZE*), and bank performance (*CAMEL)* which is composed of bank capital strength (*CAP1*), asset quality (*CREDLOSS1*), the quality of bank management (*MNGEXP1*), earnings strength (*ROA*), and bank liquidity (*LQDT1*). The set of controls includes banking market concentration (*HHI*), a dummy variable (*MA*) which accounts for M&A transactions, a crisis dummy variable (*CR1*), and the level of economic growth (*GDP*). A description of each variable and the associated data sources are included in Appendix A. Heteroskedasticity-robust *t*-statistics are reported next to coefficient estimates.

Variables	Coefficient value	*t*-statistics
constant	0.95	1.21
SIZE below threshold	4.94	1.87**
SIZE above threshold	-2.08	-2.35***
HHI	-1.39	-1.41
MA	-0.78	-1.50
CR1	2.65	3.51***
GDP	-3.98	-4.67***

Obs (N)	5,231
R^2	0.24
TSTS threshold level of *SIZE*: $1,096,342,877	

***, **, * correspond to 1%, 5%, and 10% level of significance respectively for a two-tailed distribution

The regression results in Table 6 lend support to our hypothesis that the impact of bank performance on failure probability largely depends on bank size. Indeed, we find that *CAMEL* has a positive and statistically significant coefficient if *SIZE* is smaller than $1,096,342,877, whereas the coefficient is negative and significant when *SIZE* is larger than $1,096,342.877. Markedly, the mean total assets of the failed banks during the crisis is $1.2 billion.[7] It is also worth noting that community banks are defined as those banks with less than $1 billion in assets (as earlier noted). Both these figures are very close to our estimated TSTS threshold size for the U.S. banking industry.

Small, community banks have long played a key role in the U.S. economy, providing loans and other financial services to households and small businesses within their local markets. However, the crisis took a heavy toll on these banks: approximately 400 small banks failed and several hundred remain on the problem bank list which is maintained by the FDIC. Our explanation to this phenomenon is that it may not be optimal for supervisory and regulatory authorities to rescue banks whose size is below the level of $1,096,342.877 in total assets. This is in line with the findings of Goodhart and Huang (2005) and Gong and Jones (2010) according to which the optimal bailout policy for authorities is one which considers only large-sized banks for potential rescues, disregarding small banks as they are of little or no importance for the system as a whole. Very importantly, small banks, apart from viewed as being TSTS by the authorities, also perform poorly in relative terms. Indeed, size has a significantly direct impact on performance ratings, meaning that the overall performance of community banks is weaker compared to that of larger banking enterprises.

[7] The bankruptcy of Washington Mutual Bank with $307 billion assets has been recorded as the biggest commercial bank failure in the crisis and is thus treated as an outlier here.

In addition, we claim that the reported TSTS threshold size can have a considerable impact on the performance and risk-taking decisions of bank managers. It is an undisputed fact that managers have the potential to influence the performance of their banks through their decisions regarding the composition and size of the banks' balance sheet and the quality of their oversight of the banks' operations. In case a manager knows that his bank is considered by the authorities to be TSTS and hence is not protected by bailout policies, he may turn to resort to riskier investment decisions. Indeed, Hakenes and Schnabel (2010), in a theoretical framework, establish a link between size and performance by showing that small banks which are not considered by the authorities to be systemically important take higher risk, especially when the bailout probability of the banks which are protected by the system is increased.

5. Robustness analysis

To test the robustness of our results, we use a set of alternative variables to construct *CAMEL* ratings. Capital adequacy is measured by the ratio of Tier 1&2 regulatory bank capital to risk-based assets (*CAP2*); asset quality is proxied by loan loss reserves and loan charge-offs divided by total loans (*CREDLOSS2*); the returns on equity are utilised to proxy banks' earnings (*ROE*); and the ratio of liquid deposits to total deposits (*LQDT2*) is employed in our robustness analysis to measure the degree of liquidity of the sample banking firms. As regards Management expertise, this is proxied by a measure of bank managerial efficiency (*MNGEXP2*). To calculate *MNGEXP2*, we employ the input-oriented Data Envelopment Analysis (DEA) model. DEA may be computed either as input- or output-oriented. Input-oriented DEA shows by how much input quantities can be reduced without varying the output quantities produced. Output-oriented DEA assesses by how much output quantities can be proportionally increased without changing the input quantities used. The two measures provide the same results under constant returns to scale, but give different values under variable returns to scale. Nevertheless, both output- and input-oriented models identify the same set of efficient/inefficient bank management.[8]

Let us assume that for the N sample banks there exist S inputs producing R outputs. Hence, each bank i uses a nonnegative vector of inputs denoted by $x^i = (x_1^i, x_2^i, \dots, x_S^i) \in R_+^S$ to produce a nonnegative vector of outputs, denoted by $y^i = (y_1^i, y_2^i, \dots, y_r^i) \in R_+^R$, where: $i = 1, 2, \dots, N$; $r = 1, 2, \dots, R$; $s = 1, 2, \dots, S$. Production technology, $F = \{(y, x) : x \text{ can produce y}\}$, describes the set

[8] For a more detailed discussion, see Coelli et al. (2005).

of feasible input-output vectors, and the input sets of production technology, $L(y)=\{x:(y,x)\in F\}$ describe the sets of input vectors that are feasible for each output vector.

To measure the variable returns to scale managerial cost efficiency (*MNGEXP2*), we resort to the following input-oriented DEA model, where inputs are minimised and outputs are held at constant levels:

$$MNGEXP2^{*} = \min(MNGEXP2),\ \ s.t. \tag{9}$$

$$\textstyle\sum_{i=1}^{N} \lambda_i x_{is} \leq (MNGEXP2)(x_{1s}) \tag{10}$$

$$\textstyle\sum_{i=1}^{N} \lambda_i y_{ir} \geq y_{1r} \tag{11}$$

$$\textstyle\sum_{i=1}^{N} \lambda_i = 1 \tag{12}$$

$$\lambda_i \geq 0 \tag{13}$$

Bank_1 represents one of the N banks under evaluation for $i = 1$; x_{1s} and y_{1r} are the sth input and rth output for bank_1, respectively. $MNGEXP2^{*}$ stands for the optimal managerial efficiency score in that $MNGEXP2^{*} = 1$. In such a case, the current input levels cannot be proportionally improved given output levels, indicating that bank_1 lies upon the cost efficiency frontier. If $MNGEXP2 < 1$, then bank_1 represents an inefficient bank; *MNGEXP2* gives the managerial efficiency score of bank_1. Finally, λ is the activity vector denoting the intensity levels at which the total observations are conducted. Note that this approach, through the convexity constraint $\Sigma\lambda = 1$ (which accounts for variable returns to scale) forms a convex hull of intersecting planes, since the frontier production plane is defined by combining some actual production planes.

An important concern in the empirical estimation of efficiency is the definition of bank inputs and outputs. This is strongly related to the specific role that deposits play in the operation of financial institutions. The banking literature addresses this issue by using two main approaches: the intermediation or asset approach and the production or value-added approach.[9] Under the former one, financial firms are viewed as intermediaries which transform deposits and purchased funds into loans and other earning assets. This is to say, liabilities and physical factors are treated as inputs, whereas assets are treated as outputs. The production approach, on the other hand,

[9] See Berger and Humphrey (1997) for a detailed analysis of the advantages and disadvantages of the two approaches.

regards financial institutions as producers of services for account holders, measuring output with the number of transactions or documents processed over a given period of time. Therefore, deposits are encompassed in the output and not in the input vector, which exclusively consists of physical entities.

Berger and Humphrey (1991), however, propose a third approach that, contrary to the above two approaches, captures the dual role of banking operations. In fact, the so-called 'modified production approach' can be viewed as a combination of the 'intermediation' and 'production' approaches, as it enables the consideration of both the input and output characteristics of deposits in the cost (or profit) functions. More specifically, the price of deposits is considered to be an input, whilst the volume of deposits is accounted as an output. Under this specification, banks are assumed to provide intermediation and loan services as well as payment, liquidity, and safekeeping services at the same time.

In our analysis, we adopt the 'modified production approach' to define inputs and outputs. The reason of doing so is because this approach moves one step further describing the activities of banks in a more complete setting thereby providing a closer representation of reality. We specify five variable outputs in total of which traditional banking activities are captured by three outputs, namely total loans (y_1), which is the sum of commercial, industrial and real estate loans; other earning assets (y_2); and total retail deposits (y_3) measured by the sum of time, demand, and savings deposits. Non-traditional activities are proxied by two outputs: the non-interest income (y_4) calculated as the sum of commission, fee, and trading income, and the value of Off-Balance-Sheet (OBS) items (y_5). Regarding inputs, we consider borrowed funds, labour, and physical capital in our analysis. The price of borrowed funds (x_1) is defined as the ratio of total interest expense scaled by total deposits and other purchased funds; the price of labour (x_2) is calculated by dividing total salaries and benefits by the number of full-time employees; and the price of physical capital (x_3) equals expenses of premises and equipment divided by premises and fixed assets. All variables employed in the robustness checks as well as the sources used to construct these variables are described in Appendix A.

We proceed to examine the robustness of the performance-risk-size nexus in the U.S. banking industry allowing this time the slope coefficient on size to vary across the U.S. states. The sample consists of 7,711 U.S. commercial and savings banking institutions divided into the four size clusters denoted by k. Moreover, *CAMEL* is introduced with a negative sign in eq. 14 for the reasons which have been discussed in our baseline analysis. The null hypothesis H_0 we test remains the same, *i.e.*, the slope coefficients on bank size are equal to zero for every size class. The model we examine is the following:

$$\overline{CAMEL}_{ijk} = a_j d_j^{state} + b_k d_j^{state} d_k^{size} + \varepsilon_{ijk} \tag{14}$$

Table 7 reports the regression results of eq. 14. As we can see, the null hypothesis cannot be accepted meaning that size is indeed a fundamental determinant of bank performance and risk-taking. In line with the outcome of our mainline regression analysis (see Table 3), the coefficients on size dummies increase monotonically moving up from the smallest size group to the largest one. This result reflects large-scale diversification, economies of scale and scope, and better access to capital markets for larger banks. On the other hand, smaller banks are regarded as being relatively less competent in investing in technology and risk management systems. On the whole, smaller banks underperform compared to their larger peers. Our findings remain largely unchanged when we interchangeably normalise the coefficients on *Small*, *Large*, and *Extra-large* binary variables instead of that on *Medium*.

Table 7
Bank performance-risk-size nexus: robustness check. This table presents the estimated coefficients of the bank size dummy variable for all four size categories k (*i.e.*, *Small*, *Medium*, *Large*, and *Extra-large*) based on eq. 14. The dependent variable is bank performance (*CAMEL*), which is composed of bank capital strength (*CAP2*), asset quality (*CREDLOSS2*), the quality of bank management (*MNGEXP2*), earnings strength (*ROE*), and bank liquidity (*LQDT2*). A description of each variable and the relevant data sources are included in Appendix A. White robust standard errors are used to correct for heteroskedasticity in the residuals.

	Size Coeff. Value (b_k)	***t*-stat**
Bank size (k)		
Small	0.22	2.27***
Medium	0.00	
Large	0.36	2.52***
Extra-large	0.69	2.70***
Obs (N)	7,711	
R^2	0.14	
F-statistics	14.58	

***, **, * correspond to 1%, 5%, and 10% level of significance respectively for a two-tailed distribution

We now move to explore the robustness of our results obtained by the regression of eq. 2. Together with the alternative *CAMEL* ratings, we define and use the crisis dummy *CR2* instead of *CR1*, which takes the value of one in 2008q3 when Lehman Brothers collapsed and remains equal to one thereafter. Additionally, instead of *GDP*, we employ the change in the U.S. Consumer Price Index (*CPI*) to control for variations in the level of prices; inflation data are obtained from the Bureau of Labor Statistics of the U.S. Department of Labor. Lastly, we construct a dummy variable (*LISTED*) to account for listed and non-listed banking firms in our sample. We run eq. 15 and the results we obtain are presented in Table 8 below.

$$CAMEL_{it} = a_0 + a_1 SIZE_{it-1} + \alpha_2 SIZESQ_{it-1} + \alpha_3 SIZEGR_{it-1} + \alpha_4 SYSTSIZE_{it-1}$$
$$+\alpha_5 HHI_t + \alpha_6 MA_{it} + \alpha_7 CR2_t + \alpha_8 INF_t + \alpha_9 LISTED_i + \varepsilon_{it} \quad (15)$$

Table 8
Bank performance-risk-size nexus: robustness check. This table presents the estimation results of eq.15. The dependent variable is bank performance (*CAMEL)* which is composed of bank capital strength (*CAP2*), asset quality (*CREDLOSS2*), the quality of bank management (*MNGEXP2*), earnings strength (*ROE*), and bank liquidity (*LQDT2*). The main explanatory variables are: bank size (*SIZE*), bank size squared (*SIZESQ*), bank size growth (*SIZEGR*), and systemic bank size (*SYSTSIZE*). All four size variables are lagged by one quarter to address possible endogeneity and simultaneity concerns between performance and size. The set of control variables includes banking market concentration (*HHI*), a dummy variable (*MA*) which accounts for M&A transactions, a crisis dummy variable (*CR2*), the price level (*INF*), and a dummy variable (*LISTED*) which accounts for listed banks. A description of each variable and the relevant data sources are included in Appendix A. Individual bank fixed effects, time fixed effects, and state fixed effects are incorporated in the regression model. Heteroskedasticity-robust *t*-statistics are reported next to coefficient estimates.

	Healthy Banks		**Failed banks**		**Bailed out banks**	
Variables	Coef value	*t*-stat	Coef value	*t*-stat	Coef value	*t*-stat
constant	0.88	1.26	0.59	0.98	0.93	1.64*
SIZE	0.89	1.93**	0.31	1.86**	1.38	2.03***
SIZESQ	2.10	1.87**	1.70	1.89**	2.32	2.01***
SIZEGR	3.21	1.88**	2.11	2.31***	4.43	2.99***
SYSTSIZE	-1.09	-1.22	-1.11	-1.17	-1.88	-1.81**
HHI	1.28	2.41***	1.81	1.82**	1.03	1.94**
MA	0.72	1.99***	0.68	1.90**	0.90	2.34***
CR2	-1.82	-3.77***	-4.56	-4.83***	-2.66	-3.31***
INF	1.83	2.01***	1.57	1.99***	1.65	1.86**
LISTED	0.14	1.73**	0.10	1.61*	0.21	1.99***
Obs (N)	6,481		432		798	
R^2	0.17		0.20		0.19	

Individual fixed effects	Yes	Yes	Yes
State fixed effects	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes

***, **, * correspond to 1%, 5%, and 10% level of significance respectively for a two-tailed distribution

The regression results corroborate the conclusions reached in the relevant baseline analysis. More concretely, the composite *CAMEL* ratings of the sample banks are positively and highly significantly linked to *SIZE*, *SIZESQ*, and *SIZEGR*, reflecting the long-run relationship that holds between size, performance, and risk in the U.S. banking market. Furthermore, *SYSTSIZE* is found to exert a significantly negative impact on performance, which suggests that the managers of banks which implicitly attain an important position in the system based (among other factors) on their size, cease to focus on the further improvement of the performance and risk profile of their banks following a TBTF management strategy.

The results of our robustness analysis provide further support to the view that concentration in the banking industry through M&A activities is beneficial for the performance and risk-taking behaviour of banks. We also find that the operation of listed banks is associated with superior performance when compared to that of unlisted banks. We interpret this finding as evidence of the higher degree of pressure for better performance that listed firms generally face. It is established in the literature (see, e.g., Iannotta et al., 2007) that exchange-listed banks face greater scrutiny through monitoring not only from regulators and supervisors, but also from stakeholders, financial analysts, and market participants. At the same time, listed banks, in contrast to the unlisted ones, have to deal with increased reporting and other relevant requirements, which create significant additional costs in their operation. Lastly, we report that favourable economic conditions, as echoed in the increased level of prices, positively affect the functioning of banks. This finding is corroborated by the negative effect of crisis on performance.

To test the robustness of the TSTS hypothesis we have posed, we run eq. 16 which relies on the updated set of variables described above:

$$\Pr(FAIL)_{it} = a_0 + a_1 CAMEL_{it} IF(SIZE_{it} < Threshold) + \alpha_2 CAMEL_{it} IF(SIZE_{it} > Threshold) + \alpha_3 HHI_t + \alpha_4 MA_{it} + \alpha_5 CR2_t + \alpha_6 INF_t + \alpha_7 LISTED_i + \varepsilon_{it} \quad (16)$$

Table 9
The TSTS threshold size: robustness check. This table presents the estimation results of eq. 16. The dependent variable is the probability of bank failure. The main explanatory variables include bank size (*SIZE*), and bank performance (*CAMEL)* which is composed of bank capital strength (*CAP2*), asset quality (*CREDLOSS2*), the quality of bank management (*MNGEXP2*), earnings strength (*ROE*), and bank liquidity (*LQDT2*). The set of controls includes banking market concentration (*HHI*), a dummy variable (*MA*) which accounts for M&A transactions, a crisis dummy variable (*CR2*), the price level (*INF*), and a dummy variable (*LISTED*) which accounts for listed banks. A description of each variable and the associated data sources are included in Appendix A. Heteroskedasticity-robust *t*-statistics are reported next to coefficient estimates.

Variables	Coefficient value	*t*-statistics
constant	1.02	1.18
SIZE below threshold	4.45	1.99***
SIZE above threshold	-2.76	-2.40***
HHI	-1.18	-1.32
MA	-0.64	-1.67*
CR2	2.42	3.74***
INF	-1.57	-1.88**
LISTED	-0.43	-1.67*
Obs (N)	5,184	
R^2	0.22	

TSTS threshold level of *SIZE*: $1,067,193,709

***, **, * correspond to 1%, 5%, and 10% level of significance respectively for a two-tailed distribution

The regression results in Table 9 show that *CAMEL* has a positive and statistically significant coefficient if *SIZE* is larger than $1,067,193,709, whereas the coefficient is negative when *SIZE* is smaller than $1,067,193,709. Therefore, we can postulate that it may not be in the interest of authorities to rescue banks whose size is below some particular threshold level. This time the threshold level is found to be equal to $1,067,193,709, which is very close to the one we reported in our mainline regression analysis. Moreover, the new asset size threshold is also very similar to the cut-off size of community banking institutions and to the average size of the banks that went bankrupt in the recent financial crisis (if, again, Washington Mutual Bank is excluded).

6. Conclusions

It is a common place that during financial crises, like the one started in 2007, authorities provide substantial financial support to some problem banking institutions while at the same time let several others to go bankrupt. Is this happening because some particular banks are considered important and big enough to save, whereas some others are perceived as being 'Too-Small-To-Survive'? Is, indeed, the size of banks the fundamental factor that makes the authorities to treat them differently, or it is also that some banks perform poorly and are not capable of withstanding some considerable shocks whatsoever? Our study has made an attempt to provide some concrete answers to these questions with the purpose to fill part of the void in the existing literature.

Size is found to be a crucial determinant of performance and risk-taking in banking independent of whether our empirical analysis takes place in the short-run, or in the long-run. To be more specific, we are able to establish a direct link between size and performance by showing that smaller banks perform relatively worse compared to their larger counterparts also taking riskier decisions. We interpret this result by arguing that small banking firms may not be in a position to fully exploit the technological developments that took place in the past years and to succeed in operating under increased scale and scope economies. Furthermore, the capacity of small-sized banks to efficiently diversify risk is narrow compared to that of larger banks due to the lower number of customers they have, the geographical concentration of their activities, and the limited scale and scope of products and services they offer. On the whole, the smaller a bank is, the poorer its performance and the riskier its portfolio.

We find robust evidence of nonlinearities in the relationship that holds between performance, risk, and size in the U.S. banking industry. We also document that when a bank grows in size, this has a further positive impact on its overall performance. From the whole range of banks we examine in terms of soundness, those that were bailed out during the crisis are found to have stronger incentives to increase their asset size. This finding suggests that a bank has the tendency to become larger not only because this will potentially lead to the improvement of its performance, but also because an implicit bailout guarantee is in place by the authorities in case of a financial debacle. Overall, a long-run positive relationship between size and performance is established in our paper regardless of the level of bank soundness under examination.

Importantly, we lend support to the TSTS hypothesis we pose according to which the impact of bank performance on failure probability strongly depends on bank size. We estimated a TSTS threshold size for the U.S. banking industry, which is really close to the cut-off size of the U.S. community banking institutions and to the average asset size of the banks that went bankrupt in the late 2000s financial crisis. We postulate that it may not be optimal for authorities to rescue banks whose size is below the reported TSTS threshold. This threshold size can affect the decisions of bank managers and influence the performance of their banks. In case a manager knows that his bank is considered by the authorities to be TSTS and, hence, is not protected by bailout policies, he may turn to resort to riskier investment decisions. Along the same lines, the behaviour of depositors, potential borrowers, and investors in a TSTS banking institution is expected to divert from the average behaviour.

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References

Adrian, T., Shin, H.S., 2010. Liquidity and leverage. Journal of Financial Intermediation 19, 418-437.

Berger, A.N., Bouwman, C.H.S., 2013. How does capital affect bank performance during financial crises? Journal of Financial Economics 109, 146-176.

Berger, A.N., Humphrey, D.B., 1991. The dominance of inefficiencies over scale and product mix economies in banking. Journal of Monetary Economics 28, 117-148.

Berger, A.N., Humphrey, D.B., 1997. Efficiency of financial institutions: international survey and directions for future research. European Journal of Operational Research 98, 175-212.

Berger, A.N., Miller, N.H., Petersen, M.A., Rajan, R.G., Stein, J.C., 2005. Does function follow organizational form? Evidence from the lending practices of large and small banks. Journal of Financial Economics 76, 237-269.

Bertay, A.C., Demirguc-Kunt, A., Huizinga, H., 2013. Do we need big banks? Evidence on performance, strategy and market discipline. Journal of Financial Intermediation, *forthcoming*.

Boyd, J.H., Runkle, D.E., 1993. Size performance of banking firms: Testing the predictions of theory. Journal of Monetary Economics 31, 47-67.

Brissimis, S.N., Delis, M.D., Papanikolaou, N.I., 2008. Exploring the nexus between banking sector reform and performance: Evidence from newly acceded EU countries. Journal of Banking and Finance 32, 2674-2683.

Buch, C.M., Koch, C.T., Koetter, M., 2013. Do banks benefit from internationalization? Revisiting the market power-risk nexus. Review of Finance 17, 1401-1435.

Carter, D.A., McNulty, J.E., 2005. Deregulation, technological change, and the business-lending performance of large and small banks. Journal of Banking and Finance 29, 1113-1130.

Coelli, T., Rao, D.S.P., O'Donnell, C.C., Battese, G.E., 2005. An introduction to efficiency and productivity analysis. Springer: New York.

Cornett, M.M, McNutt, J.J., Strahan, P.E., Tehranian, H., 2011. Liquidity risk management and credit supply in the financial crisis. Journal of Financial Economics 101, 297-312.

De Nicoló, G., 2000. Size, charter value and risk in banking: An international perspective. Board of Governors of the Federal Reserve System (U.S.), International Finance Discussion Papers 689.

DeYoung, R., 2003. De novo bank exit. Journal of Money, Credit, and Banking 35, 711-728.

DeYoung, R., Hasan, I., 1998. The performance of de novo commercial banks. Journal of Banking and Finance 22, 565-587.

DeYoung, R., Hunter, W.C., Udell, G.F., 2004. The past, present, and probable future for community banks. Journal of Financial Services Research 25, 85-133.

Demsetz, R.S., Strahan, P.E., 1997. Diversification, size, and risk at Bank Holding Companies. Journal of Money, Credit and Banking 29, 300-313.

Galloway, T.M., Winson, B.L., Roden, D.M., 1997. Banks' changing incentives and opportunities for risk taking. Journal of Banking and Finance 21, 509-527.

Gong, N., Jones, K.D., 2010. Monitoring, bailouts, and penalties: An integrated framework of government policies to manage the Too Big To Fail Problem. Available at http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1663619

Goodhart, C.A.E., Huang, H., 2005. The lender of last resort. Journal of Banking and Finance 29, 1059-1082.

Gujarati, D.N., 1995. Basic Econometrics. New York: McGraw-Hill.

Hakenes, H., Schnabel, I., 2010. Banks without parachutes: Competitive effects of government bail-out policies. Journal of Financial Stability 6, 156-168.

Hansen, B.E., 1999. Threshold effects in non-dynamic panels: Estimation, testing, and inference. Journal of Econometrics 93, 345-368.

Hausman, J.A., 1978. Specification tests in econometrics. Econometrica 46, 1251-1272.

Huang, X., Zhou, H., Zhu, H., 2009. A framework for assessing the systemic risk of major financial institutions. Journal of Banking and Finance 33, 2036-2049.

Iannotta, G., Giacomo, N., Sironi, A., 2007. Ownership structure, risk and performance in the European banking industry. Journal of Banking and Finance 31, 2127-2149.

Lane, W., Looney, S., Wansley, J., 1986. An application of the Cox proportional hazards model to bank failure. Journal of Banking and Finance 10, 511-531.

Leary, M.T., 2009. Bank loan supply, lender choice, and corporate capital structure. The Journal of Finance 64, 1143-1185.

O'Hara, M., Shaw,W., 1990. Deposit insurance and wealth effects: the value of being 'too big to fail'. Journal of Finance 45, 1587-1600.

Papanikolaou, N.I., Wolff, C.P., 2013. The role of on- and off-balance-sheet leverage of banks in the late 2000s crisis. Luxembourg School of Finance Working Paper Series.

Porter, M.E., 1979. How competitive forces shape strategy. Harvard Business Review 57, 137-145.

Patro, D.K., Qi, M., Sun, X., 2013. A simple indicator of systemic risk. Journal of Financial Stability 9, 105-116.

Rime, B., Stiroh, K. J., 2003. The performance of universal banks: evidence from Switzerland. Journal of Banking and Finance 27, 2121-2150.

Appendix A: Variables and data sources

This Appendix presents all variables that we use in the baseline econometric analysis as well as in the robustness checks. The abbreviation of each variable and the sources we use to collect the data are reported.

Variable	Abbreviation	Definition	Data source
CAMEL components			
Capital adequacy	*CAP1*	The ratio of total equity capital to total bank assets	
	CAP2	The ratio of Tier 1 & 2 regulatory capital to risk-based assets	
Asset quality	*CREDLOSS1*	The ratio of provisions for credit losses to total loans and leases	
	CREDLOSS2	The sum of loan loss reserves and loan charge-offs divided by total loans	
Management expertise	*MNGEXP1*	The ratio of total operating income to income generating assets	
	MNGEXP2	Managerial efficiency	Call Reports, Federal Reserve Bank of Chicago
Earnings strength	*ROA*	The ratio of total income to total assets	
	ROE	The ratio of total income to total equity	
Liquidity	*LQDT1*	The ratio of cash & cash equivalents and federal funds sold and securities purchased under agreements to repurchase to total assets	
	LQDT2	The ratio of liquid deposits to total deposits	
Right-hand-side variables			
Bank size	*SIZE*	The natural logarithm of the book value of total assets	Call Reports, Federal Reserve Bank of Chicago
	SIZESQ	The squared root of the natural logarithm of the book value of total assets	
	SIZEGR	The growth rate of the natural logarithm of the book value of total assets	

	SYSTSIZE	Sample bank's liabilities-to-GDP ratio	Call Reports, Federal Reserve Bank of Chicago & Bureau of Economic Analysis, U.S. Department of Commerce
Banking market concentration	*HHI*	The sum of squares of the market share of each sample bank	Call Reports, Federal Reserve Bank of Chicago
M&A deals	*MA*	A dummy variable which is equal to unity in the quarter *q* that bank *i* has been involved in some M&A transaction	FFIEC
Listed banks	*LISTED*	A dummy variable which is equal to unity if bank *i* is listed on the exchange market	Call Reports, Federal Reserve Bank of Chicago
Crisis dummy	*CR1*	A dummy variable which is equal to 1 in 2007q3 and thereafter	
	CR2	A dummy variable which is equal to 1 in 2008q3 and therafter	
Macroeconomic conditions	*GDP*	GDP output gap	Bureau of Economic Analysis, U.S. Department of Commerce
	CPI	The quarterly change in U.S. Consumer Price Index (CPI)	Bureau of Labor Statistics, U.S. Department of Labor