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# Are European banks too big? evidence on economies of scale

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# ARE EUROPEAN BANKS TOO BIG? EVIDENCE ON ECONOMIES OF SCALE

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**Abstract**

In light of the policy debate on too-big-to-fail we investigate evidence of economies of scale for 103 European listed banks over 2000 to 2011. Using the Stochastic Frontier Approach, the results show that economies of scale are widespread across different size classes of banks and are especially large for the biggest banks. At the country level, banks operating in the smallest financial systems and the countries most affected by the financial crises realize the lowest scale economies (including diseconomies) due to the reduction in production capacity. As for the determinants of scale economies, these mainly emanate from banks oriented towards investment banking, with higher liquidity, lower Tier 1 capital, those that contributed less to systemic risk during the crises, and those with too-big-to-fail status.

JEL codes: G21

Keywords: Bank, Economies of scale, Regulation, Too-Big-To-Fail, EU.

## 1. Introduction

Post-crises, the costs associated with 'too-big-to-fail' bailouts have heightened the policy debate concerning the role and benefits of bank size and the influence of public safety net subsidies that accrue with both size and complexity (Schmid and Walter, 2009; Stern and Feldman, 2009; Veronesi and Zingales, 2010; Wilson et al. 2010; Inanoglu et al. 2012; DeYoung, 2013; and DeYoung and Jiang, 2013).[1] Safety net subsidies are centered on the view that governments provide implicit support because the failure of a large institution could have major systemic implications for the economy.[2] State financed bank bailouts that occurred in the second half of 2008 illustrated evidence of such safety nets (Molyneux et al 2014). As a response, regulators in the US (under the Dodd Frank Act of 2010) and in the EU (as in recommendations by the Liikanen Report 2012 being implemented into EC law as well as by the Vickers Report 2011 implemented into UK law) have sought to impose restrictions on banks by asking for more capital and liquidity (in-line with Basel 3 requirements)[3] and also to restrict riskier areas of activity[4] – all of which constrains bank's size.

The motivation for these policy actions has been to reduce the negative consequences associated with the failure of systemically important banks, but as DeYoung and Jiang (2013) have argued, the policy debate has largely ignored the fact that large banks can also create positive externalities. Limiting the size of big banks could result in a net social loss if the restrictions inhibit bank's ability

[1] For European banks, when we refer to 'post-crises' we are referring to both the global financial crisis of 2007-08 and the European sovereign debt crisis of 2010-11. The starting date of the global financial crisis is defined according the definition of the Bank for International Settlements (2010) as August 2007. Therefore 'pre-crisis' is before 2007 and 'post-crises' after 2011.

[2] For a sample of bank mergers and acquisitions (M&As) in nine EU economies between 1997 and 2007, Molyneux et al. (2014) find no evidence that gaining safety net subsidies leads to an increased interdependency over peer banks of the 'too systematically important to fail' bank. An alternative view on the reasons why governments provide implicit support, as outlined in Inanoglu et al. (2012), is that the need for the government to impose restrictions on the size and scope of banks risks a reduction in the efficiency and competitiveness of the banking sector.

[3] The so-called break-up hypothesis requires to break-up TBTF banks (via gradual and partial liquidation) or to provide TBTF banks incentives to shrink (e.g., the US Vitter-Brown bill, under circulation in Congress, will require banks with more than $500 billion in assets to maintain a minimum of 15% equity-to-asset ratio instead of the current 8%).

[4] In this regard, the United States passed the Volcker rule (contained in the Dodd-Frank Act), the European Union the proposal on the structural reform of banks, the UK the 2013 Financial Services (Banking Reform) Act, and Switzerland the 2011 TBTF Banking Act (for a detailed list of structural banking reforms and their cross-border implications see Financial Stability Board, 2014). Specifically in January 2014 the European Commission made a proposal for structural reform aimed at minimizing the risky activities of the EU's 30 systemically important banks (European Commission, 2014). Starting in 2017, the proposal bans proprietary trading for banks that are labeled by international regulators as too-big-to-fail in the global economy, or whose activities surpass certain financial thresholds. The EU reform would apply in all 28 Member States.

to realize potential scale economies that can be passed onto bank customers in the form of more efficient intermediation and therefore lower prices. Social spillover costs associated with troubled banks are tangible, observable, and happen in conjunction over relatively short timeframes; whereas the benefits associated with more efficient intermediation tend to occur over time, are less tangible, and therefore are not completely observable – as such, these benefits tend to be overlooked.

The aim of this paper is to investigate evidence of scale economies for Europe's listed banks and to examine whether different business models and risk-taking features influence the realisation of scale economies as this will inform contemporary policy debate on proposed regulatory reforms that are likely to inhibit bank size/growth. Using a sample of 103 European listed banks from the Stoxx 600 Banks index over 2000 to 2011 we find that scale economies are widespread across different size classes of banks and especially for the largest (with total assets exceeding €550 billion). Furthermore, the realisation of scale economies are less prevalent in smallest financial systems (Belgium, Finland, and Iceland) and in countries most affected by financial crises (Belgium, Greece, Iceland, Ireland, Portugal and Spain). Banks more oriented towards investment banking appear to realise greater scale economies as do those with: higher liquidity (but only up to a liquidity ratio of about 7.5%; a convex curve); greater leverage (with lower Tier 1 capital); for those banks that contribute less to systemic risk, and those with too-big-to-fail status. (Granger causality tests suggest the existence of unidirectional causality for liquidity, Tier 1 capital, and systemic risk).

Scale economies, therefore, appear prevalent at big banks and particularly for those involved in investment banking. As such, the EU plans to limit the activities of EU institutions (through, among other things, the proposed ban on proprietary trading) may limit bank's ability to realize such scale economies. Tougher capital regulations appear likely to reduce cost economies in banking although the requirement to boost liquidity (up to a certain level) may have the opposite effects. While theory suggests that bank average costs curves are U-shaped and therefore exhausted at some point, empirical estimates of bank cost economies rarely finds such cost features. Traditionally the early European literature finds evidence of somewhat flattish cost curves (see Goddard et al., 2001) whereas more recent studies show positive economies of scale for all asset levels in Europe (Dijkstra

2013) and for small and especially large asset levels in the US.[5] Our findings on scale economies in European banking, echo findings from the US that suggest that the round of regulatory reform aimed at curtailing bank size may yield second-best policy solutions (DeYoung and Jiang, 2013).

The paper is organized as follows: in section 2, we present the motivation for this study in light of the literature on economies of scale. Section 3 offers a description of the methodology and the sample, and we discuss the empirical results and some robustness tests in section 4. Section 5 concludes.

## 2. Literature review

The role of large banks and recent regulatory proposals has directed renewed attention to the issue of economies of scale in banking (Davies and Tracey, 2014; DeYoung and Jiang, 2013; Wheelock and Wilson, 2012; Inanoglu et al., 2012; Hughes and Mester, 2013; DeYoung, 2010; Mester, 2010). There is an extensive literature on economies of scale in banking that mainly focuses on the US (see the recent literature review by Gambacorta and van Rixtel 2013, where one study only is reported for Europe).[6] In Europe, Vander Vennet (2002) detects the presence of economies of scale for smaller banks in 1995 and 1996, while he documents neither economies nor diseconomies of scale for universal banks and financial conglomerates.[7] Altunbas et al. (2001b), with reference to the period of 1989 to 1997, report economies of scale in the order of 5–7% for small banks (with total assets under $200 million) and medium sized banks (with total asset between $1 and $5 billion), whereas large

[5] Recent US literature finds an inverted U-shape, that is large scale economies at small banks and even larger scale economies at large banks (see Mester 2010, Wheelock and Wilson 2012, and Hughes and Mester 2013 for discussion and evidence on US banks).

[6] As for the US, early studies that analyzed bank costs in the 1980s (documented in the review of Berger et al., 1993; also see Mitchell and Onvural, 1996; Berger and Humphrey, 1994; McAllister and McManus, 1993) find little evidence of scale economies for large banks, the main result being that they are prevalent in small banks although rather modest in magnitude. However, studies in the 1990s and 2000s (Hughes and Mester, 2013, 2014; Wheelock and Wilson, 2012; Feng and Serletis, 2010; Hughes et al., 2001; Wheelock and Wilson, 2001; Hughes and Mester, 1998; Hughes et al. 1996, 2000), employing methodologies that take account risk in bank production features, tend to find evidence of significant scale economies, even for the largest banks. However, others find the opposite. Inanoglu et al. (2012) find decreasing returns for the top 50 US banks over 1990 to 2009 and Davies and Tracey (2014) find that when they control for too-big-to-fail factors scale economies tend to disappear. As for Japan, empirical evidence is more limited and tends to find a prevalence of diseconomies of scale over the 1980s and 1990s, in line with the evidence on the United States in the 1980s (Altunbas et al., 2000; Tadesse, 2006).

[7] For Europe during the nineties, there are also single-country level studies. For Italian banks, Girardone et al. (2004) confirm the presence of economies of scale only for small banks, particularly mutual and credit cooperative banks. For German banks, Altunbas et al. (2001a) document widespread economies of scale for different types of bank ownership (state-owned banks, mutual and private-sector institutions).

banks tend to show diseconomies of scale or constant returns. Mercieca et al. (2007), for small credit institutions (with total assets lower than about €450 million) over the period 1997-2003, provide circumstantial evidence for the presence of economies of scale (increasing size is positively related with risk–adjusted performance). Dijkstra (2013), for banks within the Eurozone over the period 2002 and 2011, documents that scale economies are found to be positive and significant for all years and at all asset levels. When accounting for implicit too-big-to-fail subsidies, economies of scale remain positive during the crisis, but become negative outside the crisis.

Prior studies also investigate determinants that might play a role in the realisation of economies of scale, either related to macroeconomic features or bank-specific variables. Bossone and Lee (2004) document that banks operating in larger financial markets generally enjoy greater economies of scale than those in smaller systems. Bertay et al. (2013), for publicly traded banks from 90 countries, find that banks with larger absolute size tend to be more profitable whilst those that are big relative to their domestic economies tend to be less profitable. Moreover, banks that are large in absolute size tend to earn a greater share of their income from noninterest sources, operate with higher leverage, and make extensive use of wholesale funding. In contrast, banks that are large relative to their domestic economies tend to have a concentration in lending and a greater dependence on deposit funding.

In addition to economies of scale, banks' business models have been driven by economies of scope and deregulation (as crystalized by Gambacorta and van Rixtel 2013). The trend of diversification adopted by most large global banks is associated with increased consolidation and concentration that results in fewer, larger and more complex conglomerates (Buch and DeLong, 2010; Herring and Carmassi, 2010). Given the weak evidence on the importance of economies of scope (for Europe Baele et al. 2007 and Van Lelyveld et al. 2009 document a mixed effect, whilst Mercieca et al. 2007 find a negative effect), and the mixed evidence on the positive impact of economies of scale, the business model of large and complex global banks appears to be partly motivated by regulatory considerations. Empirical studies show significant benefits for banks that are potential TBTF candidates, suggesting the importance of TBTF status (Wilson et al. 2010; Molyneux et al. 2014). Specifically, Molyneux et al. (2014), for bank M&As in nine EU economies between 1997 and 2007, find that safety net benefits derived from M&As have a significantly positive association with rescue probability, suggesting significant moral hazard problems. Relatedly, for a sample of large and complex EU banking groups, IMF suggests that almost 80 percent of banks that received official support in 2008/2009 traded significantly more than average (Chow and Surti, 2011).

The structural bank regulation initiatives currently being considered or implemented (Vickers and Liikanen proposals, and Volcker rule) generally do not include explicit size restrictions, instead they aim to reduce product diversification opportunities (potential scope economies) and also attempt to reduce implicit TBTF subsidies. Intense regulatory discussions on the possible introduction of explicit bank size restrictions (in relation to the size of the financial system as a whole or relative to GDP) are on-going (see, for example, Hoenig, 2012; Tarullo, 2012; Fisher, 2013; Haldane, 2013).

In short, traditionally the early literature finds that large European banks tend to show neither economies nor diseconomies of scale, whereas in recent years a small body of research evidence documents economies of scale for all asset levels. The opportunities for banks to exploit potential economies of scale in the future will however depend on structural reforms as well as restrictions on size imposed by other regulatory frameworks, such as the leverage rule in Basel III. Therefore, to fill the gap of evidence on economies of scale in European banking over recent years, as well as to inform the policy debate on reforms that are likely to inhibit bank size/growth, this paper aims to investigate evidence of scale economies (for the largest banks) as well as to examine if different business models and risk-taking influence economies of scale.

## 3. Methodology and data

### *3.1 Economies of scale*

Economies of scale occur in the long run when unit costs decrease as production volume increases, or if a bank is able to reduce the average cost of production when increasing the level of output. The overall level of economies of scale (ES) is computed as

$$ES = \sum_{i=1}^{m} \frac{\partial lnTC}{\partial lnQ_i} \tag{1}$$

that represents the sum of individual cost elasticities and in symbols is depicted as

$$\mathrm{ES} = \sum_{\mathrm{i}=1}^{3} \alpha_{\mathrm{i}} + \sum_{i=1}^{3}\sum_{j=1}^{3} \delta_{ij} \ln Q_j + \sum_{i=1}^{3}\sum_{j=1}^{3} \rho_{ij} \ln P_j + \sum_{i=1}^{3} \zeta_{iE} \ln E \tag{2}$$

where there are economies of scale if ES is less than one, diseconomies of scale if ES is greater than one, and constant economies of scale if ES is equal to one. The degree of scale economies is computed by using the mean values of output variables, input prices, and equity capital. For the cost function estimation, we use a model of bank costs borrowed from Berger and Mester (2003), recently adopted by Hughes and Mester (2013) and Davies and Tracey (2014), that includes off-balance sheet outputs and equity capital as a netput. The details of the estimation are provided in the appendix.

### *3.2 Determinants of economies of scale*

To extend the analysis in Bertay et al. (2013), we isolate the effects of diversification in the business model, risk-taking, and profitability on economies of scale. Whilst not measuring economies of scale, Bertay et al. (2013) focus on bank size (measured by a bank's balance sheet assets and by balance sheet size relative to the GDP of the home country) and its determinants.

We first perform a univariate quintile analysis of the relevant characteristics (bank business model, profitability of traditional banking activity, liquidity risk, credit risk, capital strength, and systemic risk) in relation to economies of scale, and then we perform the following (bank) fixed-effect OLS regression with heteroscedasticity-consistent standard errors:[8]

$$ES_{i,t} = \alpha_0 + \beta_1 SEC\_TA_{i,t} + \beta_2 NIM_{i,t} + \beta_3 LR_{i,t} + \beta_4 LRsq_{i,t}$$

$$+\beta_5 LLP\_Loans_{i,t} + \beta_6 Tier1_{i,t} + \beta_7 Tier1sq_{i,t} + \beta_8 Srisk\%_{i,t} + \varepsilon_{i,t}. \tag{3}$$

where:

[8] The Haussmann test rejects the hypothesis of random-effect in favor of the alternative hypothesis of fixed-effect at the 1% level in all the models of Eq. (3).

$ES_{i,t}$ = economies of scale for bank *i* at time *t*, measured via equation (2), where higher values indicate lower economies of scale

$SEC\_TA_{i,t}$ = securities to total asset ratio for bank *i* at time *t* that is used as a proxy for the bank business model (i.e., higher values denote business models more oriented to investment banking activities rather than to commercial banking activities)

$NIM_{i,t}$ = net interest margin (measured as net interest income to total loans) for bank *i* at time *t* that is used as a proxy for the bank profitability on traditional lending activities

$LR_{i,t}$ = liquidity ratio (measured as liquid assets to total customer deposits) for bank *i* at time *t*; this is a deposit runoff ratio and looks at what percentage of customer deposits could be met if they were withdrawn suddenly and is used as a proxy for liquidity risk (i.e., higher values, lower liquidity risk)

$LRsq_{i,t}$ = squared terms of the liquidity ratio for bank *i* at time *t* that is used to test the existence of a nonlinear relation between liquidity and economies of scale

$LLP\_Loans_{i,t}$ = loans loss provision to loans for bank *i* at time *t* that is used as a proxy for the credit risk (i.e., higher values, higher credit risk)

$Tier1_{i,t}$ = Tier 1 ratio (measured as shareholder funds plus perpetual noncumulative preference shares as a percentage of risk-weighted assets and off-balance sheet risks measured under the Basel rules) for bank *i* at time *t* that is used as a proxy for the bank's capital strength

$Tier1sq_{i,t}$ = squared terms of Tier 1 for bank *i* at time *t* that is used to test the existence of a nonlinear relation between Tier 1 and economies of scale

$Srisk\%_{i,t}$ = systemic risk for bank *i* at time *t* that represents the bank's percentage of the financial sector capital shortfall. Banks with a high percentage of capital shortfall in a crisis are not only the biggest losers in a crisis but also are the biggest contributors to the crisis. We employ the measure defined by Acharya et al. (2012), computed weekly by V-Lab, where $Srisk\%_{i,t}$ is the contribution to aggregate Srisk by any bank. To calculate systemic risk, the procedure first evaluates the losses that an equity holder would face if there is a crisis (i.e. whenever the broad index falls by 40% over the next six months). For crisis scenarios, the expected loss of equity value of firm *i* is called the Long

Run Marginal Expected Shortfall (LRMES), that is the average of the fractional returns of the firm's equity. The capital shortfall can be directly computed by recognizing that the book value of debt remains relatively unchanged during this six-month period while equity values fall by LRMES.

The motivation for the choice of bank-level determinants is based on Bertay et al. (2013) who examine the following: share of bank income from noninterest sources, leverage, use of wholesale funding, concentration in lending, dependence on deposit funding and bank probability of default. Our aim is to extend the investigation of these determinants from (balance sheet and systemic) size to economies of scale.

Finally, to take into account the importance of too-big-to-fail, in the base model we include the TBTF dummy variable and its interaction with Tier1.[9] Specifically we perform the following random-effect OLS regression with heteroscedasticity-consistent standard errors:[10]

$$ES_{i,t} = \alpha_0 + \beta_1 SEC\_TA_{i,t} + \beta_2 NIM_{i,t} + \beta_3 LR_{i,t} + \beta_4 LRsq_{i,t}$$

$$+\beta_5 LLP\_Loans_{i,t} + \beta_6 Tier1_{i,t} + \beta_7 TBTF_i + \beta_8 Tier1_{i,t} * TBTF_i + \varepsilon_{i,t}. \quad (4)$$

where:

$TBTF_i$ = dummy variable equal to 1 for Systemically Important Financial Institutions as defined by the Financial Stability Board.

### *3.3 Sample and data set*

For our sample we focus on listed European banks. Our interest in European banks is threefold. First, there is a lack of recent evidence on economies of scale in European banking. Second, over the last two decades, national European banking industries have become increasingly integrated due to deregulation via the Second Banking Directive (1989), the creation of the single market in financial products (implementation of the Financial Services Action Plan from 1999 to 2004), the introduction

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[9] We would like to thank the referee for this suggestion. To avoid multicollinearity we exclude Srisk% due to correlation between TBTF and Srisk% equal to 0.8231 (significant at 1% level), as documented in Table 4, Panel B.

[10] The Haussmann test does not rejects the hypothesis of random-error in favor of the alternative hypothesis of fixed-effect in Eq. (4). As a robustness test of the random effect OLS, we also run the OLS regression with heteroscedasticity-consistent standard errors clustered by banks; results are confirmed.

of the Euro, and through a buoyant process of cross-border consolidation (see Molyneux and Wilson 2007; Beccalli and Frantz, 2009). Third, in 2014 the European Commission passed a proposal for structural reform of EU banks restricting riskier activities and therefore constraining bank growth and size (European Commission, 2014).

The sample includes constituents of the Stoxx 600 Banks index (except for banks listed in Liechtenstein) from January 2000 to December 2011.[11] The sample comprises the largest banks in terms of asset size; these are banks of primary interest from the point of view of economies of scale and consequently for policy makers in relation to too-big-to-fail issues. Moreover, these banks also fell under scrutiny of the ECB in its 2014 Comprehensive Assessment (comprising a supervisory risk assessment, an asset quality review and stress tests) aimed at evaluating systemic bank resilience to future economic and other shocks. Data on the composition of the index are obtained from Datastream, on annual consolidated financial statements of banks from Bankscope, and information on systemic risk are obtained from the V-Lab website.

The sample consists of 103 banks (686 observations) operating in 17 European countries over the pre-crisis and crisis periods (where the crisis period here comprises two events: the 2007-08 global financial crisis and the 2010-11 European sovereign debt crisis). Table 1 reports the sample selection strategy, that is bank constituents of the Stoxx 600 Banks Index (115 banks), minus banks comprised in the index only in the first 2 quarters of year 2000 (5 banks), minus banks with missing financial data in Bankscope (3 banks), minus banks not available in Bankscope (4 banks) leaves us with a total of 103 banks. In case of mergers and acquisitions involving the constituents of the index, the original constituent is replaced by the new one (i.e. we use the consolidated financial statements of the bank resulting from the consolidation). Table 2 provides the number of banks within the sample per country and year as well as the sample representativeness (i.e. a proxy of how representative the sample is of the population of EU banks): the total assets of banks in the sample represents on average 62% of the total assets of all banks operating in the countries under analysis. Given our

[11] The introduction of IFRS in 2005 may influence our results. As a robustness test, we re-estimated economies of scale excluding values for 2005 (results available from the authors on request). The correlation coefficient among economies of scale estimated with and without 2005 is above 0.95 (statistically significant at the 1% level), thus suggesting that the introduction of IFRS does not represent a major issue in our analysis.

interest in economies of scale, we provide evidence on different size classes according to five quintiles (smallest, small, medium, large, and largest banks). Table 3 reports the descriptive statistics on the total assets of the five quintiles for the entire period of observation. The total assets of the banks included in the sample range between €959 million and €2,586,701 million, and their within and between standard deviation are 220,531 and 451,391 respectively. Table 4 provides the descriptive statistics of the bank characteristics (bank business model, profitability of traditional banking activity, liquidity risk, credit risk, capital strength, and systemic risk) and correlations. Over the study period, the securities to total asset ratio has a mean value of 0.264 (with a minimum of 0.0024 and a maximum of 0.8337), that indicates that the sample includes the biggest banks but they are not necessarily investment banks. Moreover, the securities to total assets ratio shows the highest correlation with scale economies (0.4277 significant at 1 percent level). Finally, securities to total assets and systemic risk and too-big-to-fail show very high correlations (above 60%): by introducing these variables together in a single model, the estimated coefficients could be bias and therefore interpretation of these particular coefficients should be done with caution (see fn 14 for a detail discussion).

## 4. Results

A graphical analysis of economies of scale in European banking (Figure 1) illustrates a widespread presence of economies of scale (values less than one). The figure also shows an interesting trend of moving together over time for all size classes (the within and between standard deviation for scale economies are respectively 0.0714 and 0.1656), although the largest scale economies are observed for the biggest banks. Although in theory bank average costs curves are U-shaped and therefore exhausted at some point, empirical estimates of bank cost economies rarely find such cost features; recent studies find positive economies of scale at all asset levels in Europe (Dijkstra 2013) and positive scale economies at the smallest and largest asset sizes in the US (Hughes and Mester 2013). Moreover, we find a reduction in scale economies up to 2008 and an increase in the years 2009 to 2011 (with a marginal slowdown in 2011). Furthermore, small and medium-sized banks (quintiles 2 and 3) experience the lowest economies of scale and even diseconomies of scale (values higher than one) in some years.

Table 5 reports the average values of economies of scale and their relative statistical significance in each year between 2000 and 2011 as well as for each size class. The table confirms that economies of scale - rather than diseconomies of scale - are prevalent in European banking showing an average value of around 14% (1 minus 0.8629) - a 100% increase in output quantities increases total cost on average by 86%. Moreover, an analysis of the results for the quintiles discloses that higher economies of scale are realized both for the smallest banks (with total assets between €959 million and €28.326 million), large banks (with total assets between €182.174 and €552.738 billion), and particularly for the biggest banks (with total asset between €552.738 and €258.670 billion). Among listed banks, small and medium-sized banks show lower economies and even diseconomies of scale. This evidence differs from that documented for European banks during the nineties, where diseconomies of scale were typically found for the biggest banks (Altunbas et al., 2001b; Vennet 2002). On the other hand, our findings are similar to recent U.S. studies that typically find evidence of significant economies of scale for the largest banks (Hughes et al. 1996, 2000; Hughes et al. 2001; Feng and Serletis, 2010; Wheelock and Wilson, 2012; Hughes and Mester 2013). Our evidence on the presence of economies of scale, especially for the largest banks, provides little support (from an efficiency standpoint at least) for restricting bank size.

Table 6 reports average economies of scale for each country and for different size classes of banks. With reference to all the listed banks, regardless of size, three banking systems (Belgium, Finland and Iceland) show overall diseconomies of scale.[12] Meanwhile in the other European countries, large significant economies of scale are reported (in particular for banks in the Netherlands and Switzerland). When we combine country and bank size, we observe that diseconomies of scale are experienced by the smallest banks in Finland, Germany, Ireland, and Spain; small banks in Finland, Germany, the UK, Iceland, and Portugal; and medium-sized banks in Belgium and the UK. Large banks exhibit diseconomies of scale in Ireland only, whereas the largest banks show

[12] It should be noted that the same evidence for Finland was already documented in the 1990s (Altunbas et al., 2001b).

diseconomies of scale in Belgium only. It appears that the large banks only experience diseconomies of scale when operating in small banking systems and/or in countries most heavily affected by the crises (Belgium and Ireland).[13]

Overall, the smallest financial systems (Belgium, Finland, and Iceland) and the countries most affected by the financial crises (Belgium, Greece, Iceland, Ireland, Portugal, and Spain) experience the lowest economies of scale (even diseconomies of scale) due to the reduced level of production capacity. There also seems to be an effect of the financial system as well as its size also appears to influence the bank level scale economies. Interestingly, the number of banks operating in countries most affected by the financial crises is substantial (about 20% of the overall sample) and these belong to the upper side of the size range (they represent about 32% of the biggest banks in Europe, respectively 20% and 12% of the large and largest quintile). Also, in small financial systems the biggest banks are not necessarily small on a European basis (in contrast to Finland and Iceland, 80% of the Belgian banks are above median size).

Table 7 shows the average values of economies of scale for each country and in each year under analysis. Diseconomies are more pronounced during the global financial crisis. In 2007, the number of countries that experience diseconomies of scale (Finland, Ireland, Iceland and Spain) increases; but especially in 2008, the number of countries that encountered diseconomies (Belgium, Finland, Greece, Ireland, Portugal, and Spain) increases. This evidence confirms, as expected, that the scale of European banks, when volumes decline, becomes excessive and inefficient due to excess capacity.

In order to investigate bank characteristics that determine economies of scale, we perform a univariate quintile analysis on bank characteristics (reflecting business models, risk, profitability and capital strength). Scale economies for five quintiles representing bank business models (namely, more oriented to investment banking versus more oriented to traditional commercial banking) are

[13] The countries most affected by the 2007-08 global financial crisis are identified according to the national rescue measures taken by EU Member States from October 2008 through June 2009 to counter the immediate effects of the crisis. In this regard, we refer to ECB research (Petrovic and Tusch, 2009), that provides the list of countries with the most and/or largest government guarantee measures and recapitalizations. The countries most affected by the 2010 European sovereign debt crisis are identified according to sovereign credit risk proxied by country-specific credit rating information. In this regard, we refer to ECB research (De Santis, 2012), that documents that country-specific credit ratings played a key role in the developments of the spreads for Greece, Ireland, Portugal and Spain.

shown in Table 8 (Panel A). The first quintile refers to the bottom 20% of the values in terms of securities to total assets, whereas the fifth quintile is the top 20%. We define as mainly investment banks those with higher values of securities to total assets (and consequently lower loans to total assets) and as mainly commercial banks those with lower values of securities to total assets (and consequently higher loans to total asset). Several interesting patterns emerge. First, mainly commercial banks show constant economies of scale during the dot-com crisis (2001–2002) and realise significant diseconomies of scale during the global financial crisis (2007–2008). Second, mainly investment banks realise high and significant economies of scale, especially during the financial crises. Banks more oriented towards investment banking experience a sharp reduction in asset values during the crises, and therefore an increase in their asset size might enable them to optimize their cost structure. This preliminary evidence seems to question the approach of EU regulator to address too-big-to-fail issues by banning proprietary trading. This policy choice could ignore the possibility that more diversified banks generate positive externalities and therefore may limit bank's ability to realize scale economies. The quintiles that reflect the profitability of core lending activities (Net Interest Margin, NIM) and related scale economies (Table 8, Panel B) show that banks with greater profitability (fourth and fifth quintiles) tend to experience larger economies of scale, whereas banks with lower profitability (first and second quintile) tend to enjoy lower economies. The quintiles that reflect liquidity risk (Liquidity Ratio, LR) and related economies of scale (Table 8, Panel C) show that the banks with greater liquidity (fourth and fifth quintile) experience larger scale economies, whereas banks with lower liquidity ratios (first and second quintile) experience on average minor economies or even diseconomies during the global financial crisis. Banks with higher liquidity are in a better position to develop future investments and activities and more able to exploit economies of scale whereas during the crises banks with less liquidity had to reduce their assets in the presence of the same cost structures that then resulted in diseconomies. This finding support Basel 3 requirements aimed at boosting liquidity, such regulation appears likely to increase cost economies in banking. The quintiles on credit risk (loan loss provisions over gross loans, LLP_Loans) and the related economies of scale (Table 8, Panel D) seem to suggest that credit risk does not determine the differences across banks in terms of economies of scale. The quintiles on capital strength relative to risk-weighted assets (Tier 1 ratio) and the related scale economies (Table 8, Panel E) show that banks with the highest capitalization only appear to enjoy substantial economies of scale. Greater capital strength can either be interpreted as a proxy for lower risk (Mester, 1996) or as an indicator for the greater managerial flexibility in pursuing new business opportunities that can be financed via equity capital. Across the other four quintiles, there is no difference in the level of economies of scale. Finally, quintiles that reflect systemic risk (Srisk%) and related economies (Table 8, Panel F) show that banks that contribute less to systemic risk (first quintile) do not appear to benefit from economies (they even experience diseconomies) before the crises (caution should be taken here as the number of observations is only 53 before the crises). Conversely, during the crises, banks seem to benefit from economies of scale across all five quintiles (i.e., irrespective of their systemic risk), although banks contributing more to systemic risk (fourth and fifth quintile) seem to benefit from realizing the largest scale economies. This finding suggests that during the crises banks benefited from scale expansion independently of their contribution to systemic risk.

To isolate the effects of diversification in the business model, risk-taking, profitability, and too-big-to-fail status on economies of scale, we perform a multivariate analysis by using OLS regressions with heteroscedasticity-consistent standard errors as specified in equations 3 and 4 (Table 9: Panel A for the base model, Panel B for the reduced model with only significant variables in the base model, Panel C for the reduced model with systemic risk, and Panel D for the base model with the too-big-to-fail status).[14] Several interesting results emerge on the relation between economies of scale and key bank business characteristics. First, there is a positive significant link between investment

[14] As for multicollinearity, no obvious problems affect the base and reduced models of Eq. 3 (highest VIF index is equal to 9.13 in the base model and to 8.11 in the reduced model), whereas the inclusion of systemic risk in the base model generates multicollinearity problems (highest VIF equal to 19.26). Thus, we choose to include systemic risk in the reduced model only (highest VIF index is equal to 8.72). The model with the too-big-to-fail status and its interaction with Tier1 (Eq. 4) could be affected by multicollinearity problems (highest VIF equal to 12.85). We thus check how stable coefficients are in the different models (Eq. 4 vs. Eq. 3). Given that coefficients are stable, multicollinearity should not be a problem. As for the R-squared, we note that it is not particularly high in most estimations. However we have already included the relevant characteristics identified in the literature (bank business model, profitability of traditional banking activity, liquidity risk, credit risk, capital strength, too-big-to-fail and systemic risk), and no other obvious variable (not correlated with the existing variables) seem to be available.

banking activity (SEC_TA) and economies of scale; in fact a greater emphasis of bank activity towards investment banking is associated with larger economies of scale. A Chow test shows a significant difference in the relevance of this determinant before and during the crises: mainly investment banks (i.e., banks with more proprietary trading) experience an increase in the magnitude of their economies of scale during the financial crises. This result confirms the evidence at the univariate level that banks more oriented towards investment banking could benefit most from economies of scale. This evidence is especially interesting in light of the 2014 European Commission proposal to ban proprietary trading for the largest banks as our findings suggest that such a move could limit positive efficiency externalities resulting in a net social loss. Second, the coefficient of profitability on traditional lending activities (NIM) is not statistically significant, which suggests that greater profits from traditional lending do not determine scale economies. However, the Chow test suggests a change in the impact of profitability on traditional lending activities before and during the crises. Third, there is a positive relation between the liquidity ratio and economies of scale (i.e., higher liquidity ratio, lower liquidity risk results in greater economies). To further investigate the effect of liquidity risk on scale economies, we analyze the squared value of the liquidity ratio. The coefficient of the squared term is positive suggesting that the relation is convex. This convexity means that for liquidity ratios up to 7.50% (where this minimum value is computed as $-\beta_3/2\beta_4$ as defined in Eq. 3) liquidity increases economies of scale, whereas above this level it reduces economies. The negative effect of liquidity above such a value suggests that above certain levels liquidity becomes an index of managerial inefficiency and/or lack of business investment decisions (that has a negative effect on cost efficiency). It follows that tougher Basel 3 liquidity requirements (up to a certain liquidity level) may have a positive effect on cost economies. Fourth, credit risk (LLP_Loans) has a non-significant impact on economies of scale, even during the crises. Fifth, over the entire period and during the crises, the capital strength (Tier1) coefficient is positive and significant whereas its squared value is negative and significant but close to zero. This evidence implies a concave relation, although almost flat, between Tier 1 and the economies of scale - this suggests that capital strength reduces economies of scale. Tougher Basel 3 capital requirement appears to reduce cost economies in banking. Note however the relation between capital strength and economies of scale was non-significant before the crises. Sixth, in the reduced model with systemic risk (Table 9, Panel C), the systemic risk (Srisk%) coefficient is positive and statistically significant that means higher systemic risk reduces economies of scale. The result on systemic risk suggests that banks that could benefit most from size increases are ones contributing least to systemic risk: this evidence does not support the existence of a positive link between the too-big-to-fail issue and systemic risk. The need for the break-up hypothesis does not seem to be confirmed. Finally, in the base model with a dummy variable for TBTF (Table 9, Panel D), there is a positive and significant link between the too-big-to-fail status and economies of scale. Moreover for the base group of non-TBTF banks capital strength increases scale economies, whilst for the TBTF banks it seems that capital strength decreases economies of scale. This suggests that tougher capital requirements appear to reduce cost economies specifically for too-big-to-fail banks, but not for other banks. Again the need for bank break-up's (as illustrated in the US Vitter-Brown bill) does not seem to be confirmed for our European sample.

### *4.1 Robustness tests*

Table 10 reports the results of the Granger causality tests (Granger and Newbold, 1986). In all specifications (Panels A to D), the first and second lags of economies of scale are usually significantly different from zero indicating that scale economies at time *t* are influenced by the previous years' economies. When economies of scale are estimated as a function of lagged economies of scale and lagged Tier 1 capital (Panel A), we find that an increase in the second lag of Tier 1 capital Granger-causes a fall in scale economies (Granger coefficient significant at the 1% level).[15] As for causality running from economies of scale to Tier 1, the significance of the coefficients for the first lag of Tier 1 suggest that it is affected significantly only by the previous years' Tier1, whilst Granger causality running from the economies of scale to Tier 1 is not statistically significant (p-

[15] Granger causality is assessed as the joint test of the two lags of Tier 1 on economies of scale as follows: $\beta_1 + \beta_2 = 0$. A *p*-value less than 0.10 rejects the null hypothesis of no causality at the 10% significance level. However it is not possible to infer the stability of the relation over the long run.

value > 0.10). When economies are estimated as a function of the lagged economies of scale and liquidity ratio (Panel B), we document that an increase in the second lag of the liquidity ratio Granger-causes an increase in scale economies (Granger coefficient significant at the 10% level). As for the causality running from economies of scale to the liquidity ratio, liquidity ratio is affected significantly by the previous years' liquidity ratios and by the previous years' economies of scale. Nevertheless, Granger causality running from economies of scale to the liquidity ratio is not statistically significant. When economies of scale are estimated as a function of lagged economies of scale and lagged investment banking activity (Panel C), we find that an increase in the second lag of the investment banking activity Granger-causes an increase in economies of scale (Granger coefficient significant at the 1% level). As for the causality running from economies of scale to investment banking activity, the latter is significantly influenced by the previous years' SEC_TAs and by economies of scale two years prior. Furthermore, Granger causality running from scale economies of scale to SEC_TA is statistically significant. Finally, when economies of scale are estimated as a function of the lagged economies of scale and lagged systemic risk (Panel D), we document that an increase in the first lag of systemic risk Granger-causes a decrease in the economies of scale (Granger coefficient significant at the 1% level). As for the causality running from the economies of scale to Srisk%, systemic risk is affected significantly only by the previous years' Srisk%s. Nevertheless, Granger causality running from economies of scale to the Srisk% is not statistically significant.

In short, Granger causality tests suggest the existence of a unidirectional causality running from liquidity, Tier 1 capital and systemic risk to scale economies. The null hypothesis of noncausality (economies of scale do not cause liquidity, Tier 1 capital, and systemic risk) can be rejected at the 1% level. In contrast, the null hypothesis that economies of scale do not cause diversification in the business model cannot be rejected at the 1% level.

We further check the robustness of the results by using the Generalized Methods of Moments (GMM) introduced by Hansen (1982) as an alternative estimation strategy. The instrument variable set contains the lagged (one- and two-quarter) values of the log-difference of the respective explanatory variables. For each of these instruments to be valid, they must be correlated with the endogenous variable and uncorrelated with the error term. A Hansen-Sargan test of the instrument validity is conducted. The rejection of the null hypothesis points to the validity of the instrument set we use. Table 11 shows the results obtained for the base model, the reduced model that includes systemic risk, and the base model that includes the too-big-to-fail status. Our previous results are confirmed.

## 5. Conclusions

To deal with moral hazard and government safety net subsidy issues linked to too-big-to-fail bank regulators in the US and Europe have proposed structural reforms aimed at restricting bank risk-taking – these reforms are likely to inhibit bank growth and size. Such legislation, therefore, could inhibit bank's ability to realize scale economies, and this could feed through into higher costs and other externalities. In order to investigate such issues this paper uses a sample of 103 European listed banks over the period 2000 to 2011 to analyze scale economies and its determinants. We find that scale economies are widespread across different size classes of banks. Second, these cost economies are significantly greater for the largest banks. Third, the lowest economies are typically found in the smallest financial systems (Belgium, Finland, and Iceland). Fourth, banks that operate in countries most affected by the financial crises (Belgium, Greece, Iceland, Ireland, Portugal and Spain) exhibit diseconomies of scale, probably due to reduced production capacity. Finally, as for the determinants of scale economies, higher economies are realized for banks with business models more oriented towards investment banking, with higher liquidity, lower Tier 1 capital, that contribute less to overall systemic risk, and with the too-big-to-fail status. Granger causality tests suggest the existence of unidirectional causality running from liquidity, Tier 1 capital, and bank's contribution to systemic risk through to economies of scale.

Over 2000 to 2011 the European banking industry exhibited significant economies of scale for the largest banks. As bank scale is associated with greater cost efficiency, this at least provides some justification as to why bank growth and greater size were strategically prioritised. Second, our evidence illustrates that greater economies are realized for banks that emphasize investment banking. The evidence does not seem to support EU structural reforms that seek to limit big bank trading and other activities.

Overall, these results suggest that the answer to our main research question is that European banks are not too big (as far as economies of scale are concerned). Nevertheless, we acknowledge the need for EU policy makers to balance the benefits of an efficient banking industry (or the costs of an inefficient one) with the costs of a riskier environment. Should these results remain robust in additional testing (e.g. different estimation techniques, alternative assumptions about the underlying bank production function such as the use of methodologies that take account risk) then their implications are potentially far-reaching.

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**Table 1: Sample selection**

| | Number of banks |
|---|---|
| Banks comprised in the Stoxx 600 Banks Index (located in Austria, Belgium, Denmark, Finland, France, Germany, Greece, Iceland, Ireland, Italy, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, UK. | 115 |
| (period 2000 – 2011) | |
| Minus | |
| - Banks listed in the Euro Stoxx 600 Banks Index only in the first 2 quarters of year 2000 (Banco Portugues Do Atlantico, Bank International Settlements Biz USA, Ionian Bank, National Westminster Bank, Unidanmark) | (5) |
| - Banks with missing financial data in Bankscope (Ageas NV, Glitnir Bank, National Bank of Iceland Ltd) | (3) |
| - Banks not available in Bankscope (BA Holding, Banca Nazionale del Lavoro, Banco Pastor, KBC Ancora) | (4) |
| Final bank sample | 103 |
| Final bank year observations | 686 |

**Table 2: Number of banks in the sample (per year / country)**

This table provides the total number of bank year observations comprised in the final sample per country and year (2000-2011). Sample representativeness indicates how representative the sample is of the population of EU banks in each year and over the entire period, and it is calculated as the ratio of total assets of banks in the sample over total assets of all banks operating in the countries under analysis.

| **Country\Year** | 2000 | 2001 | 2002 | 2003 | 2004 | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 | Panel |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Austria | 2 | 2 | 2 | 2 | 3 | 3 | 3 | 3 | 3 | 2 | 2 | 2 | **29** |
| Belgium | 2 | 2 | 2 | 2 | 3 | 4 | 4 | 4 | 3 | 4 | 4 | 2 | **36** |
| Denmark | | | | | 2 | 2 | 3 | 3 | 3 | 3 | 3 | 3 | **22** |
| Finland | | | | | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | **8** |
| France | | | | | 1 | 5 | 6 | 7 | 7 | 7 | 7 | 7 | **47** |
| Germany | 4 | 4 | 4 | 4 | 4 | 5 | 6 | 6 | 6 | 5 | 5 | 5 | **58** |
| Greece | | | | | 6 | 6 | 7 | 6 | 6 | 6 | 6 | 4 | **47** |
| Iceland | | | | | | 1 | 1 | 1 | | | | | **3** |
| Ireland | | | | | 1 | 5 | 5 | 5 | 5 | 3 | 3 | 3 | **30** |
| Italy | 6 | 5 | 3 | 1 | 2 | 16 | 18 | 14 | 13 | 13 | 13 | 13 | **117** |
| Netherlands | | | | | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | **8** |
| Norway | | 1 | 1 | | | 2 | 2 | 2 | 2 | 2 | 2 | 2 | **16** |
| Portugal | | | | | 1 | 3 | 3 | 3 | 3 | 3 | 3 | 3 | **22** |
| Spain | | | | | 5 | 6 | 6 | 6 | 6 | 6 | 7 | 7 | **49** |
| Sweden | | | | | | 4 | 4 | 4 | 4 | 4 | 4 | 4 | **28** |
| Switzerland | 4 | 5 | 6 | 6 | 6 | 7 | 7 | 7 | 8 | 8 | 7 | 7 | **78** |
| UK | | | | | 3 | 11 | 13 | 13 | 13 | 13 | 11 | 11 | **88** |
| **Total number** | 18 | 19 | 18 | 15 | 39 | 82 | 90 | 86 | 84 | 81 | 79 | 75 | **686** |
| ***Sample representativeness*** | *60%* | *66%* | *68%* | *61%* | *54%* | *58%* | *64%* | *64%* | *62%* | *62%* | *61%* | *59%* | ***62%*** |

**Table 3: Bank size classes: descriptive statistics**

This table reports descriptive statistics on size (expressed in terms of total assets) for each quintile (from the smallest to the largest). N. indicates the number of bank year observation. Size values are expressed in thousands of Euro.

| | N. | Mean | St.dev | Min | Median | Max |
|---|---|---|---|---|---|---|
| Quintile 1 - Smallest | 137 | 15,640,318 | 6,833,712 | 959,000 | 15,408,601 | 27,524,800 |
| Quintile 2 – Small | 137 | 45,300,082 | 11,393,042 | 28,326,600 | 44,860,100 | 69,596,000 |
| Quintile 3 - Medium | 137 | 116,645,227 | 31,331,246 | 70,920,500 | 120,733,486 | 181,703,200 |
| Quintile 4 – Large | 137 | 326,783,594 | 116,338,187 | 182,174,000 | 288,551,000 | 541,968,767 |
| Quintile 5 – Largest | 138 | 1,094,533,160 | 480,107,265 | 552,738,000 | 919,841,850 | 2,586,701,332 |
| Panel | 686 | 320,909,853 | 460,188,470 | 959,000 | 120,733,486 | 2,586,701,332 |

**Table 4: Bank characteristics: descriptive statistics and correlations**

This table reports variables used as proxies for the bank characteristics: a) $SEC\_TA_{i,t}$ is the securities to total asset ratio, used as a proxy for the bank business model; b) $NIM_{i,t}$ is the net interest margin (i.e. net interest income to total loans), used as a proxy for the bank profitability on traditional lending activities; c) $LR_{i,t}$ is the liquidity ratio (i.e. liquid assets to total customer deposits), used as a deposit runoff ratio; d) $LLP\_Loans_{i,t}$ is the loans loss provision to loans, used as a proxy for the credit risk; e) $Tier1_{i,t}$ is the Tier 1 ratio (i.e. shareholder funds plus perpetual noncumulative preference shares as a percentage of risk-weighted assets and off-balance sheet risks measured under the Basel rules), used as a proxy for the bank's capital strength; f) $Srisk\%_{i,t}$ is the systemic risk, used to represent the bank's percentage of financial sector capital shortfall (updated weekly by V-Lab for 306 observations in our sample); g) $TBTF_i$ is a dummy variable equal to 1 for Systemically Important Financial Institutions as defined by the Financial Stability Board. Values are reported for the overall period (2001-2011), pre-crisis (2001-2006) and crises (2007-2011). Panel A reports descriptive statistics for each bank characteristic, and Panel B Spearman correlations (2-tailed). *** correlation significant at 1%.

**Panel A: Descriptive statistics**

| Variable | Period | Obs | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|---|
| SEC_TA | *Overall* | *686* | 0.2640 | 0.1699 | 0.0024 | 0.8337 |
| | *Pre-crisis* | *281* | 0.2459 | 0.1496 | 0.0029 | 0.7988 |
| | *Crises* | *405* | 0.2765 | 0.1818 | 0.0024 | 0.8337 |
| NIM | *Overall* | *686* | 0.0361 | 0.0733 | -0.0048 | 0.9456 |
| | *Pre-crisis* | *281* | 0.0409 | 0.1010 | -0.0002 | 0.9456 |
| | *Crises* | *405* | 0.0327 | 0.0449 | -0.0048 | 0.6383 |
| LR | *Overall* | *686* | 0.4784 | 0.6768 | 0.0265 | 9.0351 |
| | *Pre-crisis* | *281* | 0.4971 | 0.8296 | 0.0265 | 9.0351 |
| | *Crises* | *405* | 0.4654 | 0.5470 | 0.0340 | 7.1571 |
| LLP_Loans | *Overall* | *669* | 0.0893 | 2.0595 | -0.0090 | 53.2711 |
| | *Pre-crisis* | *270* | 0.2090 | 3.2415 | -0.0090 | 53.2711 |
| | *Crises* | *399* | 0.0084 | 0.0302 | -0.0070 | 0.3655 |
| Tier1 | *Overall* | *608* | 9.9863 | 4.6128 | -0.4000 | 50.1000 |
| | *Pre-crisis* | *244* | 10.9387 | 4.3979 | -0.4000 | 39.8000 |
| | *Crises* | *364* | 9.3478 | 4.6491 | 3.4000 | 50.1000 |
| Srisk% | *Overall* | *306* | 2.0185 | 2.8658 | 0.0100 | 15.4200 |
| | *Pre-crisis* | *61* | 3.8207 | 3.9496 | 0.0300 | 15.4200 |
| | *Crises* | *245* | 1.5698 | 2.3272 | 0.0100 | 13.8200 |
| TBTF | *Overall* | *686* | 0.1924 | 0.3945 | 0 | 1 |
| | *Pre-crisis* | *281* | 0.1708 | 0.3770 | 0 | 1 |
| | *Crises* | *405* | 0.2074 | 0.4060 | 0 | 1 |

**Panel B: Correlations**

| | ES | SEC_TA | NIM | LR | LLP_Loans | Tier1 | Srisk% | TBTF |
|---|---|---|---|---|---|---|---|---|
| ES | 1 | -0.4277*** | -0.2701*** | -0.3442*** | 0.1639*** | -0.1625*** | -0.3770*** | -0.3334*** |
| SEC_TA | | 1 | 0.0459 | 0.5909*** | -0.1548*** | 0.2936*** | 0.6599*** | 0.6394*** |
| NIM | | | 1 | 0.0877** | 0.2252*** | 0.2404*** | -0.0522 | -0.0663 |
| LR | | | | 1 | -0.2578*** | 0.2961*** | 0.4777*** | 0.5672*** |
| LLP_Loans | | | | | 1 | -0.0361 | 0.0102 | 0.0158 |
| Tier1 | | | | | | 1 | 0.1952*** | 0.3061*** |
| Srisk% | | | | | | | 1 | 0.8231*** |
| TBTF | | | | | | | | 1 |

**Table 5: Economies of scale for European banks according to size classes (2000-2011)**

This table reports economies of scale (ES) for each year (from 2000 to 2001) and each size class (from the smallest to the largest, as shown in Table 3). As in equation 1), $ES = \sum_{i=1}^{m} \frac{\partial lnTC}{\partial lnQ_i}$, where TC is the actual cost of producing the average output bundle at the average input prices, equity capital and macroeconomic factors; $Q_i$ is the volume of output *i*. ES < 1 indicates increasing returns to scale (i.e. economies of scale); ES > 1 indicates decreasing returns to scale (i.e. diseconomies of scale); ES = 1 indicates constant returns to scale. Bold typeface for values significantly different from one at the 5% level.

| Years | Smallest | Small | Medium | Large | Largest | All |
|---|---|---|---|---|---|---|
| 2000 | **0.9252** | **1.0015** | **0.9608** | **0.9260** | 0.8940 | ***0.9348*** |
| 2001 | 0.8611 | **0.9763** | **1.0170** | **0.9489** | 0.8855 | ***0.9336*** |
| 2002 | **0.8082** | **0.9538** | **0.9594** | 0.8393 | **0.7975** | *0.8689* |
| 2003 | **0.7048** | **0.9441** | 0.8329 | 0.8800 | **0.6591** | ***0.8042*** |
| 2004 | 0.8207 | 0.8592 | 0.8690 | 0.8413 | **0.7583** | *0.8287* |
| 2005 | 0.8459 | **0.9255** | 0.8991 | 0.8401 | **0.7910** | *0.8593* |
| 2006 | 0.8459 | **0.9515** | **0.9366** | 0.8525 | 0.8223 | *0.8818* |
| 2007 | 0.9047 | **1.0081** | **0.9874** | 0.8743 | 0.8473 | ***0.9235*** |
| 2008 | 0.8822 | **1.0487** | **1.0096** | 0.8956 | 0.8656 | ***0.9395*** |
| 2009 | **0.7555** | **0.9586** | **0.9220** | **0.7757** | **0.7453** | *0.8304* |
| 2010 | **0.7474** | 0.8667 | 0.8360 | **0.7654** | **0.6855** | ***0.7795*** |
| 2011 | **0.7819** | **0.9165** | 0.8578 | **0.7717** | **0.6971** | ***0.8050*** |
| Panel | **0.8255** | **0.9510** | **0.9228** | **0.8351** | **0.7848** | 0.8629 |

**Table 6: Economies of scale for European banks (per country and size classes)**

This table reports economies of scale (ES, as in equation 1) for each country and for each size class (from the smallest to the largest, as shown in Table 3). ES < 1 indicates increasing returns to scale; ES > 1 indicates decreasing returns to scale; ES = 1 indicates constant returns to scale. Bold typeface for values significantly different from one at the 5% level.

| Country / Quintile | Smallest | Small | Medium | Large | Largest | All |
|---|---|---|---|---|---|---|
| Austria | | 0.8396 | **0.7978** | 0.8417 | | 0.8218 |
| Belgium | | **0.9874** | **1.1327** | 0.8691 | **0.9712** | **0.9895** |
| Denmark | **0.8063** | 0.8312 | | **0.9450** | | 0.8601 |
| Finland | **1.1084** | **1.0814** | | | | **1.0949** |
| France | 0.8818 | **0.9472** | **0.9332** | **0.7486** | 0.8363 | 0.8499 |
| Germany | **1.1003** | **1.1943** | 0.9036 | **0.8123** | 0.8155 | 0.8642 |
| UK | **0.7956** | **1.3014** | **1.1211** | 0.8335 | **0.7572** | 0.8606 |
| Greece | 0.8674 | **0.9516** | **0.9331** | | | **0.9276** |
| Ireland | **1.1473** | 0.9015 | 0.8826 | **1.0697** | | **0.9598** |
| Iceland | | **1.0958** | | | | **1.0958** |
| Italy | 0.8462 | 0.8925 | 0.8666 | **0.8081** | **0.7508** | 0.8507 |
| Norway | | 0.8713 | **0.9231** | 0.8567 | | 0.8773 |
| Netherlands | | | **0.6011** | **0.6411** | **0.7454** | **0.6963** |
| Portugal | | **0.9992** | 0.8893 | | | **0.9542** |
| Spain | **1.1026** | **0.9584** | 0.8992 | **0.8057** | 0.8339 | **0.9106** |
| Sweden | | | **0.9160** | **0.8116** | **0.6666** | 0.8325 |
| Switzerland | **0.7034** | **0.7565** | | | **0.7055** | **0.7088** |

**Table 7: Economies of scale for European banks (per country and year)**

This table reports economies of scale (ES, as in equation 1) for each country and for each year. ES < 1 indicates increasing returns to scale; ES > 1 indicates decreasing returns to scale; ES = 1 indicates constant returns to scale. Bold typeface for values significantly different from one at the 5% level.

| | 2000 | 2001 | 2002 | 2003 | 2004 | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 | All |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Austria | **0.9435** | 0.9015 | 0.8415 | **0.7883** | **0.8013** | **0.8028** | **0.8106** | 0.8398 | 0.8702 | **0.7933** | **0.7280** | **0.7327** | *0.8218* |
| Belgium | **1.0133** | **1.0636** | **1.0072** | **0.9749** | **1.0417** | **0.9437** | **0.9556** | **0.9726** | **1.1947** | **0.9970** | **0.9446** | **0.7710** | ***0.9895*** |
| Denmark | | | | | 0.8631 | 0.8860 | 0.8860 | **0.9294** | **0.9472** | 0.8664 | **0.7475** | **0.7651** | *0.8601* |
| Finland | | | | | **1.0145** | **1.1212** | **1.1100** | **1.1877** | **1.1988** | **1.0675** | **1.0205** | **1.0390** | ***1.0949*** |
| France | | | | | **0.9445** | 0.8517 | 0.8766 | **0.9265** | **0.9494** | **0.8029** | **0.7505** | **0.7826** | *0.8499* |
| Germany | **0.9511** | **0.9434** | 0.8832 | 0.8301 | **0.7954** | 0.8776 | 0.8968 | 0.8875 | 0.8870 | 0.8228 | **0.8025** | **0.7940** | *0.8642* |
| UK | | | | | **0.7242** | 0.8921 | 0.8909 | **0.9262** | **0.9163** | 0.8247 | **0.7779** | **0.8124** | *0.8606* |
| Greece | | | | | 0.8396 | 0.8646 | 0.8810 | **0.9520** | **1.0025** | **0.9491** | **0.9280** | **1.0536** | ***0.9276*** |
| Ireland | | | | | **1.0026** | **0.9621** | **1.0078** | **1.0317** | **1.0496** | 0.8707 | **0.8080** | 0.8332 | ***0.9598*** |
| Iceland | | | | | | **1.0960** | **1.1168** | **1.0747** | | | | | ***1.0958*** |
| Italy | **0.9301** | **0.9384** | **0.9166** | 0.8734 | 0.8658 | **0.7987** | 0.8415 | 0.9032 | **0.9337** | 0.8213 | **0.7592** | 0.8188 | *0.8507* |
| Norway | | **1.0751** | **1.0407** | | | 0.8397 | 0.8869 | 0.9086 | **0.9413** | **0.7893** | **0.7997** | **0.7954** | *0.8773* |
| Netherlands | | | | | **0.7829** | **0.8064** | **0.6908** | **0.6950** | **0.7520** | **0.6411** | **0.5882** | **0.6139** | ***0.6963*** |
| Portugal | | | | | 0.8347 | **0.9308** | **0.9453** | **0.9945** | **1.0406** | **0.9537** | **0.9200** | **0.9344** | ***0.9542*** |
| Spain | | | | | 0.8307 | 0.9030 | **0.9637** | **1.0054** | **1.0156** | 0.8763 | **0.8147** | 0.8829 | ***0.9106*** |
| Sweden | | | | | | 0.8355 | 0.8327 | 0.9072 | **0.9109** | **0.8012** | **0.7529** | **0.7870** | *0.8325* |
| Switzerland | 0.8819 | 0.8534 | **0.7699** | **0.7237** | **0.7012** | **0.7165** | **0.7473** | **0.7763** | **0.7388** | **0.6295** | **0.5339** | **0.5648** | ***0.7088*** |

**Table 8: The determinants of economies of scale – univariate quintile analysis**

This table shows univariate quintile analysis by reporting economies of scale for five quintiles representing bank characteristics (as defined in Table 4), namely: a) bank business models (Securities/Total Assets, Panel A); b) profitability of the core lending activities (Net Interest Margin, Panel B); c) liquidity risk (Liquidity Ratio, Panel C); d) credit risk (Loan Loss Provision/Gross Loans, Panel D); e) capital strength relative to risk-weighted assets (Tier 1 ratio, Panel E); f) systemic risk (Srisk%, Panel F). Bold typeface for values significantly different from one at the 5% level.

| **PANEL A** | | | | | | |
|---|---|---|---|---|---|---|
| | **Economies of scale on Securities /Total Asset (SEC_TA) quintiles** | | | | | |
| Year | Quintile 1 (*Lowest*) | Quintile 2 | Quintile 3 | Quintile 4 | Quintile 5 (*Highest*) | Total |
| 2000 | **0.9566** | **0.9449** | **0.9536** | 0.8386 | 0.9045 | **0.9348** |
| 2001 | **1.0595** | **0.9388** | **0.9132** | 0.8212 | **0.9301** | **0.9336** |
| 2002 | **1.0002** | **0.9502** | **0.8095** | **0.7595** | 0.8181 | 0.8689 |
| 2003 | **0.9792** | 0.8435 | **0.6726** | **0.7973** | **0.7283** | **0.8042** |
| 2004 | **0.9349** | 0.8429 | 0.8514 | **0.8093** | **0.7079** | 0.8287 |
| 2005 | **0.9415** | 0.8750 | 0.8600 | 0.8380 | **0.7817** | 0.8593 |
| 2006 | **0.9621** | 0.9078 | 0.8667 | 0.8343 | 0.8380 | 0.8818 |
| 2007 | **1.0198** | **0.9702** | **0.9224** | **0.8134** | 0.8934 | **0.9235** |
| 2008 | **1.0177** | **1.0170** | **0.9304** | 0.9040 | 0.8281 | **0.9395** |
| 2009 | 0.8657 | **0.9189** | 0.8493 | 0.8342 | **0.6923** | 0.8304 |
| 2010 | **0.8133** | **0.9108** | **0.8085** | **0.6976** | **0.6692** | **0.7795** |
| 2011 | **0.9156** | 0.9048 | 0.8186 | **0.7263** | **0.6598** | **0.8050** |
| All years | **0.9555** | **0.9187** | **0.8547** | **0.8061** | **0.7876** | **0.8658** |

| Panel B | | | | | | |
|---|---|---|---|---|---|---|
| **Economies of scale on Net Interest Margin (NIM) quintiles** | | | | | | |
| Year | Quintile 1 (*Lowest*) | Quintile 2 | Quintile 3 | Quintile 4 | Quintile 5 (*Highest*) | Total |
| 2000 | 0.8812 | **1.0180** | **0.9145** | **0.9246** | 0.8914 | **0.9348** |
| 2001 | **0.9521** | **0.9380** | **0.9841** | **0.9295** | 0.8768 | **0.9336** |
| 2002 | 0.9103 | **0.9434** | **0.9559** | 0.8195 | **0.7216** | 0.8689 |
| 2003 | **0.8118** | 0.9072 | 0.8764 | **0.7973** | **0.6282** | **0.8042** |
| 2004 | **0.9213** | 0.8536 | 0.8585 | **0.7583** | **0.7555** | 0.8287 |
| 2005 | **0.9398** | 0.8713 | 0.8875 | **0.7977** | **0.7990** | 0.8593 |
| 2006 | **0.9653** | **0.9303** | 0.8598 | 0.8404 | **0.8131** | 0.8818 |
| 2007 | **0.9635** | **0.9872** | **0.9433** | 0.8615 | 0.8654 | **0.9235** |
| 2008 | **0.9862** | **0.9662** | **0.9646** | **0.9164** | 0.8657 | **0.9395** |
| 2009 | 0.9076 | 0.8677 | 0.8288 | **0.7721** | **0.7790** | 0.8304 |
| 2010 | 0.9024 | **0.8139** | **0.7717** | **0.6412** | **0.7680** | **0.7795** |
| 2011 | 0.9000 | 0.8601 | **0.7746** | **0.7509** | **0.7394** | **0.8050** |
| All years | **0.9201** | **0.9131** | **0.8850** | **0.8174** | **0.7919** | **0.8658** |

| Panel C | | | | | | |
|---|---|---|---|---|---|---|
| **Economies of scale on Liquidity Ratio (LR) quintiles** | | | | | | |
| Year | Quintile 1 (*Lowest*) | Quintile 2 | Quintile 3 | Quintile 4 | Quintile 5 (*Highest*) | Total |
| 2000 | **1.0079** | **0.9408** | **0.9716** | **0.9618** | **0.8094** | **0.9348** |
| 2001 | **1.0390** | **0.9927** | **0.9128** | **0.9595** | **0.7587** | **0.9336** |
| 2002 | **0.9624** | **0.9535** | 0.9070 | **0.7459** | **0.7660** | 0.8689 |
| 2003 | 0.8918 | 0.8544 | 0.8862 | **0.6392** | **0.7492** | **0.8042** |
| 2004 | 0.8974 | 0.8276 | 0.8789 | **0.7377** | **0.8083** | 0.8287 |
| 2005 | **0.9233** | 0.8510 | 0.8593 | 0.8396 | 0.8217 | 0.8593 |
| 2006 | **0.9369** | 0.8847 | 0.8897 | 0.8287 | 0.8689 | 0.8818 |
| 2007 | **1.0125** | **0.9349** | 0.8983 | 0.8463 | **0.9252** | **0.9235** |
| 2008 | **0.9909** | **0.9808** | **0.9258** | 0.8492 | **0.9502** | **0.9395** |
| 2009 | 0.8961 | 0.8525 | **0.8090** | **0.7563** | 0.8375 | 0.8304 |
| 2010 | 0.8248 | 0.8225 | **0.7914** | **0.6995** | **0.7600** | **0.7795** |
| 2011 | 0.8867 | 0.8603 | **0.7460** | **0.7062** | 0.8258 | **0.8050** |
| All years | **0.9391** | **0.8963** | **0.8730** | **0.7975** | **0.8234** | **0.8658** |

| Panel D | | | | | | |
|---|---|---|---|---|---|---|
| **Economies of scale on Loss Loan Provision/Gross Loans (LLP_Loans) quintiles** | | | | | | |
| Year | Quintile 1 (*Lowest*) | Quintile 2 | Quintile 3 | Quintile 4 | Quintile 5 (*Highest*) | Total |
| 2000 | **0.9227** | **0.9855** | **0.9824** | 0.8819 | **0.9361** | **0.9262** |
| 2001 | 0.8785 | **0.9140** | **0.9954** | **0.9271** | 0.9015 | **0.9236** |
| 2002 | **0.7551** | **0.9795** | 0.9030 | 0.8753 | 0.8181 | 0.8568 |
| 2003 | **0.6084** | 0.8390 | **0.7889** | 0.8167 | 0.8800 | **0.7864** |
| 2004 | 0.8226 | 0.8576 | 0.8249 | **0.8071** | 0.8188 | 0.8259 |
| 2005 | 0.8249 | **0.9126** | 0.8332 | 0.8515 | 0.8641 | 0.8573 |
| 2006 | 0.8442 | **0.9242** | 0.8531 | 0.9043 | 0.8623 | 0.8771 |
| 2007 | 0.8729 | **0.9500** | **0.9582** | 0.9021 | **0.9196** | **0.9201** |
| 2008 | **0.9518** | **0.9612** | **0.9297** | 0.8777 | **0.9509** | **0.9346** |
| 2009 | **0.7787** | **0.8134** | 0.8437 | 0.8532 | 0.8529 | 0.8284 |
| 2010 | **0.6825** | **0.7899** | 0.8202 | **0.7593** | 0.8421 | **0.7789** |
| 2011 | **0.7012** | 0.8867 | **0.7913** | **0.7622** | 0.8813 | **0.8047** |
| All years | **0.8036** | **0.9011** | **0.8770** | **0.8515** | **0.8773** | **0.8600** |

| Panel E | | | | | | |
|---|---|---|---|---|---|---|
| **Economies of scale on Tier 1 ratio (Tier1) quintiles** | | | | | | |
| Year | Quintile 1 (*Lowest)* | Quintile 2 | Quintile 3 | Quintile 4 | Quintile 5 (Highest) | Total |
| 2000 | 0.8822 | 0.8734 | **0.9415** | **0.9485** | 0.828 | 0.9093 |
| 2001 | 0.8556 | **0.9696** | **0.9805** | **0.9601** | **0.7391** | 0.9042 |
| 2002 | **0.9506** | 0.8426 | 0.8415 | **0.9876** | **0.6599** | 0.8479 |
| 2003 | 0.8393 | **0.7594** | 0.8498 | **0.6608** | **0.6806** | **0.7509** |
| 2004 | **0.7652** | 0.8780 | 0.8482 | **0.7863** | **0.7003** | **0.7956** |
| 2005 | 0.8479 | 0.8447 | **0.9232** | 0.8621 | **0.7918** | 0.8540 |
| 2006 | 0.8927 | 0.8728 | **0.9256** | **0.9112** | **0.8094** | 0.8822 |
| 2007 | 0.9075 | **0.9426** | **0.9779** | 0.9101 | 0.8643 | **0.9202** |
| 2008 | **0.9511** | **0.9555** | **0.9481** | **0.9308** | 0.8582 | **0.9283** |
| 2009 | 0.8975 | 0.8851 | **0.8132** | 0.847 | **0.675** | 0.8236 |
| 2010 | **0.8010** | **0.8007** | 0.8200 | **0.7911** | **0.6129** | **0.7636** |
| 2011 | 0.8883 | 0.8249 | **0.8047** | **0.7003** | **0.6947** | **0.7811** |
| All years | **0.8733** | **0.8708** | **0.8895** | **0.858** | **0.7429** | **0.8467** |

| Panel F | | | | | | |
|---|---|---|---|---|---|---|
| **Economies of scale on Systemic Risk % (Srisk%) quintiles** | | | | | | |
| Year | Quintile 1 (*Lowest*) | Quintile 2 | Quintile 3 | Quintile 4 | Quintile 5 (*Highest*) | Total |
| 2000 | 0.8948 | | **1.0815** | | **0.9542** | **0.9348** |
| 2001 | **0.7465** | **1.1130** | | **0.9213** | **0.9712** | **0.9336** |
| 2002 | **1.0738** | 0.8468 | **0.6899** | **0.9346** | **0.6525** | 0.8689 |
| 2003 | **1.0526** | **0.7991** | **0.6895** | **0.6320** | 0.8632 | **0.8042** |
| 2004 | 0.8996 | **1.0725** | **0.7608** | **0.7491** | **0.8032** | 0.8287 |
| 2005 | **0.9788** | **0.9791** | 0.8417 | **0.7974** | **0.7953** | 0.8593 |
| 2006 | **1.0163** | **1.0275** | 0.8391 | 0.8328 | **0.8114** | 0.8818 |
| 2007 | **0.9333** | **0.9518** | **0.9916** | 0.8721 | 0.8177 | **0.9235** |
| 2008 | **0.9607** | **0.9893** | **0.9754** | 0.8861 | 0.8582 | **0.9395** |
| 2009 | 0.8983 | **0.9406** | 0.8415 | **0.7443** | **0.7455** | 0.8304 |
| 2010 | 0.8480 | 0.8924 | 0.8353 | **0.7181** | **0.7034** | **0.7795** |
| 2011 | **0.7652** | **0.9327** | 0.9031 | **0.7403** | **0.6798** | **0.8050** |
| All years | **0.9223** | **0.9586** | **0.8591** | **0.8026** | **0.8046** | **0.8658** |

**Table 9: The determinants of economies of scale - OLS multivariate regressions**

This table reports the results on the determinants of economies of scale estimated by using multivariate OLS regressions as specified in equation 3 and 4 (Panel A for the base model as in equation 3, Panel B for the reduced model with only significant variables in the base model, Panel C for the reduced model with systemic risk, and Panel D for the base model with too-big-to-fail status as in equation 4). Based on the Haussmann test, we estimate the three models of equation 3 by using bank fixed-effect (Panels A-C), whilst we estimate equation 4 by using random-effect (Panel D). Overall refers to the entire period (2001-2011), pre-crisis to years 2001-2006, and crises to years 2007-11. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

| | **PANEL A** Eq. 3 - Base model | | | | | **PANEL B** Eq. 3 - Reduced model | | | | **PANEL C** Eq. 3- Reduced model with Srisk% | | | **PANEL D** Eq. 4 | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Dep variable: ES** | **Overall** | **VIF** | **Pre-crisis** | **Crises** | **Chow Pre vs. Post** | **Overall** | **VIF** | **Pre-crisis** | **Crises** | **Overall** | **VIF** | **Crises** | **Overall** | **VIF** | **Pre-crisis** | **Crises** |
| SEC_TA | -0.2259*** | 1.77 | -0.2243** | -0.2412* | 6.30** | -0.2243*** | 1.73 | -0.2173** | -0.2648** | -0.1648 | 2.14 | -0.1342 | -0.2528*** | 1.98 | -0.1885*** | -0.3555*** |
| | (0.0613) | | (0.1036) | (0.1309) | | (0.0598) | | (0.0926) | (0.1227) | (0.1159) | | (0.2236) | (0.0524) | | (0.0680) | (0.0690) |
| NIM | 0.5660 | 5.9 | -0.3514 | 0.1920 | 3.36** | | | | | | | | 0.2868 | 5.93 | -1.5455** | -0.3393 |
| | (0.6471) | | (1.1171) | (1.7179) | | | | | | | | | (0.5697) | | (0.6590) | (0.7817) |
| LR | -0.1120** | 5.75 | -0.1562 | -0.1341 | 4.50*** | -0.1073** | 5.63 | -0.1747 | -0.1405* | -0.0695 | 8.23 | -0.0923 | -0.0825** | 5.91 | -0.1033 | -0.0466 |
| | (0.0476) | | (0.1457) | (0.0859) | | (0.0461) | | (0.1358) | (0.0850) | (0.0551) | | (0.0751) | (0.0358) | | (0.1052) | (0.0498) |
| LRsq | 0.0075** | 9.13 | 0.0674 | 0.0113 | 3.69*** | 0.0091** | 4.24 | 0.0647 | 0.0131* | 0.0043 | 6.75 | 0.0059 | 0.0114 | 9.12 | 0.0615 | 0.0136 |
| | (0.0037) | | (0.0845) | (0.0102) | | (0.0038) | | (0.0614) | (0.0068) | (0.0049) | | (0.0073) | (0.0075) | | (0.0546) | (0.0117) |
| LLP_Loans | 0.1296 | 2.25 | 0.1593 | 0.3953 | 3.19*** | | | | | | | | 0.2392 | 2.25 | 0.1197 | 0.5206 |
| | (0.1832) | | (0.3715) | (0.3189) | | | | | | | | | (0.2355) | | (0.2949) | (0.4462) |
| Tier1 | 0.0066* | 8.92 | -0.0002 | 0.0155* | 3.64*** | 0.0069* | 8.11 | -0.0010 | 0.0151* | 0.0672*** | 8.72 | 0.0814 | -0.0027 | 1.36 | -0.0003 | -0.0060** |
| | (0.0042) | | (0.0056) | (0.0094) | | (0.0041) | | (0.0050) | (0.0091) | (0.0219) | | (0.0496) | (0.0021) | | (0.0027) | (0.0025) |
| Tier1sq | -0.0002* | 7.84 | 0.0001 | -0.0003* | 3.23*** | -0.0002* | 7.75 | 0.0001 | -0.0003* | -0.0028*** | 8.00 | -0.0035 | | | | |
| | (0.0001) | | (0.0001) | (0.0002) | | (0.0001) | | (0.0001) | (0.0002) | (0.0010) | | (0.0027) | | | | |
| TBTF | | | | | | | | | | | | | -0.1252* | 12.85 | -0.0603 | -0.3702*** |
| | | | | | | | | | | | | | (0.0669) | | (0.0814) | (0.0943) |
| TBTF * Tier1 | | | | | | | | | | | | | 0.0113** | 12.80 | 0.0035 | 0.0408*** |
| | | | | | | | | | | | | | (0.0056) | | (0.0061) | (0.0105) |
| Srisk% | | | | | | | | | | 0.0058*** | 1.66 | 0.0159* | | | | |
| | | | | | | | | | | (0.0020) | | (0.0094) | | | | |
| Constant | 0.8952*** | | 0.9565*** | 0.8539*** | | 0.9081*** | | 0.9581*** | 0.8753*** | 0.5775*** | | 0.5122** | 0.9768*** | | 0.9832*** | 1.0313*** |
| | (0.0473) | | (0.0637) | (0.1204) | | (0.0286) | | (0.0463) | (0.0965) | (0.1348) | | (0.2287) | (0.0306) | | (0.0383) | (0.0366) |
| Observations | 604 | | 240 | 364 | | 608 | | 244 | 364 | 270 | | 217 | 604 | | 240 | 364 |
| R-squared (within) | 0.0949 | | 0.0967 | 0.0968 | | 0.0919 | | 0.998 | 0.0907 | 0.1885 | | 0.1573 | 0.0842 | | 0.0738 | 0.0949 |
| R-squared (between) | 0.1195 | | 0.0839 | 0.1022 | | 0.0647 | | 0.0725 | 0.0672 | 0.1667 | | 0.1483 | 0.2442 | | 0.1648 | 0.3969 |
| R-squared (overall) | 0.1465 | | 0.1740 | 0.1205 | | 0.1456 | | 0.1663 | 0.1083 | 0.0638 | | 0.0528 | 0.2220 | | 0.2419 | 0.3272 |
| Number of banks | 95 | | 89 | 84 | | 95 | | 89 | 84 | 59 | | 59 | 95 | | 89 | 84 |
| Fixed-effect | YES | | YES | YES | | YES | | YES | YES | YES | | YES | NO | | NO | NO |
| ALL Years | YES | | NO | NO | | YES | | NO | NO | YES | | NO | YES | | NO | NO |
| Prob > F | 0.0000 | | 0.0014 | 0.0015 | | 0.0000 | | 0.0005 | 0.0086 | 0.0000 | | 0.0000 | 0.0000 | | 0.0000 | 0.0000 |

**Table 10: Does economies of scale Granger-cause Tier 1/liquidity ratio/ business model or vice versa?**

This table reports the results of the Granger causality tests. Economies of scale are estimated as a function of: a) lagged economies of scale and lagged Tier 1 capital (Panel A); b) lagged economies of scale and liquidity ratio (Panel B); c) lagged economies of scale and lagged investment banking activity (Panel C); d) lagged economies of scale and lagged systemic risk (Panel D). Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

| | **PANEL A** | | **PANEL B** | | **PANEL C** | | **PANEL D** | |
|---|---|---|---|---|---|---|---|---|
| VARIABLES | ES | Tier1 | ES | LR | ES | SEC_TA | ES | Srisk% |
| L.Tier1 | -0.0014 | 0.6737*** | | | | | | |
| | (0.0033) | (0.0582) | | | | | | |
| L2.Tier1 | 0.0055** | 0.0134 | | | | | | |
| | (0.0025) | (0.0568) | | | | | | |
| L.LR | | | -0.0046 | 0.6316*** | | | | |
| | | | (0.0114) | (0.0315) | | | | |
| L2.LR | | | -0.0164** | -0.0127 | | | | |
| | | | (0.0069) | (-0.0191) | | | | |
| L.SEC_TA | | | | | -0.0750 | 0.6044*** | | |
| | | | | | (0.0549) | (0.0475) | | |
| L2.SEC_TA | | | | | -0.1190** | -0.0369 | | |
| | | | | | (0.0553) | (0.0478) | | |
| L.Srisk% | | | | | | | 0.0167*** | 0.3957*** |
| | | | | | | | (0.0056) | (0.0734) |
| L2.Srisk% | | | | | | | -0.0004 | 0.0075 |
| | | | | | | | (0.0043) | (0.0572) |
| L.ES | 0.6750*** | -2.2035 | 0.7282*** | 0.2683** | 0.6989*** | -0.0141 | 0.5955*** | 0.5972 |
| | (0.0492) | (1.6462) | (0.0464) | (0.1278) | (0.0471) | (0.0408) | (0.0825) | (1.0983) |
| L2.ES | -0.5033*** | -0.6072 | -0.4868*** | -0.3220** | -0.4838*** | 0.1260*** | -0.3548*** | -0.6983 |
| | (0.0567) | (1.8871) | (0.0535) | (0.1475) | (0.0532) | (0.0460) | (0.0876) | (1.1739) |
| Constant | 0.6587*** | 5.1532*** | 0.6629*** | 0.2262* | 0.7267*** | 0.0208 | 0.6037*** | 1.3971 |
| | (0.0497) | (1.6638) | (0.0460) | (0.1267) | (0.0505) | (0.0436) | (0.0714) | (0.9442) |
| Observations | 428 | 416 | 483 | 483 | 483 | 483 | 181 | 177 |
| Number of banks | 84 | 82 | 92 | 92 | 92 | 92 | 52 | 52 |
| Fixed-effect | YES | YES | YES | YES | YES | YES | YES | YES |
| R-squared | 0.3973 | 0.3931 | 0.4018 | 0.5517 | 0.4085 | 0.3566 | 0.4064 | 0.2964 |
| Test of $\beta_1+\beta_2=0$ p-value | 0.0096 | 0.1230 | 0.0504 | 0.7060 | 0.0006 | 0.0132 | 0.0007 | 0.9270 |

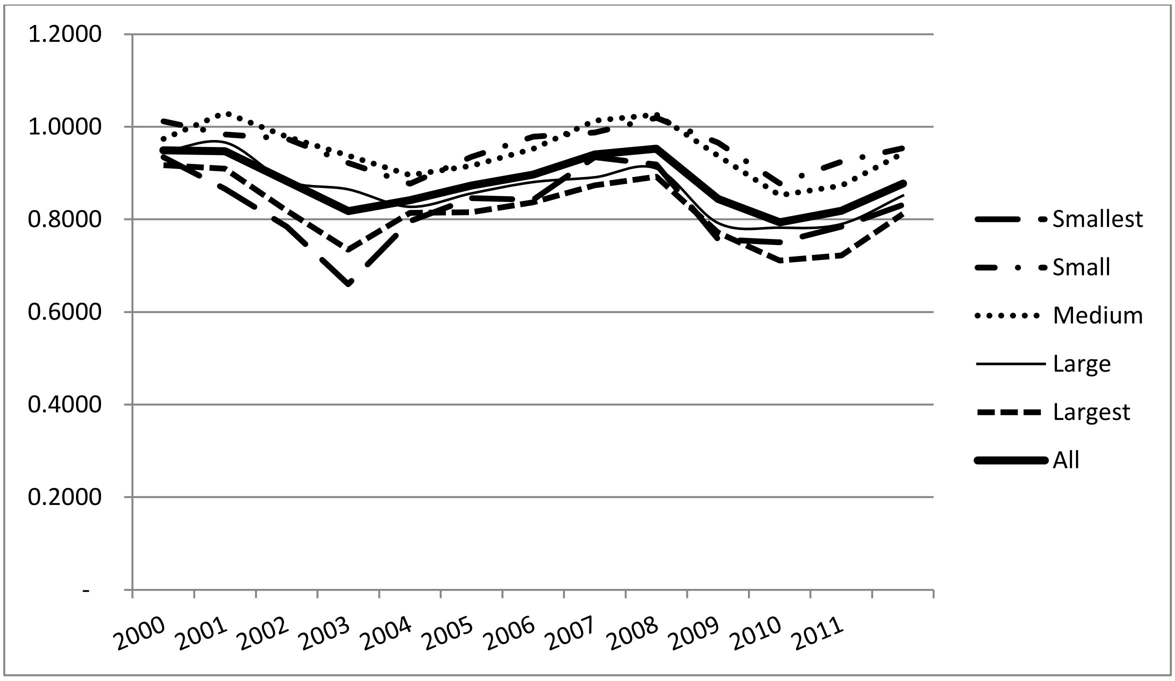
**Table 11: The determinants of economies of scale – GMM multivariate regressions**

This table reports the results on the determinants of economies of scale estimated by using GMM multivariate regressions (Panel A for the base model in the overall period, pre-crisis period and during the crises, Panel B for the reduced model with systemic risk in the overall period and during the crises, and Panel C for the base model with too-big-to-fail status in the overall period and during the crises). The instrument variable set contains the lagged (one- and two-quarter) values of the log-difference of the respective explanatory variables. Overall refers to the entire period (2001-2011), pre-crisis to years 2001-2006, and crises to years 2007-11. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

| | **PANEL A** | | | **PANEL B** | | **PANEL C** | |
|---|---|---|---|---|---|---|---|
| **Dep variable: ES** | **Overall** | **Pre-crisis** | **Crises** | **Overall** | **Crises** | **Overall** | **Crises** |
| SEC_TA | -0.3681*** | -0.1881*** | -0.4184*** | -0.3502*** | -0.3757*** | -0.3645*** | -0.4270*** |
| | (0.0010) | (0.0293) | (0.0093) | (0.0168) | (0.0110) | (0.0023) | (0.0365) |
| NIM | -2.5832*** | -3.4879*** | -3.286017 | | | -2.7500*** | -4.0523*** |
| | (0.0148) | (0.0948) | (0.0883) | | | (0.0285) | (0.4270) |
| LR | -0.0181*** | -0.3849*** | 0.0426593 | -0.1130*** | -0.0708*** | -0.0134*** | -0.1896*** |
| | (0.0015) | (0.0198) | (0.0055) | (0.0076) | (0.0040) | (0.0014) | (0.0371) |
| LRsq | 0.0375*** | 0.1641*** | 0.0383267 | 0.0268*** | 0.0194*** | 0.0412*** | 0.1528*** |
| | (0.0005) | (0.0154) | (0.0020) | (0.0011) | (0.0006) | (0.0010) | (0.0195) |
| LLP_Loans | 1.4915*** | 0.4778** | 1.5577*** | | | 1.2799*** | 0.1679 |
| | (0.0272) | (0.2077) | (0.0886) | | | (0.0496) | (0.6570) |
| Tier1 | 0.0036*** | 0.0079*** | 0.0061536 | 0.0032*** | 0.0200*** | -0.0116*** | -0.0104*** |
| | (0.0003) | (0.0024) | (0.0013) | (0.0009) | (0.0011) | (0.0001) | (0.0008) |
| Tier1sq | -0.0003*** | -0.0001 | -0.0004205 | -0.0002*** | -0.0005*** | | |
| | (0.0000) | (0.0001) | (0.0000) | (0.0000) | (0.0000) | | |
| Srisk% | | | | 0.0112*** | 0.0072*** | | |
| | | | | (0.0007) | (0.0004) | | |
| TBTF | | | | | | -0.2333*** | -0.4830*** |
| | | | | | | (0.0027) | (0.0628) |
| TBTF*Tier1 | | | | | | 0.0212*** | 0.0551*** |
| | | | | | | (0.0002) | (0.0070) |
| Constant | 1.0174*** | 1.0254*** | 1.013374 | 0.9634*** | 0.8444*** | 1.1342*** | 1.2095*** |
| | (0.0033) | (0.0183) | (0.0125) | (0.0098) | (0.0091) | (0.0014) | (0.0162) |
| Observations | 604 | 240 | 364 | 270 | 230 | 604 | 364 |
| ALL Years | YES | NO | NO | YES | NO | YES | NO |
| Hansen's J (p-value) | 0.398 | 0.115 | 0.153 | 0.458 | 0.339 | 0.343 | 0.0396 |

**Figure 1: A graphical analysis**

The figure shows economies of scale for each size quintile (from the smallest to the largest, as identified in Table 3) and for all banks in the sample in each year over the period 2000-2011.



**Appendix**

The overall level of economies of scale (ES) is computed as the sum of individual cost elasticities. To generate estimates of cost elasticities for each bank we use the standard Stochastic Frontier Approach (SFA) along the lines first suggested by Aigner et al. (1977). Specifically, we use the Battese and Coelli (1992) model of a stochastic frontier function for panel data with firm effects that are assumed to be distributed as truncated normal random variables ($\mu \neq 0$) and are also permitted to vary systematically over time (see for more details on the SFA methodology, Coelli et al., 1998). The standard translog functional form as well as a two-component error structure is estimated using a maximum likelihood procedure.

This procedure is specified as follows:

$$\begin{aligned}
\ln TC \quad = \quad & \alpha_0 + \sum_{i=1}^{3} \alpha_i \ln Q_i + \sum_{j=1}^{3} \beta_j \ln P_j + \lambda_1 \ln E + \\
& + \frac{1}{2}\left[ \sum_{i=1}^{3}\sum_{j=1}^{3} \delta_{ij} \ln Q_i \ln Q_j + \sum_{i=1}^{3}\sum_{j=1}^{3} \gamma_{ij} \ln P_i \ln P_j + \varphi_{11} \ln E \ln E \right] + \\
& + \sum_{i=1}^{3}\sum_{j=1}^{3} \rho_{ij} \ln Q_i \ln P_j + \sum_{j=1}^{3} \kappa_{i1} \ln P_j \ln E + \sum_{i=1}^{3} \varsigma_{i1} \ln Q_i \ln E + \\
& + \tau_1 (EC_FREE) + \psi_1 (LNMARKET_CAP) + \chi_1 (PERF_EQ) + \\
& + \eta_1 (LNGNI_CAPITA) + \varepsilon_i
\end{aligned} \qquad \text{(A.1)}$$

The variable definitions are as follows: TC = total costs of production comprising operating costs and interest paid on deposits. Bank outputs (with 1.0 added to avoid taking the log of zero) are $Q_1$= total loans; $Q_2$= securities; and $Q_3$= off-balance sheet output.[16] Bank input prices for labor, loanable funds, and physical capital, respectively, are $P_1$ personnel expenses/total assets; $P_2$ = interest expenses/total funds; $P_3$ = depreciation and other capital expenses/fixed assets; equity capital (E) is

[16] In our sample, bank/year observations with no off-balance sheet represent 22% of the total according to the data on annual financial statements obtained from Bankscope. As a further robustness test, we have re-estimated economies of scale excluding this output, and previous results are confirmed. These results are available from the authors on request.

included in the specification to control for differences in bank risk preferences (Hughes and Mester, 1993; Mester, 1996; Hughes and Mester, 2013; Davies and Tracey, 2014). Note that E is fully interactive with the output and the input price variables. Note also that we assume that factor input markets are competitive, and that government guarantees and recapitalizations (as detailed in fn 14) may have affected the cost of inputs and equity of the banks that received government help. All of the variables are deflated by using country specific GDP deflators with 2005 as a base year. Given the cross-country nature of our sample, we adopt a common frontier for the 17 industries that also includes the exogenous environmental variables (as in Battese and Coelli, 1992)[17]: economic freedom (EC_FREE) of the state in which each individual bank operates, the natural logarithm of the market capitalization to the gross domestic product (LNMARKET_CAP) of the state in which each individual bank operates, the annual performance of the equity market (PERF_EQ) of the country in which each individual bank operates, and the natural logarithm of the gross national income per capita (LNGNI_CAPITA) of the country in which each individual bank operates. The $t$ is a linear time trend. The $\varepsilon_i$ is the two-component stochastic error term. The $\varepsilon_i$ is the stochastic error term sum of two components $\varepsilon_i = u_i + v_i$, while $\alpha, \beta, \lambda, \delta, \gamma, \varphi, \rho, \kappa, \varsigma, \tau, \psi, \chi, \eta$ are the parameters to be estimated.

About the definitions of input and output used in the function, we follow the traditional intermediation approach of Sealey and Lindley (1977) in which inputs (labor, physical capital, and deposits) are used to produce earning assets. Two of our outputs (loans and securities) are earnings assets, and we also include off-balance sheet items (comprising managed securitized assets reported off-balance sheet, other off-balance sheet exposure to securitization, guarantees, acceptance and

[17] We are aware that the pooled frontier with environmental variables, although extensively used (see Dietsch and Lozano-Vivas, 2000; Lozano-Vivas et al., 2001; Lozano-Vivas et al., 2002; Beccalli, 2004; Fiordelisi et al., 2010), does not settle the issue of cross-border efficiency comparisons of banks having access to different types and standards of technologies in different countries, and that a meta-frontier would be a better solution (Bos and Schmiedel, 2007). However, the estimation of the meta-frontier requires a large number of observations per country (e.g. Bos and Schmiedel 2007 state: "As a rule of thumb, we include all European countries for which we have at least 200 observations"). Given the number of banks per country in our sample, we would be forced to estimate joint frontiers for combinations of countries. Therefore we privilege the use of a pooled frontier with country-specific environmental variables.

documentary credits, committed credit lines, other contingent liabilities) as a third output. Although off-balance sheet items are not earnings assets, they do represent an increasing source of income for all types of banks and are therefore included in order to avoid understating the total output (Jagtiani and Khanthavit, 1996).

Our environmental variables (EC_FREE, LNMARKET_CAP, PERF_EQ, LNGNI_CAPITA) are included to take into account the macroeconomic conditions faced by each bank. The EC_FREE is obtained from the Heritage Foundation database. It takes values from 0 to 100: 100 expresses the highest forms of economic freedom that should provide an absolute right of property ownership; full freedom of movement for labor, capital, and goods; and an absolute absence of coercion or constraint of economic liberty. The LNMARKET_CAP is taken from the World Bank database. The PERF_EQ comes from the S&P Global Equity Indices taken from Datastream. The LNGNI_CAPITA is taken from the World Bank database, ATLAS METHOD.

The symmetric conditions imply the following restrictions on the second order parameters of the function:

$\delta_{ij} = \delta_{ji}$ per $1< i < 3$ e $1 < j < 3$

$\gamma_{ij} = \gamma_{ji}$ per $1< i < 3$ e $1 < j < 3$ (A. 2)

In addition, the first grade of homogeneity in the input prices of the cost function TC requires the following restrictions on the parameters:

$$\sum_{j=1}^{3}\beta_j = 1 \quad \sum_{i=1}^{3}\gamma_{ij} = 0 \quad \sum_{j=1}^{3}\rho_{ij} = 0 \quad \delta_{ij} = \delta_{ji} \quad \gamma_{ij} = \gamma_{ji} \qquad \text{(A. 3)}$$

The usual input price homogeneity restrictions are imposed on logarithmic price terms. Accordingly, TC, $P_1$, and $P_2$ are normalized by the price of capital, $P_3$.

Table A.1 summarizes the specification of the variables used in the model. Table A.2 reports the descriptive statistics for the input, output, netput and the environmental variables in real terms.

**Table A.1: Variable description**

| SYMBOL | VARIABLES | DESCRIPTION |
|---|---|---|
| *Dependent variable:* | | |
| TC | *Total Cost* | Labour costs, depreciation of fixed assets, other operating expenses, marketing and administrative expenses, interest expenses. |
| *Output:* | | |
| Q1 | *Loans* | Total amount of loans granted by banks, as expressed in the balance sheet |
| Q2 | *Securities* | Total amount of securities, as expressed in the balance sheet |
| Q3 | *Off-balance sheet items* | Amount of off-balance sheet items (comprising managed securitized assets reported off-balance sheet, other off-balance sheet exposure to securitization, guarantees, acceptance and documentary credits, committed credit lines, other contingent liabilities) as expressed in the balance sheet Same definition used pre- and post-IFRS adoption. |
| *Input:* | | |
| P1 | *Labor price* | Average unit price of labour, given by total personnel expenses divided by total assets |
| P2 | *Price of financial capital* | Interest expenses on total customer deposits |
| P3 | *Price of physical capital* | Operating expenses – less labor costs and interests – divided by total fixed-assets (including both tangible and intangible assets) |
| *Fixed netput quantities* | | |
| E | *Equity* | Common stockholders' equity |
| *Environmental variables* | | |
| EC_FREE | *Economic Freedom* | Overall indicator of economic freedom that encompasses freedom and rights on production, distribution, or consumption of goods and services *(Heritage Foundation database)* |
| LNMARKET_CAP | *Logarithm of market capitalization* | Natural logarithm of stock market capitalization to - in the country in which the bank operates - to Gross Domestic Product *(World Bank database)* |
| PERF_EQ | *Performance Equity* | Performance of the equity market in the country proxied by S&P Global Equity Indices *(Datastream)* |
| LNGNI_CAPITA | *Logarithm of Gross National Income per Capita* | Natural logarithm of Gross National Income per Capita in the country in which each individual bank operates *(World Bank database, ATLAS METHOD)* |

**Table A.2: Descriptive statistics for the input, output, netput and environmental variables**

This table reports descriptive statistics of the input ($P_1$, $P_2$, $P_3$), output ($Q_1$, $Q_2$, $Q_3$), netput (E) and environmental variables (EC_FREE, LNMARKET_CAP, PERF_EQ, LNGNI_CAPITA) used in the estimation of economies of scale. Values of output and netput are expressed in thousands of Euro (with the exception of the minimum value of $Q_3$). Values are expressed in real terms.

| | Mean | Median | St. dev. | Min | Max |
|---|---|---|---|---|---|
| E (Equity) | 13,776,221 | 5,419,350 | 19,642,740 | 7,000 | 128,373,275 |
| $Q_1$ (Loans) | 135,538,512 | 67,861,000 | 171,141,744 | 8,218 | 1,128,650,689 |
| $Q_2$ (Securities) | 127,231,798 | 20,756,450 | 247,648,654 | 27,500 | 1,695,177,000 |
| $Q_3$ (Off Balance Sheet) | 50,588,684 | 11,506,200 | 95,504,203 | 1 | 599,854,200 |
| $P_1$ (Personnel exp /Total Assets) | 0.0095 | 0.0083 | 0.007 | 0.0005 | 0.0758 |
| $P_2$ (Interest exp /Deposits) | 0.0455 | 0.0359 | 0.0567 | 0.0008 | 1.2766 |
| $P_3$ (Other operating exp/Fixed assets) | 1.5498 | 0.9574 | 2.3534 | 0.0734 | 46.4338 |
| EC_FREE | 70.28 | 70.1 | 7.1 | 58.7 | 82.6 |
| LNMARKET_CAP | 4.17 | 4.15 | 0.77 | 2.45 | 5.73 |
| PERF_EQ | 3.04 | 5.16 | 30.54 | -69.94 | 91.41 |
| LNGNI_CAPITA | 10.54 | 10.56 | 0.32 | 9.67 | 11.4 |