Realized Bank Risk during the Great Recession

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Abstract: In the years preceding the 2007-2009 financial crisis, empirical evidence on the effect of bank characteristics on risk was mixed while forward-looking indicators of individual bank risk suggested unusually low expectations of bank default. Using a tailor-made dataset we assess whether the ex-ante (i.e. prior to the crisis) cross-sectional variability in bank characteristics is consistently related to the ex-post materialization of the different dimensions of bank risk. We find that less reliance on deposit funding, more aggressive credit growth, larger size and lower levels of capital were associated with higher systemic risk exposure. The impact of these characteristics is particularly relevant for predicting the systemic but not the idiosyncratic dimension of bank risk. Importantly, the effect of certain bank characteristics becomes stronger for the tail of the riskier banks. We show that those characteristics were also useful to predict bank risk as materialized before the 2007-2009 financial crisis.

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The 2007-2009 financial crisis resulted in the largest realization of bank risk since the Great Depression, producing record levels of unemployment giving way to what is now referred to as the "Great Recession". Banks' market capitalisation in Europe and the United States decreased by 82% between May 2007 and March 2009. The crisis revealed also huge variability across individual banks, as evidenced by the increased dispersion of cross-sectional stock market returns after the crisis, suggesting a strong degree of heterogeneity in *ex-ante* (i.e. pre-crisis) risk-taking. Surprisingly, most market-based indicators of bank risk in the years preceding the crisis showed, first, a fairly benign picture, as suggested for instance by forward-looking measures regularly used by financial institutions, investors, central banks, and regulators to monitor the health of the financial system (IMF, 2009). Second, these signals of bank risk were also highly clustered across institutions making it difficult to disentangle *ex-ante* between riskier and safer institutions (see Figure I).

{Insert Figure I}

These developments on markets' perceptions of bank risk were especially important as much of the supervisory action had progressively moved away from regulating banks' activities and business models towards an increased reliance on market discipline often exercised via market based indicators (Bliss, 2015) as an important source of constraint on risk-taking behaviour. Partly as a result of this stronger reliance on market-based indicators of bank risk, supervisors, rating agencies and investors have repeatedly pointed at the benign outlook provided by market-based indicators prior to the crisis to emphasise the unexpected dimension of the recent crisis.[2]

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[2] See for instance Gorton (2012).

Despite this move away from regulating banks' business models, most of the previous findings tended to find a link between certain bank characteristics and risk. At the same time, there were also strong limitations regarding the consistency of the results that significantly limited its applicability for practical purposes. For instance, empirical evidence on the impact of leverage, securitization, asset composition, size and non-interest income on banks' risk profile remains mixed and often non-conclusive (Berger, Wilson, Molyneux, 2015). Two major potential reasons for the inconsistent findings are that, first, most of the studies analyse a single dimension of bank risk. This narrow focus is related to data limitations that make it empirically challenging to account for the different aspects of bank risk. Second, it is highly likely that the findings might be different during crises and non-crises periods as many of the risks taken during normal times might only materialize in the event of a large systemic crisis.

The objectives of our paper are, first, to shed light on which bank characteristics are *consistently* associated with the different dimensions of bank risk. Second, to assess whether the effects of these characteristics evolve across the different levels of realized risk. Indeed, the effect of bank characteristics on the tail of the riskier banks would be potentially more relevant from a supervisory perspective. Third, we consider whether the predictability of bank characteristics on bank risk also held before a crisis takes place.

Using a database laboriously compiled for the purposes of this study we incorporate seven different measures of bank risk ranging from the liquidity assistance of the central bank, to the idiosyncratic and systemic dimensions of risk. Building on the pre-crisis literature (see for instance the extensive survey provided in Berger, Wilson, Molyneux, 2015), we group individual bank information into four broad categories – capital, asset, funding, and income structures – which concisely summarize the underlying, bank business models. We have three sets of findings.

First, we show that bank size, the rate of credit expansion, lower dependence on customer deposits, a weaker capital base for undercapitalised banks and diversified sources of revenues in the run-up to the crisis consistently accounted for higher levels of *ex-post* distress. The impact of these characteristics is strong for the systemic dimension of bank risk while their predictive impact on idiosyncratic measures of bank risk is almost negligible. These results are robust to the inclusion of a series of controls including macroeconomic, risk aversion and institutional factors, as well as to the use of instruments to account for potential endogeneity between the dependent variable and the regressors.

Second, we also re-run our baseline estimations using all available measures of bank risk *prior* to the crisis. The idea is to ascertain whether the muted expectations of bank risk by market participants and banking supervisors prior to the crisis could be linked to a lack of predictability of bank characteristics on risk *before* a crisis takes place. We find that most of the mentioned bank characteristics also predicted risk *prior* to the crisis. Also in this setting, we find that their impact is considerably stronger for the systemic dimension of bank risk. We illustrate this point graphically by showing that banks with high relative systematic risk before the crisis were also those institutions with the higher systematic risk during the crisis thereby buttressing the argument of ex-ante predictability.

Third, we show that the effect of balance sheet variables on bank risk evolves across levels of realized risk. This impact was identified by estimating a quantile regression to reveal whether the risk determinants of the riskiest banks (those belonging to the upper part of the cross-sectional distribution of distress during the crisis) are similar to those of the less risky institutions (those belonging to the lower part of the same distribution). In the event of a crisis, we find that the degree of sheltering provided by deposit funding and capital becomes stronger as realized risk increases.

The direct impact of loan growth on risk is more important (up to three times larger) for the quantiles of banks with the higher levels of realized risk while dependence on short-term market funding seems to be particularly aggravating factor for the group of the riskier banks.

An important caveat is that although we subject our results to a battery of robustness tests, our findings could be influenced by potential bank unobserved factors not included in our model and might be subject to the Lucas critique.[3] At the same time, from a practical (and forecasting) perspective, our findings suggests that banks with these balance sheet characteristics deserve closer scrutiny from supervisors, as they are more likely to display higher levels of distress.

The remainder of this paper is organized as follows. Section I reviews the literature on bank characteristics and risk. Section II describes the model, data sources, and how the dataset was constructed. Section III presents the main empirical findings and section IV the robustness tests. Section V concludes.

I. BANK RISK, BALANCE SHEETS AND BUSINESS MODELS: A LITERATURE REVIEW

We structure our review of the literature by grouping bank characteristics into four main broad categories, used later in our empirical investigation.

Capital structure – The literature offers contradictory results as to the effects of capital on bank risk (Freixas and Rochet, 2008). In principle, the higher the capital, the stronger the buffer to withstand losses. Higher levels of capital – by increasing the skin in the game of shareholders – may also reduce risk-shifting incentives towards excessively risky projects at the expense of debt holders. While this is true in general for any firm, it is especially so in the banking industry, where

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[3] Due, for instance, to the introduction of a major relevant regulatory intervention.

the presence of deposit insurance creates an additional incentive for shareholders to take advantage of this guarantee by taking on excessive risks (Bhattacharya and Thakor, 1993).

There are related reasons that could bring about a positive relationship between capital and risk. For instance, agency problems between shareholders and managers can lead to excessive risk-taking via managerial rent-seeking. According to the corporate finance literature, higher leverage (and therefore lower levels of capital) reduces agency conflicts between managers and shareholders, since informed debt holders intensify the pressure on bank managers to become more disciplined (Jensen and Meckling, 1976; Calomiris and Kahn, 1991; Diamond and Rajan, 2001). It is also possible to envisage a non-linear relationship, whereby both very low and very high levels of capital induce banks to take on more risk (Calem and Rob, 1999). Higher levels of capital may simply be the result of regulators forcing riskier banks to hold larger buffers. The empirical literature on the effect of capital on bank soundness remains mixed (Haldane and Madouros, 2012; Demirgüç-Kunt and Huizinga, 2010; Berger and Bouwman, 2013; Delis and Staikouras, 2011).[4]

Asset structure – The widespread use of private securitization techniques represented a major structural development in the decades prior to the 2007-2009 crisis. Evidence on their impact on individual bank solvency remains unclear. On the one hand securitization allowed banks to actively manage the asset structure of their balance sheet, by off-loading part of the loans in their books to financial market investors. In particular, it permitted banks to swiftly turn traditionally illiquid claims (overwhelmingly in the form of bank loans) into marketable securities. This, in turn, lowered banks' regulatory pressures on capital requirements (Shin, 2009; Marques-Ibanez and Scheicher, 2010). In principle, from the perspective of individual banks, securitization helped

[4] There is some recent evidence suggesting that high quality forms of capital might have supported bank stability during the 2007-2009 crisis (Demirgüç-Kunt, Detragiache and Merrouche, 2013).

banks to manage and diversify their credit risk portfolio more effectively, both geographically and by sector. In this direction, some of the empirical evidence suggests that banks that were more active in the securitization market often had lower solvency risk and higher profitability levels (Cebenoyan and Strahan, 2004; Wu et al., 2011). In contrast, banks might also respond to the static reduction in risks due to securitization by taking on new ones, for instance by loosening their lending standards, increasing their leverage, or becoming systemically riskier (Mian and Sufi, 2009; Nijskens and Wagner, 2011; Keys et al., 2010). The latter finding, however, does not seem to apply to all types of lending (Benmelech, et al., 2012) or to some countries (Albertazzi et al., 2011).

Funding structure – Banks' traditional source of funding is represented by customers' deposits. It is well known that high switching costs and the presence of government insurance makes retail deposits a stable source of funding also during periods of crisis (Kim et al., 2003; Shleifer and Vishny, 2010). Deposits, however, are often less flexible in adapting to changes in financing needs (for instance, to fund new investment opportunities) compared to wholesale markets' sources of financing, where funds are usually raised on a rollover basis through instruments such as mortgage bonds, repurchase agreements and commercial paper.

The empirical literature on the role of funding choices on bank risk remains scant particularly prior to the crisis. According to earlier literature, financial market investors – being relatively more sophisticated than retail depositors – could provide useful market discipline (Calomiris and Kahn, 1991). At the same time, the recent financial crisis pointed also to a "dark side" of market funding underlying some limitations on the monitoring ability of wholesale investors for systemic risks during certain periods (Huang and Ratnovski, 2011; Gorton and Metrick, 2012).

Income structure – The global trend towards diversification in bank income sources has led to a steady and significant expansion of non-interest income revenues (such as those derived from trading, investment banking, brokerage fees and commissions) by most banks in developed countries (Stiroh, 2015). The findings on the final effect of such diversification on bank stability remains, however, mixed from an empirical perspective. Studies considering the impact of diversification on the total risk of financial firms using equity market returns' are not conclusive. In principle, diversification, fosters stability in banks' overall income and it might also lead to lower risk via the indirect effect of higher bank profitability (Jorion, 2007; Elsas, et al., 2010). At the same time, since this type of income tends to be particularly volatile, it may suffer by more than other sources of income in periods of financial stress (De Jonghe, 2010). It is also possible that the effects of non-interest income are different during crises versus non-crises periods. Namely, the financial stability benefits that may be obtained from diversification may accrue only in cases of minor idiosyncratic risk, but not in the context of a wider systemic shock (Brunnermeier et al., 2012). In contrast, there is also parallel evidence supporting the benefits of diversification particularly during extreme events (Slijkerman et al., 2005).

Historically, most systemic banking crises have been preceded by periods of excessive lending (Reinhart and Rogoff, 2009). This is confirmed by some microeconomic evidence from large international banks, which shows that loan growth represents an important driver of risk (Laeven and Majnoni, 2003; Foos et al., 2010). Interestingly, very few countries actively use direct limits on loan growth as a supervisory tool and microeconometric evidence on the role of loan growth on financial stability remains limited.

Finally, size can also be an important determinant of banks' risk (Huang et al., 2012; Tarashev et al., 2009; Laeven et al., 2014). Compared to smaller banks, larger institutions could have different incentives due to the "too-big-to-fail" problem or diversification possibilities (Demirgüç-Kunt and Huizinga, 2010).[5]

II. MODEL AND DATA

Our baseline specification draws on the previous discussion, grouping the variables by balance sheet structures:

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\begin{aligned}
r_{i,c} = \beta_0 + \beta_1 \text{Size}_{i,b} + \underbrace{\beta_2 \text{Capital}_{i,b} + \beta_3 \text{Undercapitalized}_{i,b}}_{\text{Capital structure}} + \\
+ \underbrace{\beta_4 \text{Loan to total assets}_{i,b} + \beta_5 \text{Securitization}_{i,b}}_{\text{Asset structure}} + \\
+ \underbrace{\beta_6 \text{Short-term market funding}_{i,b} + \beta_7 \text{Deposit funding}_{i,b}}_{\text{Funding structure}} + \\
+ \underbrace{\beta_8 \text{Excessive loan growth}_{i,b} + \beta_9 \text{Non interest income}_{i,b}}_{\text{Income structure}} + \varepsilon_i
\end{aligned}
\tag{1}
$$

The dependent variable ($r_{i,c}$) measures the distress of bank i during the crisis period c (2007Q4 to 2009Q4),[6] while the regressors are computed as the average bank characteristics in the pre-crisis period b (2003Q4 to 2007Q3). The use of average information from the pre-crisis period to forecast distress during the crisis serves to minimize endogeneity problems. A similar strategy has been adopted by Beltratti and Stulz (2012), Bekaert et al. (2014) and Demirgüç-Kunt et al. (2013). From an econometric perspective, these variables can be considered predetermined, which

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[5] A related strand of the literature focused on the determinants of stock market performance for large banks during the recent crisis (Beltratti and Stulz, 2012; Bekaert et al., 2014; Demirgüç-Kunt et al., 2010). For instance Beltratti and Stulz (2012) find that banks with higher capital (in countries with stronger capital supervision) and lower loan to total assets ratio performed better in the initial stages of the crisis, while banks with more shareholder-friendly boards performed worse.

[6] Hence, our sample horizon excludes the period of tension in sovereign bond markets. This is because the spillover effects on the banking sector would distort our model and, thus, our final results. For instance, between 2009 and 2010, the yield for 10-year Greek government bonds increased from 5.2% to 9.3%, raising the spread with the government bonds of euro area counterparts from 110 basis points to 530 basis points. This also affected all the indicators of bank risk for Greek banks.

guarantees consistent forecasts. Whether these forecasting relationships can be also given a causal interpretation is of course a different matter. We will come back to this issue in section IV.

The statistical sources used and brief description of the main variables included in our study are provided in Table I, while Table II shows the main descriptive statistics. Our initial dataset has more than 1,100 listed banks from 16 countries.[7] It is a highly representative sample, as it covers around three-fourths of the total aggregate balance sheet of banks operating in the European Union and United States. The rest of this section describes in detail the construction of each variable.

{Insert Tables I and II}

II.A   Construction of bank risk variables

The first purpose of our analysis is to identify the main determinants behind the accumulation of bank risk and its subsequent realization during the recent financial crisis. In order to obtain robust results it is crucial to recognize that during a crisis, the appearance of bank risk unfolds progressively and manifests itself in several and different dimensions. We employ seven alternative measures of bank risk to capture these different dimensions to capture the impact of bank characteristics on the different components of bank risk. As indicated, we believe that the use of all these measures is also crucial to assess the validity of our findings. Indeed, a major possible reason for the contradictory findings of earlier empirical studies is probably the difficulty in finding sufficiently informative variables accounting for the different aspects of bank risk.[8]

i. Financial support – Our first measure of bank risk describes whether an institution received any government support. The construction of this variable is based on the collection of

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[7] Namely: Austria, Belgium, Denmark, Germany, Greece, Finland, France, Ireland, Italy, Luxembourg, the Netherlands, Portugal, Spain, Sweden, the United Kingdom and the United States.
[8] Probably also an important reason for the diverging results is that for practical purposes, some of the variables that are able to capture some of the major dimensions of realized bank risk (such as central bank liquidity or government assistance) are not widely accessible to most researchers.

information relating to the public rescue of banks via capital injections, the issuance of state-guaranteed bonds, or other government-sponsored programmes during the crisis (2007Q4-2009Q4). It is compiled from several sources, including the European Commission, central banks, the Bank for International Settlements, Bloomberg, and the websites of a number of government institutions.[9] The resulting dummy variable takes the value of one if public financial support was received during the crisis and zero otherwise. This is matched with information on listed banking groups (around 1,100 institutions) for which consolidated financial statements are available via Bloomberg (see below).[10]

ii. Systematic risk – Our second measure describes the average (i.e. systematic) stock market reaction of each bank to movements on the overall stock market index. It is constructed using a simple capital asset pricing model, based on the following equation:

$$R_{i,k,t} = \beta_{i,k} \; R_{m,k,t} + \varepsilon_{i,k,t} \qquad\qquad (2)$$

where $R_{i,k,t}$ is the daily logarithmic excess stock market returns for each bank i from country k at time t;[11] $R_{m,k,t}$ is the daily logarithmic excess stock market returns from the broad stock market index m for country k; and the term $\varepsilon_{i,k,t}$ is a bank-specific residual. To ensure comparability, we use the broad stock market index for each country available from Datastream. For each bank i, we calculate the systematic component $\beta_{i,k}$ by running separate regressions on daily data for every quarter q. We then calculate the average beta for each individual bank during the crisis (2007Q4-2009Q4) and non-crisis (2003Q4-2007Q3) periods. Obviously this would reduce our original

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[9] For a comprehensive overview of the public measures in support of the financial sector see Stolz and Wedow (2010).
[10] We consider commercial or universal banks only. Hence foreign subsidiaries, investment banks, and non-bank financial institutions are not included in our sample.
[11] We calculate excess returns as the difference between stock market returns and the 10-year government bond yield for the country concerned.

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sample to only those banks which are listed and actively traded during our period of study (around 483 institutions).

iii. Systemic risk – Our third measure of bank risk broadly captures how exposed individual banks are to the occurrence of a systemic event. It measures tail dependence in the stock market returns of individual banks and equates the magnitude of tail dependence estimates to measure of systemic risk. It is estimated via the marginal expected shortfall (*MES*) following the model by Acharya, Pedersen, Philippon and Richardson (2010) using a risk level of 5% calculated from daily data of individual banks' and countries' stock market equity returns from Datastream during the crisis (2007Q4-2009Q4) and non-crisis (2003Q4-2007Q3) periods.

iv. Structural credit risk – Our fourth measure of bank is the expected (one-year ahead) default frequency (*EDF*) of individual banks. *EDF* is a calculated forward-looking firm-specific measure of actual probability of default constructed by Moody's KMV using a structural approach which builds on Merton's model to price corporate bond debt (Merton, 1974).[12] The final EDF value, expressed as a percentage, represents the implied risk of default and is constructed by combining banks' financial statements with stock market information and a proprietary default database maintained by Moody's KMV. We obtain the average *EDF* for each individual bank from monthly data as averages for the crisis (2007Q4-2009Q4) and non-crisis (2003-Q4-2007Q3) periods. *EDF* developments are regularly used as an indicator by financial institutions, investors, central banks and regulators to monitor the health of the financial system broadly assuming that *EDF*s track closely physical expectations of default.

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[12] The calculation of *EDF* builds on Vasicek and Kealhofer's extension of the Black-Scholes-Merton option pricing framework, which makes it suitable for practical analysis, and on the proprietary default database owned by KMV. For further details on the construction of *EDF*s and an application see Crosbie and Bohn (2003) and Garlappi, Shu and Yan (2007).

v. Central bank liquidity – Our fifth measure of bank risk is based on confidential information on the liquidity provided to individual banks by the European Central Bank via the Eurosystem. It measures bank risk during a crisis by taking advantage of a change in the central bank's liquidity policy. Namely, in October 2008, following the collapse of Lehman Brothers, the central bank switched to a policy of full allotment and fixed rates which meant that euro area banks were able to get unlimited liquidity from the Eurosystem at the main refinancing rate provided they pledge adequate collateral.[13] It is constructed as the overall liquidity position of each institution with the ECB. The liquidity amount is divided by total assets in order to make amounts comparable across institutions. Compared to other measures, this variable also accounts for liquidity risk, covering a key aspect of bank risk. By construction, this variable reduces our sample further as we limit it to the largest 83 euro area banking groups. They cover, nonetheless, more than 90% of the average liquidity provided by the Eurosystem.[14]

vi. Idiosyncratic risk1 – Our sixth measure describes the individual (i.e. non-systematic) dimension of bank risk constructed from the component of stock market movements of each bank i which is unrelated to movements on the overall stock market index. It is constructed using a simple capital asset pricing model (see above) as the average of the quarterly non-overlapping standard deviations of the unexplained component $\varepsilon_{i,k,t}$ (or bank-specific residual) calculated for each bank i from country k using daily stock market prices for the crisis (2007Q4-2009Q4) and non-crisis (2003-Q4-2007Q3) periods.

vii. Idiosyncratic risk2 – We construct our seventh measure of risk following Campbell et al. (2001) by decomposing the stock market prices of each bank i into three components of

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[13] Hence we restrict our results to the period of full allotment of liquidity provision by the European Central Bank (starting in October 2008) to avoid any distortions arising from changes in the central bank operational framework.

[14] We narrow our sample to the largest banking groups to ensure representativeness as in some countries many of the smallest banks often draw liquidity with the central bank indirectly via a larger institution.

realized volatility: market wide, banking industry-specific, and bank-specific volatility. We use the latter as our second variable accounting for idiosyncratic bank risk (Idiosyncratic risk2). We use daily stock market data (see above) and calculate Idiosyncratic risk2 for every bank i for each quarter q. We then calculate the average Idiosyncratic risk2 for each individual bank i during the crisis (2007Q4-2009Q4) and non-crisis (2003-Q4-2007Q3) periods.

II.B   Bank characteristics

We next match information on average bank risk with data on bank characteristics from the pre-crisis period (2003Q4 to 2007Q3), using a dataset of consolidated quarterly financial statements obtained from Bloomberg. We also complete our database with information from other sources, such as Dealogic, BIS, Moody's KMV, Thomson Reuters, Bankscope and Datastream (see Table I).

The first variable determining banks' characteristics is size, measured as the average natural logarithm of total assets of the consolidated institution before the crisis. As in our literature review, we separate the other variables into four main groups.

Capital structure – We approximate bank capital by using a ratio of Tier I capital to total assets. Tier I capital is the regulatory term for core capital, essentially composed of common stocks and disclosed reserves. In line with Calem and Rob (1999) and the proposals made by the Basel Committee on Banking Supervision (2010), our measure of capital is interacted with a dummy indicator for banks with low capital ratios (below 6%) to account for possible non-linear effects for less-capitalized banks.

Asset structure – A variable capturing an important aspect of the asset structure is the ratio of loans to total assets. It provides a summary indication of the extent to which a bank is involved

in traditional lending activities. The other variable characterizing the asset structure is the amount of securitization activity. The data – based on Dealogic, an independent data provider – has been matched with balance sheet information from individual banks and then used to calculate the private securitization originated per quarter by each bank (i.e. percentage of bank credit sold on to the markets) as a proportion of total bank assets during the same period.[15]

Funding structure – The third group of regressors is concerned with the structure of on-balance sheet funding. It accounts for reliance on short-term wholesale funding, measured as the ratio of short-term marketable securities to total assets, and more traditional retail deposit funding, also relative to total assets.

Income structure – We look at the two major income drivers of strategic importance to financial institutions. First, banks' lending strategy is measured as a bank's average quarterly loan growth minus the national average. Second, we capture the degree of income diversification and the extent to which a bank has moved towards more volatile non-interest income sources by calculating their value as a percentage of total revenue.

II.C   Additional controls

In our empirical analysis, we also include a number of additional controls. First, some of our specifications incorporate a group of macroeconomic factors that have been found to be related to banking crises in developed countries. These include changes in real housing prices, based on the country series constructed by the Bank for International Settlements (Borio and Drehmann, 2009), and changes in the broad stock market indices for non-financial corporations, as calculated by

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[15] We look at individual deal-by-deal issuance patterns in the private securitization market. The advantage of using data on securitization activity from Dealogic is that the name of the originator, date of issuance and deal proceeds are registered. The sample includes public offerings of funded asset-backed securities (ABSs) as well as issues of cash flow (balance-sheet) collateralized debt obligations (CDOs). In other words, the securities included in the sample involve a transfer of funding from market investors to originators so that pure synthetic structures (such as synthetic CDOs which transfer credit risk only) and public securitization are not included.

Datastream. Both of these asset price indices are demeaned from their long-term historical averages to capture abnormal changes in borrowers' collateral values. Second, we account for the impact on bank risk of potential corporate governance frictions arising from the bank ownership structure (Laeven and Levine, 2009; Erkens et al., 2012) with a Herfindahl index of ownership concentration of significant shareholders. It is calculated using information from Thomson Reuters as the sum of the squared values of the percentage of equity held by each individual shareholder. Third, as a proxy for bank risk-taking, we also consider banks, which underwent M&A activities. The data include registered merger and acquisitions taking place in the European Union and the United States banking sector between 2002 and 2007. Individual deal-by-deal data on M&A activity on financial firms are collected from the Thomson Reuters SDC Platinum database. Fourth, we account for bank risk aversion as revealed during a crisis using stock market returns from the previous crisis. This variable constructed using information from Datastream controls for the possibility that banks were accumulating certain risks that only materialized during a crisis.

III. MAIN RESULTS

This section discusses the main empirical findings of our analysis. We first present the results from probit and linear regression models applied to our seven measures of bank risk. In the next subsections, we test the robustness of the results to the pre-crisis period and discuss the insights that can be derived from regression quantile estimates applied to systematic risk.

III.A   Baseline results

Table III provides the estimates of the baseline specification for seven different measures of bank risk. The first column (I) reports the results of the probit regression using as a measure of distress the dichotomous variable indicating whether a bank received government support. Columns (II) to

(V) contain the coefficients of OLS regressions where distress is measured by systematic risk, systemic risk, structural credit risk and central bank liquidity respectively while columns (VI) and (VII) include two measures accounting for idiosyncratic risk.[16]

{Insert Table III}

The results are quite stark and strongly suggest that bank characteristics are highly predictive of risk particularly for the broader measures of bank risk (i.e. systemic, systematic, rescue, structural credit risk and central bank liquidity). In contrast, the predictive power of the idiosyncratic measures of bank risk (columns VI and VII) are very weak as suggested by the very mild results obtained for the idiosyncratic risk1 and idiosyncratic risk2 variables.

Except for the idiosyncratic risk variables, the results are also remarkably consistent across all other dimensions of bank risk, both in terms of sign and statistical significance.[17] This already speaks to the robustness and validity of our empirical findings, as they do not depend on a particular definition of bank risk or specific samples (sample sizes vary widely in the seven models due to different availability of data). Our results remain robust to the inclusion of additional controls (see next section).

We start by focusing on the results for the non-idiosyncratic measures of bank risk (columns I to V). Bank size is positively related to measures of bank risk in the first three columns. This positive sign is consistent with the view that large banks were significantly riskier during the recent crisis. Large banks might also have been considered as "too big to fail", thus inducing government to rescue them more often (Huang, et al., 2012; Demirgüç-Kunt and Huizinga, 2010;

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[16] In this table, we report only the estimates of the marginal effects of the probit model. The estimates and statistical significance of the coefficients of the probit model are fully consistent with the interpretation given to the marginal effects. Results are available upon request.

[17] It is important to bear in mind that the results in column (I) calculated via a probit are not directly comparable to those of the other columns.

Tarashev et al., 2009). The apparently contradictory negative sign for size in column (V) is probably explained by the fact that the dependent variable is constructed as the ratio of central bank liquidity demand scaled by the size of the financial institution. Since size appears in the denominator of the dependent variable, higher size is mechanically associated with lower liquidity/size ratio. It could also be that larger banks made less use of central bank liquidity in the euro area having access to alternative sources of finance internationally. It could also be that larger banks were considered as too-big-to-fail by the financial markets and access to the short-term liquidity markets was more open for them than for smaller institutions requiring, as a result, less liquidity from the central bank. We next discuss the impact of the difference balance sheet structures.

Capital structure – A higher level of capital *ex-ante* generally tends to decrease the severity of bank distress during the crisis although this result does not hold for all definitions of bank risk. A novel and important finding of our analysis is that capital is far more important for undercapitalised banks, as indicated by the negative and highly statistically significant coefficients for most bank risk variables. This non-linear relationship between capital and risk is in line with Calem and Rob (1999), Perotti et al. (2011) and the proposals made by the Basel Committee on Banking Supervision in 2010 requiring banks to have a binding minimum leverage ratio (BIS, 2010).

Asset structure – The ratios of loans to total assets are positively related to our measures of bank risk (Blaško and Sinkey, 2006). The negative sign for funded securitization suggests that banks, as originators, tended to use traditional securitization to off-load riskier loans from their balance sheets rather than as an instrument for taking on more risk. This is line with findings by Knaup and Wagner (2012) on the determinants of tail risks for US banks.

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Funding structure – Consistent with our theoretical discussion, customer deposits tend to provide funding stability to banks and reduce the probability of a bank rescue. In contrast, the use of short-term marketable securities increases the probability of distress (Demirgüç-Kunt and Huizinga, 2010). It appears that those institutions more reliant on short-term market funding are more exposed to liquidity risk during the crisis, as it becomes problematic to roll over short-term debt to finance illiquid assets. These findings corroborate recent country evidence (Hahm, Shin and shin, 2013) and proposals to strengthen anticyclical liquidity regulations such as the use of liquidity charges (see for instance, Brunnermeier, Gorton and Krishnamurthy, 2012; Perotti and Suarez, 2011).

Income structure – Income generated through an aggressive expansion in loan growth in the run-up to the crisis is generally associated with higher distress during the crisis, arguably due to a relaxation of credit standards and a deterioration in the credit quality of the asset side of the balance sheet. This result emphasises the similarity of the recent crisis with macroeconomic evidence from earlier episodes of financial turmoil (Tornell and Westermann, 2002), raising the question of why remedial measures were not implemented at the supervisory level to smooth the credit cycle.

Interestingly, the results on non-interest income suggest that there might be some diversification benefits on bank stability once other factors are taken into account. While our data does not allow to deepen into the different streams of non-interest income revenues, it suggest that it would be highly relevant from a supervisory perspective to distinguish the possible impact of the different sources of non-traditional activities on bank risk (DeYoung and Torna, 2013).

III.B   Results before the crisis

Given previous results, an important relevant question is whether bank characteristics were also helpful predicting realized values of bank risk *before* the crisis materialized. The idea is to ascertain whether some of the divergences in the findings of the empirical literature as well as the lack of action on the policy side could be linked to a lack of predictability of bank characteristics ex-ante.

In Table IV we also run our main estimations including information on the variables accounting for bank risk calculated as averages of quarterly data for individual banks during the 2006Q1 to 2006Q4 period. The variables accounting for bank characteristics are calculated as averages of quarterly data for individual banks during the 2003Q4 to 2005Q4 period.

Table IV shows that bank characteristics did predict the broad (systemic, systematic and structural) components bank risk *before* it materialized during the crisis. At the same time, bank characteristics did not help to forecast the idiosyncratic elements of risk. Hence bank characteristics are good at predicting the systemic component of bank risk not only when a crisis takes place, but also before a crisis strikes thereby enhancing the practical implications and validity of our results. In a way, our findings provide supportive evidence at the microeconometric level to the Reinhart and Rogoff's (2009) macroeconomic results.

{Insert Table IV}

An important practical implication of our findings is that banks with high systemic and systematic risks prior to the crisis would also be those institutions with relatively high materialized risk during the crisis. Figure II (below) shows that that this was indeed the case. On the X axis, it shows the percentile values for the systematic risk variable during the pre-crisis period (2003Q4 to 2007Q3) including the 5% (i.e. low systematic risk) and 95% (i.e. high systematic risk)

percentiles. On the Y axis, the diagram shows the 5% (i.e. low systematic risk) and 95% (i.e. high systematic risk) percentile values for the systematic risk variable for the crisis period (2007Q4 to 2009Q4). It clearly shows that those institutions with very high (low) systematic risk before the crisis were also well above (below) the average of systematic risk during the crisis.

{Insert Figure II}

We also re-run the regressions of bank risk during the crisis on bank characteristics before the crisis (as in our baseline specification, Table III) as well as a systemic and an idiosyncratic measure of bank risk as calculated prior to the crisis. Even before the crisis materializes, the systemic but not the idiosyncratic component of bank risk, contains useful predictive information on bank risk during the crisis. In addition, also in this setting, bank characteristics contribute to forecast bank risk during a crisis period on top of the information content already incorporated on the variables accounting for bank risk prior to the crisis.[18]

III.C   Quantile results

The next step when considering the relationship between bank characteristics and risk, is to see whether the role of certain characteristics is *stronger* (i.e. quantitatively and statistically more important) *for the riskier banks* (as materialized during the crisis). This is particularly important as central statistical measures might blur the information content for the tail of riskier banks. This

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[18] Results available upon demand.

is a highly relevant segment of the population as those are precisely the institutions that might be more relevant from a financial stability perspective.

To do this we classify and rank banks during the crisis by quantiles according to their realized levels of bank risk. As indicated, by construction, probit and linear regression models give only a measure of the central tendency of the relationship between dependent and independent variables. This assumes that covariates affect only the location of the conditional distribution of *y*. Still, covariates can affect the conditional distribution in other ways, for instance, by affecting one tail but not the other. To give a concrete example, our baseline model shows that undercapitalized banks tend to be in greater distress during the crisis. But does this result necessarily hold for all banks – as the ordinary least squares, OLS, estimates would suggest – or do poorly capitalized banks disproportionately increase the risk for riskier banks relative to the less risky ones? We can obtain a more complete picture of the distributional dependence between the bank business model and bank risk by estimating quantile regressions.

Regression quantiles were first introduced by Koenker and Bassett (1978) and have been widely used ever since (for an introductory survey, see Koenker and Hallock, 2001). Our regression quantile estimates are obtained by minimizing the objective function

$$\min_{\beta} \sum_{i=1}^{N} \rho_\tau(r_{i,c} - X_{i,b}\beta_\tau).$$ Here $r_{i,c}$ is the systematic risk variable for bank *i* defined in section II.A, $X_{i,b}$ contains the same set of regressors as in equation (1), *N* is the number of observations, ,

$\rho_\tau(\lambda) \equiv \lambda(\tau - I(\lambda < 0))$ *I* is the indicator function whereby *I* equals one if the expression in parenthesis is true and zero otherwise, and $\tau \in (0,1)$ is the probability associated with the quantile *c*. To facilitate a comparison with our baseline model, we use the same empirical specification.

We estimate the model using as dependent variable systematic risk. Results for the 10%, 25%, 50%, 75% and 90% quantiles are presented in Table VI. The last column in the Table reports the results of the equality test that the slope coefficients of the regression quantiles are all the same. Unsurprisingly, the signs of the regression quantile coefficients are coherent with the OLS results. For variables related to the asset and funding structure, we notice that the test results reported in the last column of the table reject the null hypothesis that all regression quantile coefficients are equal.[19]

The results show that size, low levels of capital, low deposit base and excessive loan growth all unambiguously increase the level of distress during the crisis, irrespectively of which part of the risk distribution we are analyzing. Stronger capital levels and funding via bank deposits buttress bank stability particularly for the riskier banks. Fast paced loan growth and dependence on short-term market funding lead to progressively stronger impact on bank distress as the banks join the upper part of the risk distribution. This implies that the effects of certain bank characteristics become indeed stronger, as the intensity of the realization of bank risk becomes larger. This has the important policy implication that supervisors should be particularly alert by the effect of certain bank characteristics due to their impact on the group of riskier banks. As a result, early and more intense supervisory intensity would be warranted for banks with those characteristics.

{Insert Table V}

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[19] The test for the size variable does not reject the null hypothesis that the coefficient of size is equal across all the quantile specifications.

III.D   Size

Size is potentially a major determinant of bank risk. Very large banks might have more incentives to take on more risks than smaller counterparts as they might be considered as "too-big-to-fail" by supervisors or the markets. In this direction also, larger banks might have the ability to diversify more widely geographically or in terms of the products offered and have, as a result, a different propensity to take on new risks.

To account for the potential non-linear impact of size, we first create a dummy variable for the very large banks (i.e. it takes the value of 1 for the 20% of the largest banks in our sample). The results of the bank size coefficient on bank risk are in line (and stronger) with previous results: it is highly significant, positive and large for all measures of bank risk. [20]

We then allow for the possibility of a non-linear relationship by adding size square as an additional term to our baseline estimation. The results on Table VI, suggest a concave relationship between size and bank risk. Bank risk increases with size although the rate of increase becomes smaller as bank size also augments. That is, as banks become progressively larger, the role of bank business models seems to become more dominant than size by itself. The combination of very large institutions with a particularly unstable business models seem to be particularly correlated with bank risk.

{Insert Table VI}

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[20] Results available upon request.

IV. ROBUSTNESS

Strictly speaking, the results presented in earlier sections are simple correlations and not causal relations, because of possible endogeneity concerns affecting our estimates. In fact, banks with a stronger risk attitude may be more likely to choose riskier business models, resulting in higher *ex-post* distress during times of crisis. In this case, the causality chain would run from risk to bank characteristics, rather than vice versa as implicit in our discussion so far. Tackling causality is generally not easy and our set up is no exception.

To start with, we would like to point out that our results remain of interest, regardless of whether they can be given a causal interpretation. From a purely forecasting perspective, since all dependent variables are predetermined, the policy maker can reasonable infer that the banks more likely to be in trouble in most occasions in case of crisis are those with poor capital ratios, excessive loan growth, too much reliance on market funding and so on. Whether the more risky business model of the bank is driven by the risk preferences of its management is of additional interest (and can possibly be exploited by the policy maker), but does not subtract from the relevance of our results: banks with certain characteristics should be more carefully and critically monitored by supervisors and eventually asked to reduce their overall level of risk.[21]

These considerations notwithstanding, we address endogeneity concerns by including additional control variables in the main regressions and by using appropriate instruments. Table VII reports the results of our robustness tests on our main bank risk specification. It includes additional controls to the baseline specification presented in table III. It shows that the majority of our findings are robust to the inclusion of country dummies – columns (I), (III), (V), (VII) and

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[21] Our findings may still be subject to the Lucas critique: if regulators start targeting certain types of business models, the relationship between risk and business model may disappear.

(IX) – as well of additional variables capturing banks' profitability, and major macroeconomic variables (GDP, house prices and stock market returns) – (II), (IV), (VI) and (VIII). Probit estimates in columns (I) and (II) are qualitatively similar to our baseline specification. OLS regression results are also robust, although in this case some of the coefficients on non-interest income of the systematic risk regression become non-significant.

As an additional test we also account for the possible (lurking) effect of possible long-lived risk-taking preferences of individual banks on our findings that affect both business models and risk that only materializes in the event of a crisis. We do this by checking that our results remain robust to the inclusion of banks' return during the previous crisis (as suggested in Fahlenbrach et al., 2012). [22]

{Insert Table VII}

An alternative strategy to tackle endogeneity concerns is to split the sample between banks which have been involved in mergers and acquisitions (M&A) and those who did not, or alternatively between banks with a more (or less) dispersed ownership structure. The idea is that management and shareholders' risk preferences are unlikely to remain the same across these different groups. For instance, managers involved in M&A activities may have higher risk propensity than the other institutions.[23] Similarly, a more concentrated ownership has a better control over management and is probably more likely to undertake riskier and possibly more profitable strategies (Laeven and Levine, 2009; Erkens et al., 2012). The results of Table VIII

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[22] Following Fahlenbrach et al (2012), the previous crisis return was calculated for the 1998 crisis. We identified the lowest stock price level between the 3rd of August and 31st of December 1998 then using daily return data we calculate the return from the 3rd of August to the minimum stock price level of the crisis period in 1998. Results are available upon request.

[23] Indeed, we show that banks undergoing a merger on average score higher levels of bank risk. Results are available upon request.

show that our findings remain robust to different groupings of banks, therefore adding further evidence in favor of causality running from balance sheet to risk.[24]

As a final robustness test – results available upon request – we ran an instrumental variable regression for systematic risk, using as instruments the average balance sheet variables of other banks in the country,[25] as suggested by Laeven and Levine (2009).[26] This instrument captures the industry and country factors driving our regressors and should in general not be affected by the risk propensity of the single bank.

{Insert Table VIII}

V. CONCLUSION

In the years prior to the 2007-2009 crisis, most forward-looking indicators of bank risk clustered and suggested an unusually benign outlook while the empirical literature on the effect of bank characteristics on risk often produced mixed or non-conclusive results. Hence, was the ex-post realization of bank risk during the crisis largely unexpected?

We show that in the run-up to the crisis different bank characteristics can explain a significant portion of the cross-sectional realization of bank risk during the 2007-2009 financial crisis. Banks with large size, very low levels of capital, unstable funding and aggressive credit expansion in the years before the crisis experienced more troubles after the Lehman default. We also show that the impact of these characteristics is relevant for consistently predicting several broader dimensions of bank risk but does not predict the idiosyncratic dimensions of bank risk.

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[24] The only exception is the size variable for banks involved in M&A activities. This may be explained by the fact that those banks may have been forced to deep restructuring and have been able to exploit economies of scale of the newly created entity.

[25] That is, we define the instrument as:

$$\tilde{x}_{ib}^{c} \equiv (\# \, j \in \text{country } c; \, j \neq i)^{-1} \sum_{j \in \text{country } c; \, j \neq i} x_{jb}$$

[26] For US banks we have considered a breakdown at state level.

We also find that those bank characteristics that were related to risk were useful to predict systemic bank risk as materialized also *before* financial crisis erupted. We also show that the impact of the balance sheet variables is non-linear and usually stronger for the riskier banks: our regression quantile analysis reveals how dependence on less stable balance sheet funding, more aggressive growth strategy and lower capital are conducive to more realized risk, in particular for the group of the riskier institutions.

We subject our results to an extensive battery of robustness tests, to ensure that they are not affected by possible endogeneity biases. At the same time we cannot claim causality in our findings and our results might be affected if there is a major structural change targeting bank business models – for instance due to a relevant modification in the regulatory framework –. Bearing in mind these caveats, our findings are relevant for the current prudential regulatory debate. They suggest that aggressive loan growth and excessive reliance on short-term market funding are correlated to the accumulation of risk suggesting that it is worthwhile to increase the supervisory intensity for banks exhibiting those characteristics. This is in principle consistent with the introduction of capital and liquidity charges linked to those variables. They are also in line with the Basel III initiatives targeting simple leverage ratios aimed at raising the capital levels of institutions, in particular of undercapitalized ones (see BIS, 2010).

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Table I
Summary Statistics

This table reports summary statistics for the primary variables used in this study (see Section II and Table I for further details on the variables). Variables accounting for bank risk are calculated using the average values for each bank during the crisis period (2007Q4 to 2009Q4) except for the variable accounting for central bank liquidity. The latter is constructed only for the period of full liquidity allotment by the European Central Bank (2009Q1 to 2009Q4). The variables accounting for size, capital structure, asset structure, funding structure, income structure, profitability and corporate governance are calculated from the averages of quarterly data for individual banks for the pre-crisis period (2003Q4 to 2007Q3). GDP growth, house prices and stock market are calculated as country averages from quarterly data during the pre-crisis period already mentioned.

Variable	Source	Description
Panel A: Bank risk variables		
Financial support	European Commission, national central banks, Bank for International Settlements, other public institutions and Bloomberg	Binary variable – with a value of 1 if public financial support was received during the crisis period (2007Q4 to 2009Q4) and 0, if otherwise.
Systematic risk	Datastream and authors' calculation	Average of the quarterly non-overlapping betas in a capital asset pricing model constructed for each bank i on country j using daily stock market data calculated during the crisis (2007Q4 to 2009Q4) and non-crisis (2003Q4 to 2007Q3) periods.
Systemic risk	Authors' calculation following Acharya et al. (2010)	Estimated via the marginal expected shortfall (MES) following Acharya et al. (2010), using a risk level of $\alpha=5\%$ calculated for the crisis (2007Q4 to 2009Q4) and non-crisis (2003Q4 to 2007Q3) periods from daily data of individual banks' and countries' stock market equity returns.
Structural credit risk (EDF)	Moody's KMV	One-year ahead probability of default. It is computed by Moody's KMV building on Merton's model to price corporate bond debt (Merton, 1974). The EDF value, expressed as a percentage, is calculated by combining banks' financial statements with stock market information and a proprietary default database. We calculate the average of quarterly data for the crisis (2007Q4 to 2009Q4) and non-crisis (2003Q4 to 2007Q3) periods.
Central bank liquidity	European Central Bank	Average of the liquidity received from the ECB to total assets * 100 during the period of full liquidity allotment from the central bank (2009Q1 to 2009Q4).
Idiosyncratic risk1	Authors' calculation	Average of the quarterly non-overlapping standard deviations of the unexplained component in a capital asset pricing model calculated for each bank i on country j using daily stock market prices calculated during the crisis (2007Q4 to 2009Q4) and non-crisis (2003Q4 to 200Q3) period.
Idiosyncratic risk2	Authors' calculation following Campbell et al. (2001)	Following Campbell et al. (2001) we decomposed the realized volatility of stock market prices for each bank i into three components: market wide, banking industry-specific, and bank-specific volatility. The Idiosyncratic risk2 variable is calculated for every bank i quarterly as the bank specific component of the realized volatility. We calculate the average of quarterly data for the crisis (2007Q4 to 2009Q4) and non-crisis (2003Q4 to 2007Q3) periods.
Panel B: Balance sheet variables		
Size	Bloomberg	Average of the quarterly logarithm of total assets (USD millions).
Capital structure		
Capital	Bloomberg	Average of the quarterly tier I capital to total assets' ratio * 100 during the pre-crisis period (2003Q4 to 2007Q3).
Undercapitalised	Authors' calculation	Average of the quarterly interaction between tier I capital and a low capital dummy variable (for which 1 indicates a bank with a Tier I ratio below 6%) for the pre-crisis period (2003Q4 to 2007Q3).
Asset structure		
Loans to total assets	Bloomberg	Average of the quarterly total loans to total assets' ratio * 100 during the pre-crisis period (2003Q4 to 2007Q3).
Securitization	DCM Analytics Dealogic	Average of the quarterly total securitization flow to total assets' ratio * 100 of each originating bank during the pre-crisis period (2003Q4 to 2007Q3).
Funding structure		
Short-term market funding	Bloomberg	Average of the quarterly short-term market debt (i.e. less than 2 years) to total assets' ratio * 100 during the pre-crisis period (2003Q4 to 2007Q3).
Deposit funding	Bloomberg	Average of the quarterly customer deposits to total assets' ratio * 100 during the pre-crisis period (2003Q4 to 2007Q3).
Excessive loan growth	Authors' calculation	Average of the quarterly individual bank lending growth minus the average loan growth of all banks in each country over that quarter during the pre-crisis period
Non-interest income	Bloomberg	Average of the quarterly non-interest income to total revenues' ratio * 100 during the pre-crisis period (2003Q4 to 2007Q3).
Panel C: Control variables		
Profitability	Bloomberg	Average of the quarterly net income to total assets' ratio * 100 during the pre-crisis period (2003Q4 to 2007Q3).
GDP growth	Bank for International Settlements	Average of the quarterly changes in real GDP during the pre-crisis period (2003Q4 to 2007Q3).
House prices	Bank for International Settlements	Average of the quarterly changes in real housing prices during the pre-crisis period (2003Q4 to 2007Q3) demeaned from their long-term historical averages (prior 20 years).
Stock market	Datastream	Average of the quarterly changes in broad country's non-financial corporations stock market indices constructed by Datastream during the pre-crisis period (2003Q4 to 2007Q3) de-meaned from their long-term historical averages (prior 20 years).
Corporate governance	Thomson Reuters and authors' calculation	Calculated as the average of the yearly sum of the squares of the percentages of the ownership's shares controlled by each shareholder on each individual bank during the pre-crisis period (2003Q4 to 2007Q3) .
Dispersed ownerships	Thomson Reuters and authors' calculation	Binary variable – with a value of 1 if the average ownership concentration is less than 10% during the pre-crisis period (2003Q4 to 2007Q3) and 0, if otherwise.
M&A Involvement	Thomson Reuters - SDC Platinum database	Binary variable – with a value of 1 if the institution was involved in one or more mergers and acquisitions (M&A) during the pre-crisis period (2003Q4 to 2007Q3) and 0, if otherwise.

Table II
Summary Statistics

This table reports summary statistics for the primary variables used in this study (see Section II and Table I for further details on the variables). Variables accounting for bank risk are calculated using the average values for each bank during the crisis period (2007Q4 to 2009Q4) except for the variable accounting for central bank liquidity. The latter is constructed only for the period of full liquidity allotment by the European Central Bank (2009Q1 to 2009Q4). The variables accounting for size, capital structure, asset structure, funding structure, income structure, profitability and corporate governance are calculated from the averages of quarterly data for individual banks for the pre-crisis period (2003Q4 to 2007Q3). GDP growth, house prices and stock market are calculated as country averages from quarterly data during the pre-crisis period already mentioned.

Variables	N	Average	Median	Standard Deviation	Minimum	Maximum
Panel A: Bank Risk						
Financial support	852	0.26	0.00	0.44	0.00	1.00
Systematic risk	483	0.70	0.47	0.60	-0.33	2.29
Systemic risk	483	3.25	2.97	2.60	2.94	15.97
Structural credit risk (EDF)	547	0.93	0.32	2.30	0.01	27.78
Central bank liquidity	84	2.66	1.24	3.45	0.00	18.87
Idiosyncratic risk1	483	0.00	0.00	0.01	-0.13	0.02
Idiosyncratic risk2	483	0.21	0.12	0.54	0.00	11.06
Panel B: Balance Sheet Variables						
Size	852	7.29	6.62	2.07	1.57	13.98
Capital Structure						
Capital	852	9.63	8.82	5.62	1.62	72.14
Undercapitalised	852	0.52	0.00	1.47	0.00	5.98
Asset Structure						
Loans to total assets	852	65.53	68.17	15.21	0.96	92.92
Securitization	852	0.10	0.00	0.84	0.00	19.68
Funding Structure						
Short-term market funding	852	19.33	17.03	12.97	1.00	90.00
Deposit funding	852	70.78	74.91	15.13	7.05	90.09
Income Structure						
Excessive loan growth	483	6.27	5.75	2.33	-2.12	13.27
Non-interest income	483	20.01	16.53	14.24	2.05	97.02
Panel C: Control Variables						
Profitability	852	0.99	0.96	0.75	-6.24	8.70
GDP growth	852	1.29	1.34	0.20	0.58	2.09
House prices	852	1.19	1.33	0.58	-1.62	2.42
Stock market	852	1.56	1.36	0.63	-0.19	5.57
Dispersed ownerships	684	0.84	1.00	0.36	0.00	1.00
M&A Involvement	852	0.24	0.00	0.43	0.00	1.00

Table III
Effects of Balance sheet Structures on Bank Risk

This table reports the results from our bank risk regressions. Column (I) reports the results of the probit regression using government support as a measure of bank risk. Columns (II) to (VII) contain the coefficients of OLS regressions where bank risk is measured as systematic risk, systemic risk, structural credit risk, central bank liquidity and two measures of idiosyncratic risk. See Section II for further details and Table I for variables' definitions. The dependent variables are calculated as averages of quarterly data for individual banks during the pre-crisis period (2007Q4 to 2009Q4) except for the variable accounting for central bank liquidity. The latter is constructed only for the period of full liquidity allotment by the European Central Bank (2009Q1 to 2009Q4). The variables accounting for size, capital structure, asset structure, funding structure and income structure are calculated from the averages of quarterly data for individual banks during the pre-crisis period (2003Q4 to 2007Q3). *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

		Dependent Variable: Measures of Bank Risk						
		Rescue	Systematic risk	Systemic risk	Structural credit risk	Central bank liquidity	Idiosyncratic risk1	Idiosyncratic risk2
		(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)
	Size	0.0409 ***	0.1090 ***	0.6949 ***	-0.0358	-0.2979 ***	0.0006 ***	0.0948 **
		(0.003)	(0.032)	(0.134)	(0.109)	(0.023)	(0.000)	(0.042)
Capital structure	Capital	-0.0207 ***	-0.0097	-0.0349	-0.0638 **	-0.1814 ***	-0.0001	-0.0002
		(0.001)	(0.007)	(0.036)	(0.025)	(0.053)	(0.000)	(0.011)
	Undercapitalized	-0.0415 ***	-0.0811 ***	-0.1116 ***	-0.0969 *	-0.0097	-0.0008 ***	-0.0051
		(0.008)	(0.017)	(0.040)	(0.057)	(0.020)	(0.000)	(0.019)
Asset structure	Loans to total assets	0.0047 ***	0.0061 ***	0.0356 ***	0.0255 **	0.0781 ***	0.0000	-0.0028
		(0.001)	(0.002)	(0.013)	(0.011)	(0.004)	(0.001)	(0.003)
	Securitization	-0.0103 ***	-0.2076 ***	-0.5671 ***	-0.2427 **	-0.6012 ***	0.0005 ***	0.0566
		(0.001)	(0.054)	(0.189)	(0.099)	(0.143)	(0.000)	(0.071)
Funding structure	Short-term market funding	0.0071 ***	0.0097 ***	0.0494 *	0.0249 *	0.1483 ***	0.0001 *	-0.0021
		(0.001)	(0.003)	(0.025)	(0.013)	(0.006)	(0.000)	(0.004)
	Deposit funding	-0.0103 ***	-0.0201 ***	-0.0655 ***	0.0027	-0.0759 ***	-0.0002	-0.0117 ***
		(0.001)	(0.003)	(0.016)	(0.012)	(0.014)	(0.001)	(0.004)
Income structure	Excessive loan growth	0.0385 ***	0.1597 ***	0.2765 ***	0.0544	0.4453 ***	0.0004 ***	-0.0230
		(0.005)	(0.027)	(0.075)	(0.091)	(0.008)	(0.000)	(0.037)
	Non-interest income	-0.0034 ***	-0.0043 **	-0.0099	-0.0068	-0.2350 ***	-0.0001	-0.0046 *
		(0.000)	(0.002)	(0.011)	(0.014)	(0.001)	(0.005)	(0.003)
	Constant	-2.8028 ***	-1.3420 ***	-5.9516 ***	-0.5569	2.9702 ***	-0.0074 ***	-0.3538
		(0.391)	(0.257)	(1.258)	(0.997)	(0.143)	(0.001)	(0.362)
	No. of observations	852	483	483	547	83	483	483
	R^2	0.111	0.517	0.378	0.025	0.641	0.086	0.059
	Percent true positives/negatives	54.84/76.53						
	Percent correctly classified	75.0						
	Hosmer–Lemeshow test	4.44						
	Hosmer–Lemeshow test p-value	0.8155						

Table IV

Effects of Balance Sheet Structures on Bank Risk before the Crisis

This table reports the results from our primary bank risk regressions before the 2007-2009 crisis. Columns (I) to (V) contain the coefficients of OLS regressions where bank risk is measured as systematic risk, systemic risk, structural credit risk and two measures idiosyncratic risk. See Section II for further details and Table I for variables' definitions. The dependent variables are calculated as averages of quarterly data for individual banks during the 2006Q1 to 2006Q4 period. The variables accounting for size, capital structure, asset structure, funding structure and income structure are calculated from the averages of quarterly data for individual banks during the 2003Q4 to 2005Q4 period. *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

		Dependent Variable: Measures of Bank Risk				
	Dependent Variable:	Systematic risk	Systemic risk	Structural credit risk	Idiosyncratic risk1	Idiosyncratic risk2
		(I)	(II)	(III)	(IV)	(V)
	Size	0.1991 ***	0.2962 ***	0.0409 ***	-0.0119 ***	0.0108 ***
		(0.0178)	(0.011)	(0.0093)	(0.0021)	(0.0020)
Capital structure	Capital	-0.0011	-0.0141	-0.0139 ***	0.0000	0.0011
		(0.0092)	(0.010)	(0.0041)	(0.0011)	(0.0009)
	Undercapitalized	-0.0702 ***	-0.0443 **	-0.0231 **	0.0061 **	-0.0041 *
		(0.0154)	(0.020)	(0.0107)	(0.0024)	(0.0022)
Asset structure	Loans to total assets	0.0124 ***	0.0060	0.0002	-0.0005	0.0002
		(0.0031)	(0.004)	(0.0016)	(0.0004)	(0.0002)
	Securitization	-0.0968 *	0.0296	-0.0015	0.0017	-0.0001
		(0.0529)	(0.080)	(0.0232)	(0.0088)	(0.0033)
Funding structure	Short-term market funding	0.0177 ***	0.0112 ***	-0.0031 *	-0.0001	-0.0002
		(0.0036)	(0.003)	(0.0018)	(0.0004)	(0.0003)
	Deposit funding	-0.0214 ***	-0.0142 **	-0.0028 *	0.0008	-0.0005 *
		(0.0032)	(0.006)	(0.0016)	(0.0005)	(0.0003)
Income structure	Excessive loan growth	0.0174 *	0.0290 ***	0.0120 ***	-0.0009	0.0011 *
		(0.0094)	(0.006)	(0.0046)	(0.0013)	(0.0007)
	Non-interest income	-0.0023	-0.0008	-0.0020	0.0004	-0.0006 *
		(0.0020)	(0.002)	(0.0013)	(0.0003)	(0.0003)
	Intercept	-1.6796 ***	-1.3968 ***	-0.2310	0.1691 ***	-0.1140 ***
		(0.3470)	(0.499)	(0.1685)	(0.0441)	(0.0214)
	No. of observations	426	426	544	426	426
	R^2	0.231	0.343	0.120	0.109	0.187

Table V
Quantile Estimates for Systematic Risk:
The Distributional Effects of Bank Balance Sheet Structures on Bank Risk

This table reports the regression quantile estimates of our baseline specification, using individual bank systematic risk as dependent variable. See Table I for variables' definitions. Columns (I) to (V) contain the coefficients of quantile estimates regressions for the 10%, 25%, 50%, 75% and 90% quantiles of bank systematic risk calculated as averages of quarterly data during the pre-crisis period (2007Q4 to 2009Q4). The variables accounting for size, capital structure, asset structure, funding structure and income structure are calculated from the averages of quarterly data for individual banks during the pre-crisis period (2003Q4 to 2007Q3). The equality test applied is the F-test where the null hypothesis purports that the estimated slope coefficients for each variable are not statistically different across all the quantile estimates. The p-value for this test is given below the equality test value. *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

		Q10 (I)		Q25 (II)		Q50 (III)		Q75 (IV)		Q90 (V)		Equality Test[1]
	Size	0.1207	***	0.1148	***	0.0949	**	0.1209	**	0.0724		0.490
		(0.032)		(0.034)		(0.038)		(0.050)		(0.047)		*0.743*
Capital structure	Capital	0.0128		-0.0005		-0.0067		-0.0290	**	-0.0476	***	3.170
		(0.008)		(0.009)		(0.010)		(0.013)		(0.012)		*0.076*
	Undercapitalized	-0.0559	***	-0.0649	***	-0.0615	***	-0.0751	***	-0.0889	***	0.490
		(0.014)		(0.016)		(0.017)		(0.022)		(0.021)		*0.740*
Asset structure	Loans to total assets	-0.0007		-0.0005		0.0033		0.0107	***	0.0065	*	9.800
		(0.003)		(0.003)		(0.003)		(0.004)		(0.004)		*0.002*
	Securitisation	0.0277		-0.0140		-0.1058	*	-0.1332	*	-0.1768	**	8.160
		(0.054)		(0.054)		(0.058)		(0.076)		(0.074)		*0.005*
Funding structure	Short-term market funding	0.0014		0.0029		0.0074	**	0.0161	***	0.0146	***	12.430
		(0.003)		(0.003)		(0.004)		(0.005)		(0.005)		*0.001*
	Deposit funding	-0.0145	***	-0.0151	***	-0.0194	***	-0.0298	***	-0.0321	***	8.110
		(0.003)		(0.003)		(0.003)		(0.004)		(0.004)		*0.005*
Income structure	Excessive loan growth	0.0589	**	0.0840	***	0.1396	***	0.1294	***	0.1443	***	4.270
		(0.027)		(0.030)		(0.034)		(0.044)		(0.041)		*0.039*
	Non-interest income	0.0025		0.0026		-0.0024		-0.0053		-0.0071	**	3.400
		(0.002)		(0.002)		(0.003)		(0.003)		(0.003)		*0.066*
	Intercept	-1.1053	***	-0.9905	***	-1.0841	***	-1.0673	**	0.0059		
		(0.275)		(0.299)		(0.333)		(0.433)		(0.409)		
	No. of observations	483		483		483		483		483		
	Pseudo R^2	0.175		0.270		0.353		0.287		0.218		

Table VI
Effect of Size on Bank Risk

This table reports the results from our bank risk regressions accounting for non-linear effects for bank size. Column (I) reports the results of the probit regression using government support as a measure of bank risk. Columns (II) to (VII) contain the coefficients of OLS regressions where bank risk is measured as systematic risk, systemic risk, structural credit risk, central bank liquidity and two measures of idiosyncratic risk. See Section II for further details and Table I for variables' definitions. The dependent variables are calculated as averages of quarterly data for individual banks during the pre-crisis period (2007Q4 to 2009Q4) except for the variable accounting for central bank liquidity. The latter is constructed only for the period of full liquidity allotment by the European Central Bank (2009Q1 to 2009Q4). The variables accounting for size, capital structure, asset structure, funding structure and income structure are calculated from the averages of quarterly data for individual banks during the pre-crisis period (2003Q4 to 2007Q3). *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

		Dependent Variable: Measures of Bank Risk						
		Rescue	Systematic risk	Systemic risk	Structural credit risk	Central bank liquidity	Idiosyncratic risk I	Idiosyncratic risk II
		(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)
	Size	0.0278 ***	0.2138 ***	0.9033 ***	0.0590	-0.1489	0.0012 *	0.1117 **
		(0.004)	(0.022)	(0.188)	(0.076)	(1.050)	(0.001)	(0.044)
	Size square	0.0037 ***	-0.0339 ***	-0.0857 ***	-0.0407 ***	-0.0766	-0.0002 ***	-0.0058
		(0.001)	(0.006)	(0.022)	0.014036	(0.127)	(0.000)	(0.005)
Capital structure	Capital	-0.0203 ***	-0.0081 *	-0.0446 **	-0.0581 ***	-0.1858 ***	-0.0001	-0.0014
		(0.001)	(0.004)	(0.018)	(0.009)	(0.051)	(0.000)	(0.011)
	Undercapitalized	-0.0439 ***	-0.0647 ***	-0.0832 ***	-0.0979 ***	-0.1170 ***	-0.0007 **	-0.0042
		(0.007)	(0.009)	(0.029)	(0.025)	(0.025)	(0.000)	(0.019)
Asset structure	Loans to total assets	0.0053 ***	0.0009	0.0192 *	0.0155 *	0.0130	0.0000	-0.0040
		(0.001)	(0.003)	(0.011)	(0.009)	(0.017)	(0.000)	(0.003)
	Securitization	-0.0120 ***	-0.1560 ***	-0.5681 ***	-0.2421 **	-0.3407	0.0004	0.0562
		(0.001)	(0.018)	(0.064)	(0.112)	(0.295)	(0.001)	(0.071)
Funding structure	Short-term market funding	0.0076 ***	0.0058 ***	0.0405 ***	0.0262 ***	0.0737 ***	0.0001	-0.0029
		(0.001)	(0.001)	(0.014)	(0.006)	(0.004)	(0.000)	(0.004)
	Deposit funding	-0.0106 ***	-0.0210 ***	-0.0657 ***	0.0081	-0.0586 ***	-0.0002 ***	-0.0117 ***
		(0.001)	(0.005)	(0.021)	(0.019)	(0.013)	(0.000)	(0.004)
Income structure	Excessive loan growth	0.0409 ***	0.1628 ***	0.3380 ***	0.0739 *	0.6951 ***	0.0006	-0.0205
		(0.004)	(0.025)	(0.094)	(0.043)	(0.062)	(0.001)	(0.037)
	Non-interest income	-0.0034 ***	-0.0019 *	-0.0047	-0.0001	-0.2165 ***	-0.0001	-0.0044
		(0.000)	(0.001)	(0.008)	(0.004)	(0.010)	(0.000)	(0.003)
	Constant	-2.7531 ***	-1.6622 ***	-6.3235 ***	-0.7868	5.2570	-0.0088 *	-0.3757
		(0.434)	(0.312)	(1.506)	(1.206)	(8.489)	(0.005)	(0.362)
	No. of observations	852	483	483	547	83	483	483
	R^2	0.113	0.583	0.407	0.032	0.513	0.106	0.062
	Percent true positives/negatives	76.81/59.02						
	Percent correctly classified	75.6						
	Hosmer–Lemeshow test	10.77						
	Hosmer–Lemeshow test p-value	0.215						

Table VII
Robustness Tests on the Effects of Balance sheet Structures on Bank Risk

This table reports the results from our robustness tests on our bank risk regressions. It includes additional controls to the baseline specification presented in table III. The majority of the results remain robust to the inclusion of country dummies, as well of additional variables capturing banks' profitability, and major country macroeconomic developments, such as GDP growth, house prices and stock market returns. Columns (I) and (II) report the results of the probit regression using government support as a measure of bank risk. Columns (III) to (IX) contain the coefficients of OLS regressions where bank risk is measured as systematic risk, systemic risk, structural credit risk, and central bank liquidity. See Section II for further details and Table I for variables' definitions. The dependent variables are calculated as averages of quarterly data for individual banks during the pre-crisis period (2007Q4 to 2009Q4) except for the variable accounting for central bank liquidity. The latter is constructed only for the period of full liquidity allotment by the European Central Bank (2009Q1 to 2009Q4). The variables accounting for size, capital structure, asset structure, funding structure, income structure and profitability are calculated from the averages of quarterly data for individual banks during the pre-crisis period (2003Q4 to 2007Q3). GDP growth, house prices and stock market are calculated as country averages from quarterly data during the pre-crisis period already mentioned. *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

| | Dependent Variable: Measures of Bank Risk | | | | | | | | |
| | Rescue | | Systematic risk | | Systemic risk | | Structural credit risk | | Central bank liquidity |
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)	(IX)
Size	0.0563 *	0.0369 ***	0.1329 ***	0.1161 ***	0.7082 ***	0.6307 ***	-0.0460	-0.0829	-0.5844 ***
	(0.029)	(0.014)	(0.019)	(0.038)	(0.101)	(0.162)	(0.048)	(0.145)	(0.042)
Capital structure									
Capital	-0.0248 ***	-0.0240 ***	-0.0005	-0.0185 **	-0.0191	-0.0583 ***	-0.0478 ***	-0.0588 **	-0.3308 ***
	(0.001)	(0.001)	(0.002)	(0.008)	(0.013)	(0.011)	(0.007)	(0.023)	(0.043)
Undercapitalized	-0.0059	-0.0206 ***	-0.0360 ***	-0.0462 **	-0.1117 **	-0.0915 **	-0.1004 ***	-0.0392	-0.1115 ***
	0.0145	(0.002)	(0.011)	(0.018)	(0.049)	(0.038)	(0.025)	(0.066)	(0.005)
Asset structure									
Loans to total assets	0.0033 ***	0.0032 ***	0.0036	0.0048 *	0.0337 ***	0.0323 ***	0.0233 **	0.0221 ***	0.0695 ***
	(0.000)	(0.000)	(0.002)	(0.003)	(0.012)	(0.011)	(0.010)	(0.008)	(0.004)
Securitization	-0.0099 ***	-0.0046 ***	-0.1097	-0.1337 **	-0.6977 ***	-0.5169 ***	-0.1702	-0.1055	-0.9080 ***
	(0.001)	(0.001)	(0.125)	(0.061)	(0.141)	(0.147)	(0.122)	(0.143)	(0.096)
Funding structure									
Short-term market funding	0.0028 ***	0.0034 ***	0.0037 *	0.0080 ***	0.0420 ***	0.0485 ***	0.0284 ***	0.0289 **	0.1403 ***
	(0.000)	(0.000)	(0.002)	(0.003)	(0.013)	(0.012)	(0.007)	(0.015)	(0.009)
Deposit funding	-0.0069 ***	-0.0068 ***	-0.0081 ***	-0.0147 ***	-0.0442 ***	-0.0462 ***	0.0190	0.0269	-0.0628 ***
	(0.001)	(0.001)	(0.002)	(0.003)	(0.013)	(0.014)	(0.023)	(0.021)	(0.017)
Income structure									
Excessive loan growth	0.0422 *	0.0548 ***	0.1429 ***	0.1504 ***	0.3045 ***	0.3313 ***	0.0539	0.0748	0.7737 ***
	(0.023)	(0.008)	(0.042)	(0.030)	(0.051)	(0.087)	(0.043)	(0.118)	(0.022)
Non-interest income	-0.0028 ***	-0.0023 ***	-0.0013	-0.0037	-0.0091	-0.0028	0.0004	0.0024	-0.2574 ***
	(0.000)	(0.000)	(0.002)	(0.002)	(0.007)	(0.006)	(0.004)	(0.019)	(0.010)
Control variables									
Profitability		-0.0208 ***		0.1391 **		0.1805		-0.0647	0.7259
		(0.008)		(0.055)		(0.193)		(0.419)	(0.732)
GDP growth		0.1875		0.2913 ***		2.0110 ***		0.5782	1.6483 ***
		(0.215)		(0.107)		(0.269)		(0.499)	(0.487)
House prices		0.1857 **		0.1384 ***		0.4074		0.3905	
		(0.073)		(0.041)		(0.115)		(0.155)	
Stock market		-0.0659 ***		-0.1199 ***		0.1107		-0.2495	
		(0.002)		(0.038)		(0.186)		(0.108)	
Country dummies	Yes		Yes		Yes		Yes		
Intercept	-2.4757 ***	-3.5289 ***	-1.3049 ***	-1.7491 ***	-6.2326 ***	-9.1621 ***	-0.7607	-1.4011	2.5345 ***
	(0.227)	(0.650)	(0.286)	(0.330)	(1.349)	(1.604)	(1.131)	(1.109)	(0.906)
No. of observations	852	852	483	483	483	483	547	547	83
R²	0.137	0.124	0.568	0.551	0.410	0.416	0.032	0.037	0.676
Percent true positives/negatives	59.30/75.55	52.94/77.25							
Percent correctly classified	73.7	74.86							
Hosmer–Lemeshow test	3.24	9.99							
Hosmer–Lemeshow test p-value	0.9187	0.2654							

Table VIII
Robustness Tests on Balance Sheet Structures on Bank Risk
Splitting the samples according to M&A activities and types of ownership

This table presents the results of the baseline specification presented in table III, after splitting the sample between banks which have been or not involved in an M&A activity, or alternatively, between banks with a more or less dispersed ownership structure. The idea is that management and shareholder's risk preferences are unlikely to remain the same across these different groups. The results show that our findings remain robust to different groupings of banks. Columns (I) and (IV) report the results of the probit regression using government support as a measure of bank risk. See Section II for further details and Table I for variables' definitions. The variables accounting for size, capital structure, asset structure, funding structure and income structure are calculated from the averages of quarterly data for individual banks during the pre-crisis period (2003Q4 to 2007Q3). *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively. *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

| | | M&A Activities | | Ownership | |
		Not-involved (I)	Involved (II)	Dispersed (III)	Concentrated (III)
	Size	0.0572 ***	-0.1145 ***	0.0375	-0.0001
		(0.0055)	(0.0378)	(0.0563)	(0.0013)
Capital structure	Capital	-0.0217 ***	-0.0227 ***	-0.0291 ***	-0.0023 *
		(0.0015)	(0.0040)	(0.0026)	(0.0012)
	Undercapitalized	-0.0323 ***	-0.0638 *	-0.0548 ***	0.0012 ***
		(0.0046)	(0.0344)	(0.0136)	(0.0001)
Asset structure	Loans to total assets	0.0077 ***	-0.0059 ***	0.0052 ***	0.0004 ***
		(0.0003)	(0.0008)	(0.0003)	(0.0001)
	Securitization	-0.0140 ***	-0.1195 ***	-0.1157 *	-0.0841 ***
		(0.0006)	(0.0423)	(0.0641)	(0.0261)
Funding structure	Short-term market funding	0.0092 ***	-0.0017	0.0060 ***	0.0001 ***
		(0.0006)	(0.0015)	(0.0009)	(0.0000)
	Deposit funding	-0.0097 ***	-0.0099 ***	-0.0116 ***	-0.0009 **
		(0.0001)	(0.0023)	(0.0016)	(0.0004)
Income structure	Excessive loan growth	0.0182 ***	0.1599 ***	0.0716 **	0.0025 *
		(0.004)	(0.044)	(0.032)	(0.001)
	Non-interest income	-0.0028 ***	-0.0022 ***	-0.0026 **	-0.0001 ***
		(0.0004)	(0.0002)	(0.0012)	(0.0000)
	Intercept	-4.0723 ***	1.1960 ***	-2.6261 ***	-2.2002 **
		(0.1460)	(0.4343)	(0.2732)	(1.0076)
	No. of observations	651	201	595	89
	R^2	0.114	0.101	0.112	0.261
	Percent true positives/negatives	55.77/76.20	47.24/77.99	50.00/78.90	28.21/74.39
	Percent correctly classified	74.97	73.46	74.28	72.42
	Hosmer–Lemeshow test	7.14	6.57	11.56	7.64
	Hosmer–Lemeshow test p-value	0.5215	0.5833	0.1721	0.4690

Marginal effect calculation of Probit estimates for the likelihood of being a rescued institutions:

Figure I
Box plot distribution of the stock market returns of individual banks

The diagram below shows the cross-sectional distribution of stock market returns for the combined sample of listed European and US banks included in our exercise for the pre-crisis (2003Q4 to 2007Q3) and crisis (2007Q4 to 2009Q4) periods. It is based on monthly stock market prices obtained from Datastream. For the pre-crisis and crisis periods, for each banks we calculate the 10%, 25%, 50%, 75% and 90% quantiles of the distribution of average stock market returns. The "box plot" consists of a "box" that moves from the first to the third quartile (Q1 to Q3) of the distribution of stock market returns for the pre-crisis (2003Q4 to 2007Q3) and crisis (2007Q4 to 2009Q4) periods. Within the box itself, the thick horizontal line represents the median. The area below the bottom whisker moves from the 25% to the 10% quantile, while the area above the top whisker moves from the 75% to the 90% quantile of the distribution.
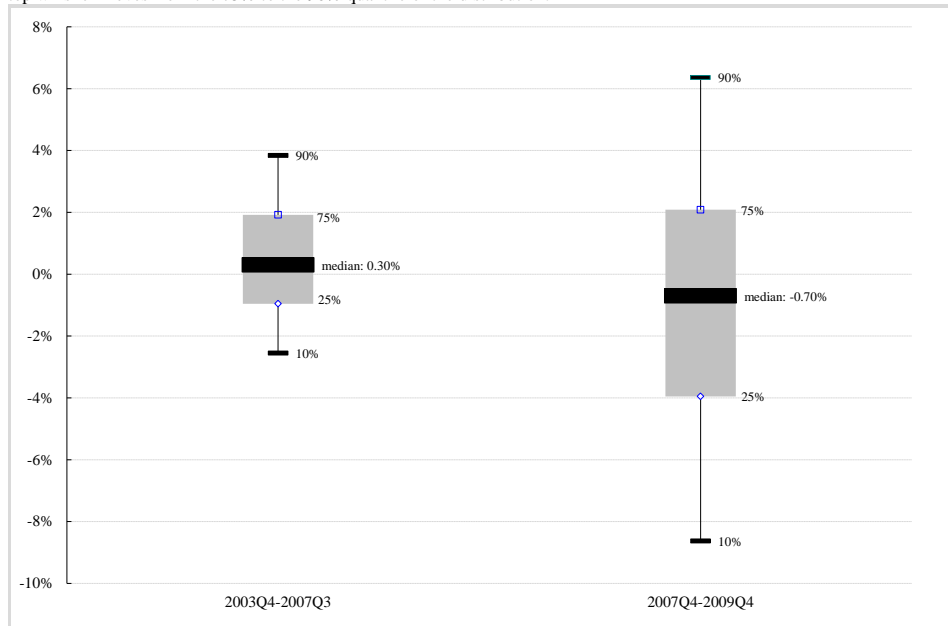
Figure II

Scatter plots of the systematic risk levels for the pre- and post-crisis periods

On the X axis, the diagram below shows the 5 (i.e. low systematic risk) and 95% (i.e. high systematic risk) percentile values for the systematic risk variable during the pre-crisis period (2003Q4 to 2007Q3). Systematic risk is calculated as the average of the quarterly non-overlapping betas in a capital asset pricing model calculated for each bank i on country j using daily stock market data using stock market prices obtained from Datastream for the listed European and US banks included in our sample. On the Y axis, the diagram shows the 5 (i.e. low systematic risk) and 95% (i.e. high systematic risk) percentile values for the systematic risk variable for the crisis period (2007Q4 to 2009Q4).