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Realized bank risk during the great recession[☆]

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ABSTRACT

We find that certain bank characteristics—aggressive credit growth, less reliance on deposit funding, and size—prior to the 2007–2009 crisis are consistently related to the systemic dimensions of bank risk during the crisis. Exposures to real estate play a major role explaining this relationship: Banks with larger real estate betas exhibited higher levels of systemic risk during the crisis. The impact of real estate betas on systemic risk increases for larger banks, following aggressive credit growth policies in the presence of housing bubbles. We show that the relationship between bank characteristics and risk could also be detected using measures of systemic risk calculated prior to the financial crisis.

The 2007–2009 financial crisis resulted in the largest realization of bank risk since the Great Depression as illustrated by the spectacular declines in banks' stock market capitalisation. Between May 2007 and March 2009, banks listed in the European Union and the United States lost around 82 percent of their value. Interestingly in the years preceding the crisis, forward-looking measures of bank risk—regularly used by financial investors, central banks, and supervisors to monitor the health of the financial system—showed a fairly benign picture and suggested very low levels of expected risk (IMF, 2009). Also, these signals were highly clustered making it difficult to disentangle *ex-ante* between riskier and safer institutions (see Fig. 1). Partly due to this benign picture provided by market-based indicators of bank risk prior to the crisis, supervisors, rating agencies and financial practitioners repeatedly emphasised the *unexpected* dimension of the recent crisis.[1] The eruption of the crisis, however, revealed a huge variability in realized risk across individual banks, as evidenced by the cross-sectional dispersion of stock market returns during the crisis, suggesting a strong degree of heterogeneity in *ex-ante* risk-taking.

These developments in markets' perceptions of bank risk were important, as in the decades before the crisis much of the prudential regulatory action progressively moved away from regulating

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[1] Gorton (2012, pg.2) suggests that "The recent financial crisis of 2007-2009 in the United States and Europe shows that market economies, however much they grow and change, are still susceptible to collapse or near-collapse from financial crisis. This is a staggering thought. And it came as a surprise, as financial crises were thought to be things of the past for developed economies, now only occurring in emerging markets". Hoening (2008, pag. 6) also emphasises that "the recent crisis has revealed some new and unexpected vulnerabilities in the financial system".

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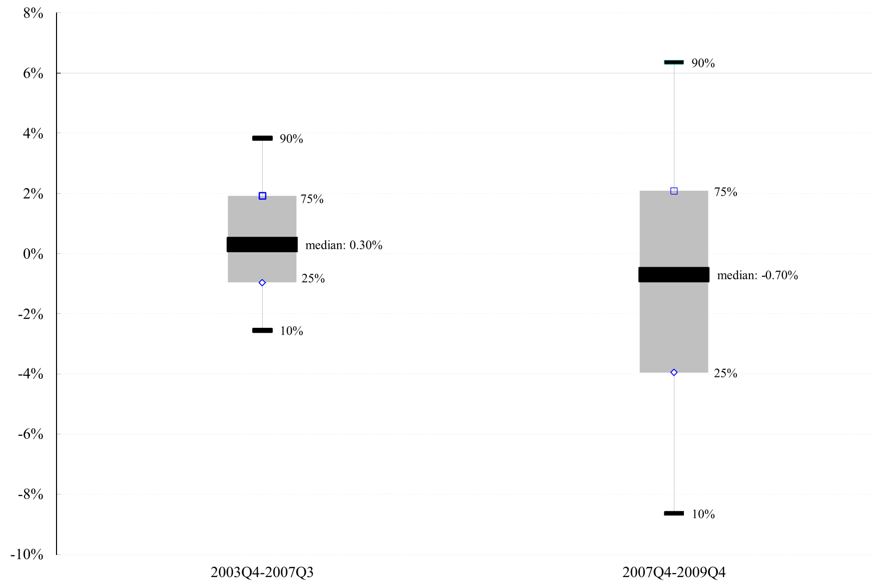

Fig. 1. Box plot distribution of the stock market returns of individual banks.
The diagram below shows the cross-sectional distribution of stock market returns for the combined sample of listed European and US banks included in our exercise for the pre-crisis (2003Q4 to 2007Q3) and crisis (2007Q4 to 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 percent 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 percent quantile, while the area above the top whisker moves from the 75 to the 90 percent quantile of the distribution.

certain banks' characteristics traditionally considered as sources of bank risk—such as excessive loan growth or unstable funding. Instead it focused on bank capital as the main buffer against excessive risk-taking by banks, and increasingly relied on financial markets' discipline.[2] Coinciding with this move away from regulating banks' characteristics, most of the previous empirical literature tended to find mixed results on the impact of certain bank characteristics on risk. For instance, empirical evidence on how certain bank characteristics—such as leverage, securitization, asset composition, size and non-interest income—impact on banks' risk profile often remains contradictory and non-conclusive (Berger et al. 2015). As a result one useful empirical exercise would be to "go back to basics" and understand whether certain bank characteristics prior to the crisis were associated with banking risks.

This is the objective of our paper: We test which bank characteristics were associated with higher likelihood of bank default and would have helped in the early identification of risks during the 2007–2009 crisis. This seems relevant, given the relatively poor performance of market-based indicators of bank risk and the mentioned focus of bank capital and financial markets' discipline on the supervisory toolbox at the expense of other bank characteristics.

A critical challenge is how to incorporate the different dimensions of realised bank risk in such a way that the consistency of the results can be assessed. Using a database laboriously compiled for the purposes of this study we incorporate several measures of bank risk and analyse how they are related to key bank characteristics in the pre-crisis period. Building on the pre-crisis literature (see Berger et al. 2015), we group individual bank information into four broad categories—capital, asset, funding, and income structures—which concisely aggregate the underlying banks' characteristics.

Another challenge would be whether those characteristics impact on systemic, as opposed to idiosyncratic, bank risks. This distinction seems crucial as the buildup of systemic risks at the individual bank level would be typically associated with systemic banking crises which are very costly and have become more frequent in recent decades (Reinhart and Rogoff, 2009; Calomiris and Haber, 2014). We do this by creating different variables accounting for the systemic and idiosyncratic dimensions of bank risk. We also create a variable—real estate beta—to proxy for real estate exposure and another variable accounting for housing bubbles as there is significant evidence showing that severe financial crises often follow housing bubbles and concentration on real estate (Taylor 2014).

Our empirical analysis offers a few key robust results. First, bank size, the rate of credit expansion, lower dependence on customer deposits, a weaker capital base for undercapitalised banks in the run-up to the crisis consistently accounted for higher levels of ex-post distress.

Second, the impact of these characteristics is concentrated on the systemic dimension of bank risk and developments in real estate in the run-up to the crisis explain the build-up of this systemic risk. We also show that the impact of real estate on systemic risk is heterogeneous and becomes stronger for larger banks, following expansionary loan policies, in the presence of housing bubbles and making more use of mortgage-backed securities for funding purposes.

Third, the effect of certain balance sheet variables on systemic bank risk is non-linear. For instance, the direct impact of loan growth on systemic risk is up to three times larger as realized risk increases. These results are robust to the inclusion 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.

Finally, we 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 real estate beta and other bank char-

[2] The Basel II package specifically introduced disclosure and market discipline principles as part of its pillar 3 (Basel Committee on Banking Supervision, 2017) while pillar I deals with minimum capital requirements (Basel Committee on Banking Supervision, 2011).

acteristics on risk *before* a crisis takes place. We find that real estate beta, size and less funding via stable bank deposits predicted risk also *prior* to the crisis. Also in this setting, we find that their impact is concentrated on the systemic dimension of bank risk.

Our findings have a bearing on the current prudential regulatory debate. They unambiguously suggest that aggressive loan growth and less reliance on deposits for funding purposes lead to the accumulation of systemic risk thereby supporting the introduction of additional supervisory actions linked to these variables.

The remainder of this paper is organized as follows. Section 1 reviews the literature on bank characteristics and risk. Section 2 describes the model, data sources, and how the dataset was constructed. Section 3 presents the main empirical findings and Section 4 the robustness tests. Section 5 concludes.

1. Bank characteristics and risk: A literature review

We structure our review of the literature by grouping bank characteristics into broad categories, which have been traditionally related to bank risk, used later in our empirical investigation. We then review the evidence on real estate developments as a plausible driver of the relationship between bank characteristics and the systemic dimension of bank risk.

1.1. Capital structure

While financial regulation has given more prominence to bank capital in recent decades (Rochet, 2010), 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[3]. 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. In this direction, Beltratti and Stulz (2012) find that banks with higher capital performed better in the initial stages of the crisis, and the empirical literature tends to show that holding more capital supports bank soundness, particularly during crises (Demirgüç-Kunt and Huizinga, 2010; Berger and Bouwman, 2013).

In contrast, there are 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, lower levels of capital (i.e. higher leverage) can intensify the pressure on bank managers by informed debt holders to take on fewer risks (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) model a U-shaped relationship between capital and risk-taking in which as bank's capital increases the bank first takes less risk and then more risk. More recently, Bahaj and Malherber (2017) find a U-shaped relationship between capital and lending which also depends on economic prospects.

Empirically, higher levels of capital may simply be the result of regulators forcing riskier banks to hold higher buffers. There is, in fact, some evidence finding a positive relationship between higher levels of bank capital and risk (see for instance Delis and Staikouras, 2011).[4]

[3] This is particularly useful in the banking industry, where 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).

[4] In this respect many of the banks failing during the crisis had capital levels above the average of their peers (Haldane and Madouros, 2012).

1.2. Asset structure

The widespread use of private securitization techniques represented a major structural development in the decades prior to the 2007–2009 crisis. It allowed banks to sell more easily part of their loan book to investors and swiftly turn traditionally illiquid claims (such as bank of bank loans) into marketable securities. This, in turn, lowered regulatory pressures on banks' capital requirements (Shin, 2009; Marques-Ibanez and Scheicher, 2010). In principle, from the perspective of individual banks, securitization helped banks to manage and diversify their credit risk portfolio more effectively, both geographically and by sector. Indeed, most of the empirical evidence from the pre-crisis period suggests that banks more active in securitization markets were more profitable and better capitalized (Cebenoyan and Strahan, 2004; Wu et al. 2011). At the same time, 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).

1.3. Funding structure

Banks' traditional source of funding is represented by customers' deposits. High switching costs and the presence of government insurance makes banks' deposits a stable source of funding particularly during periods of crises (Kim et al. 2003; Shleifer and Vishny, 2010). Deposits are, however, usually a less flexible source of funding than wholesale markets' financing such as mortgage bonds, repurchase agreements and commercial paper. Financial market investors—being relatively more sophisticated than retail depositors—could in principle 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).

1.4. Income structure

The global trend towards more diversification in bank income sources has led to an expansion of non-interest income revenues, such as those derived from trading, investment banking, brokerage fees and commissions. Such diversification can, in principle, foster stability in banks' overall income (Stiroh, 2015). At the same time, it is not clear whether the stronger reliance on non-interest income reduces overall banking risk as it tends to be a particularly volatile source of revenue which may suffer more in periods of financial stress. As a result, it is also possible that the financial stability benefits that may be obtained from diversification accrue only in cases of minor idiosyncratic risk, but not in the context of a wider systemic shock (De Jonghe, 2010; Brunnermeier et al. 2012b).

We also include under this heading loan growth: There is historical evidence suggesting that excessive lending preceded most systemic banking crises (Reinhart and Rogoff, 2009). This is also confirmed by microeconomic evidence showing that loan growth represents an important driver of risk (Laeven and Majnoni, 2003; Foos et al. 2010; Fahlenbrach et al. 2016).

1.5. Size

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 which might encourage larger institutions to take more risks than smaller ones. At the same time bigger institutions might be able to diversify their risks better (Demirgüç-Kunt and Huizinga, 2010).

1.6. Systemic risk and real estate

A crucial consideration, when assessing the impact of these variables on bank risk, would be their impact on systemic—as opposed to idiosyncratic—dimensions of risk. This as an important aspect as the aggregation of systemic risks would often result on major financial crises which tend to be costly and lead to deep recessions (Laeven and Valencia, 2013).

There is historical evidence showing that systemic banking crises have become more frequent over the last four decades, and that real estate developments tend to be a major factor underlying these crises (Reinhart and Rogoff, 2009; Calomiris and Haber, 2014). Supporting this argument it has been shown that for more than a century real estate booms have been strongly connected with a higher likelihood of systemic crisis (Reinhart and Rogoff, 2008). In recent decades, as real estate lending has progressively become an increasingly larger component of banks' balance sheet, housing developments have become a major driver of bank risk (Jordà et al., 2015).

2. Construction of bank risk variables

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

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

The dependent variable ($r_{i,c}$) measures the distress of bank i during the crisis period c (2007Q4 to 2009Q4),[5] 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 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 4.

The statistical sources used and brief description of the main variables included in our study are provided in Table 1, while Table 2 shows the main descriptive statistics. Our initial dataset has more than 1100 listed banks from 16 countries.[6] The dataset is highly representative, 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.

2.1. Construction of bank risk variables

In order to capture the realization of bank risk, it is crucial to recognize that during a crisis, the materialization of bank risk unfolds progressively and manifests itself in several and different dimensions. We employ alternative measures of bank risk to capture these different dimensions and to ensure that our results do not depend on a narrow definition of bank risk. We believe that the use of all these measures is crucial to assess the validity of our findings. Indeed, a major possible reason for the contradictory findings of earlier empirical studies (see Section 1) was probably related to the different dimensions of risk.[7]

2.1.1. Financial support

Our first measure describes whether an institution received any government support. The construction of this variable is based on the collection of information relating to the public rescue of banks via capital injections, the issuance of state-guaranteed bonds, or other government-sponsored programmes.[8] 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. 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 1100 institutions) for which consolidated financial statements are available via Bloomberg (see below).[9]

2.1.2. Systematic risk

Our second measure of bank risk 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:

$$R_{i,k,t} = \beta_{i,k,t^*} R_{m,k,t} + \varepsilon_{i,k,t} \tag{2}$$

where $R_{i,k,t}$ is the daily logarithmic excess stock market returns for each bank i from country k at time t;[10] $R_{m,k,t}$ 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 $\beta_{i,k,t}$ by running separate regressions on daily data for every quarter q from 2007Q4 to 2009Q4. We then calculate the average beta for each individual bank during the crisis period. Obviously this would reduce our original sample to only those banks which are listed and actively traded during our period of study (around 483 institutions).

5 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 percent, 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.

6 Namely: Austria, Belgium, Denmark, Germany, Greece, Finland, France, Ireland, Italy, Luxembourg, the Netherlands, Portugal, Spain, Sweden, the United Kingdom and the United States.

7 A lingering limitation of all our measures of bank risk is that their values would be all affected by the safety net.

8 For a comprehensive overview of the public measures in support of the financial sector see Stolz and Wedow (2010). The choice of such as a broad measure of government support is pragmatic. When analysing the data, there were many instances of banks receiving several types of government support which would have complicated the estimation using a more precise definition of government support including the different interventions.

9 We consider commercial or universal banks only. Hence foreign subsidiaries, investment banks, and non-bank financial institutions are not included in our sample.

10 We calculate excess returns as the difference between stock market returns and the 10-year government bond yield for the country concerned.

Table 1
Data Sources and Variable Definitions.
This table reports the main variables used in the estimations indicating their name, data sources and a brief description of how the variables have been constructed. More detailed information, plus all publicly available data, are available upon request.

Variable	Source	Description
Panel A: Bank risk		
Financial support	European Commission, national central banks, Bank for International Settlements, other public institutions and Bloomberg.	Binary variable – 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 of a capital asset pricing model constructed using daily logarithmic excess stock market returns for each bank *i* on the broad market index of country *j* calculated for the crisis (2007Q4-2009Q4) and non-crisis (2003Q4-2007Q3) periods.
Systemic risk	Datastream and authors' calculation following Acharya et al. (2010).	Marginal expected shortfall (MES) – Acharya et al. (2010) – constructed from daily bank and country logarithmic stock market returns. It uses a risk level of $\alpha = 5\%$ calculated for the crisis (2007Q4-2009Q4) and non-crisis (2003Q4-2007Q3) periods.
Structural credit risk (EDF)	Moody's KMV.	Expected default frequency (*EDF*). It is calculated as the one-year ahead probability of default as 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 *EDF* for the crisis (2007Q4-2009Q4) and non-crisis (2003Q4-2007Q3) periods.
Central bank liquidity	European Central Bank.	Liquidity received from the ECB to total assets of each bank * 100. Average outstanding values for 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 (ε_{ijt}) of a capital asset pricing model calculated from daily logarithmic excess stock market returns for each bank *i* on the broad market index of country *j* calculated for the crisis (2007Q4-2009Q4) and non-crisis (2003Q4-2007Q3) periods.
Idiosyncratic risk2	Authors' calculation following Campbell et al. (2001).	Average of the quarterly non-overlapping idiosyncratic (i.e. bank specific) risk component of the realized volatility following Campbell et al. (2001). It is calculated from daily logarithmic stock market returns decomposing the realized volatility of stock market prices for each bank *i* into three components: market, banking industry, and bank-specific volatility. We calculate the average for the crisis (2007Q4-2009Q4) and non-crisis (2003Q4-2007Q3) periods.
Panel B: Bank characteristics		
Size	Bloomberg.	Average of quarterly logarithm of total assets (USD millions).
Capital ratio	Bloomberg.	Average of quarterly Tier I capital to risk-weighted assets' * 100 during the pre-crisis period (2003Q4 to 2007Q3).
Undercapitalised	Authors' calculation.	Average of quarterly interaction between Tier I capital and a low capital dummy variable – 1 indicates a bank with a Tier I ratio below 6% – during the pre-crisis period (2003Q4 to 2007Q3).
Total capital ratio	Bloomberg.	Average of quarterly total capital (Tier I and Tier II) to risk-weighted assets' * 100 during the pre-crisis period (2003Q4 to 2007Q3).
Core capital ratio	Bloomberg.	Average of quarterly Tier I capital to total assets' * 100 during the pre-crisis period (2003Q4 to 2007Q3).
Loans to total assets	Bloomberg.	Average of quarterly total loans to total assets' * 100 during the pre-crisis period (2003Q4 to 2007Q3).
Securitization	DCM Analytics Dealogic, S&P and HMDA.	Average of quarterly total securitization flow to total assets' * 100 of each originating bank during the pre-crisis period (2003Q4 to 2007Q3).
Real estate loans to total assets	Bloomberg and authors' calculation.	Average of quarterly total real estate lending to total assets' * 100 during the pre-crisis period (2003Q4 to 2007Q3).
Mortgage-backed securitization	DCM Analytics Dealogic S&P and HMDA.	Average of quarterly total mortgage-back securitization flow to total assets' * 100 of each originating bank during the pre-crisis period (2003Q4 to 2007Q3).
Short-term market funding	Bloomberg.	Average of quarterly short-term market debt (i.e. less than 2 years) to total assets' * 100 during the pre-crisis period (2003Q4 to 2007Q3).
Deposit funding	Bloomberg.	Average of quarterly total deposits to total assets' * 100 during the pre-crisis period (2003Q4 to 2007Q3).
Excessive loan growth	Authors' calculation.	Average of annual lending growth calculated using quarterly data calculated during the pre-crisis period (2003Q4 to 2007Q3) minus the average long-trend loan growth in each country.
Excessive real estate loan growth	Authors' calculation.	Average of annual real estate lending calculated using quarterly data calculated during the pre-crisis period (2003Q4 to 2007Q3) minus the excessive loan growth variable.
Non-interest income	Bloomberg.	Average of quarterly non-interest income to total revenues' * 100 during the pre-crisis period (2003Q4 to 2007Q3).
Securities income	Bloomberg.	Average of quarterly fee from securities income – including underwriting activities – to total assets' * 100 during the pre-crisis period (2003Q4 to 2007Q3).
Trading income	Bloomberg.	Average of quarterly trading income to total assets' * 100 during the pre-crisis period (2003Q4 to 2007Q3).
Panel C: Control variables		
Housing bubble dummy	Authors' calculation.	Binary variable – 1 if observation is from the USA, United Kingdom, Spain, Portugal and Ireland; 0 otherwise.
Real estate beta	Datastream and authors' calculation following Beltratti and Stulz (2012).	Average of the quarterly non-overlapping real estate betas of a capital asset pricing model constructed using daily logarithmic excess stock market returns for each bank *i* on the real estate market index of country *j* calculated for the crisis (2007Q4-2009Q4) and non-crisis (2003Q4-2007Q3) periods.

(*continued on next page*)

Table 1 (*continued*)

Variable	Source	Description
Profitability	Bloomberg.	Average of quarterly net income to total assets' * 100 during the pre-crisis period (2003Q4 to 2007Q3).
GDP growth	Bank for International Settlements.	Average of quarterly changes in real GDP during the pre-crisis period (2003Q4 to 2007Q3) demeaned from long-term historical averages.
House prices	Bank for International Settlements.	Average of quarterly changes in real housing prices during the pre-crisis period (2003Q4 to 2007Q3) demeaned from long-term historical averages.
Stock market	Datastream.	Average of 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.
Corporate governance	Thomson Reuters and authors' calculation.	Average of yearly sum of the squares of the percentages of the ownership's shares controlled by each shareholder on each bank during the pre-crisis period (2003Q4 to 2007Q3).
Dispersed ownerships	Thomson Reuters and authors' calculation.	Binary variable – 1 if the average ownership concentration is less than 10% during the pre-crisis period (2003Q4 to 2007Q3); 0 otherwise.
M&A involvement	Thomson Reuters - SDC Platinum database.	Binary variable – 1 if the institution was involved in one or more mergers and acquisitions (M&A) during the pre-crisis period (2003Q4 to 2007Q3); 0 otherwise.
Sifi	European Central Bank, National central banks, Bank for International Settlements, and Bloomberg .	Binary variable – 1 if the institution was categorised as a systemically important financial institution (Sifi); 0 otherwise.

Table 2
Data Sources and Variable Definitions.
This table reports summary statistics for the primary variables used in this study (see Section 2 and Table 1 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 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, Corporate governance and Dispersed ownership 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. M&A involvement and Sifi are also constructed for the pre-crisis period.

Variable	N	Average	Median	Standard deviation	Q_1	Q_3
Panel A: Bank risk variables						
Financial support	852	0.26	0.00	0.44	0.00	1.00
Systematic risk	483	0.70	0.47	0.60	0.17	1.28
Systemic risk	483	3.32	3.07	2.62	1.21	5.23
Structural credit risk (EDF)	540	0.91	0.32	2.22	0.13	0.79
Central bank liquidity	83	2.64	1.25	3.43	0.47	4.41
Idiosyncratic risk1	483	0.02	0.01	0.02	0.00	0.02
Idiosyncratic risk2	483	0.20	0.12	0.54	0.07	0.22
Panel B: Balance Sheet Variables						
Size	852	7.29	6.62	2.07	5.87	8.20
Capital Structure						
Capital ratio	852	9.63	8.82	5.62	7.31	10.91
Undercapitalised	852	0.52	0.00	1.47	0.00	0.00
Total capital ratio	852	13.73	12.83	3.24	11.69	14.64
Core capital ratio	852	4.72	4.53	2.49	3.08	6.00
Asset Structure						
Loans to total assets	852	65.53	68.17	15.21	59.58	75.07
Securitization	852	0.10	0.07	0.10	0.02	0.14
Real estate loan to total assets	483	19.26	17.18	12.25	11.10	25.04
Mortgage-back securitization	483	0.08	0.06	0.09	0.01	0.12
Funding Structure						
Short-term market funding	852	19.41	17.08	12.96	11.10	24.65
Deposit funding	852	70.78	74.91	15.13	65.77	81.00
Income Structure						
Excessive loan growth	852	6.27	5.75	2.33	4.72	7.47
Excessive real estate loan growth	852	2.51	1.37	5.77	−0.34	4.11
Non-interest income	852	20.01	16.53	14.24	10.98	24.79
Securities income	483	2.23	1.30	3.79	0.46	3.15
Trading income	483	4.64	3.85	4.23	1.78	6.47
Panel C: Control Variables						
Housing bubble dummy	852	0.83	1.00	0.37	1.00	1.00
Real estate beta	483	0.50	0.60	2.06	−0.45	1.41
Profitability	852	0.97	0.96	0.95	0.65	1.26
GDP growth	852	1.29	1.34	0.20	1.34	1.34
House prices	852	1.19	1.33	0.58	1.33	1.33
Stock market	852	1.56	1.36	0.63	1.36	1.36
Corporate governance	676	6.00	1.62	12.58	0.70	3.42
Dispersed ownership	676	0.87	1.00	0.33	1.00	1.00
M&A involvement	852	0.24	0.00	0.43	0.00	0.00
Sifi	852	0.05	0.00	0.22	0.00	0.00

2.1.3. Systemic risk

Our third measure of bank risk broadly captures the reaction of individual banks to systemic events. It measures tail dependence in the stock market returns of individual banks and equates the magnitude of tail dependence estimates as a measure of systemic risk. It is estimated via the marginal expected shortfall (MES) following the model and parametrization by Acharya et al. (2010) calculated from daily data of individual banks' and countries' stock market equity returns from Datastream.

2.1.4. Central bank liquidity

Our fourth 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.[11] Our central bank liquidity variable 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. These banks cover, nonetheless, more than 90 percent of the average liquidity provided by the Eurosystem.[12]

2.1.5. Idiosyncratic risk

Our fifth 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 during the crisis period (2007Q4 to 2009Q4).

2.1.6. Idiosyncratic risk2

Our sixth measure of bank risk follows Campbell et al. (2001) by decomposing the stock market prices of each bank i into three components of 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).

2.1.7. Structural credit risk

Our last measure of bank risk is the expected default frequency (*EDF*) and captures the constructed one-year ahead probability of default for each individual bank. It is computed by Moody's KMV based 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. *EDF* developments are regularly used as an indicator by financial institutions, investors, central banks and regulators to monitor the health of the financial system.[13]

2.2. 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, Bank for International Settlements, Moody's KMV, Bankscope and Datastream (see Table 1).

The first variable characterizing the banks' characteristics is real estate beta:

2.2.1. Real estate beta

We construct the real estate beta ($\gamma_{i,k,t}$) by adding to our CAPM regression (2) a real estate index:

$$R_{i,k,t}=\beta_{i,k,t}{}^*R_{m,k,t}+\gamma_{i,k,t}{}^*R_{e,k,t}+\varepsilon_{i,k,t} \tag{3}$$

where $R_{e,k,t}$ are the excess stock market returns for the real estate market index of country k at time t. As in Eq. (2) $R_{i,k,t}$ is the daily logarithmic excess stock market returns for each bank i from country k at time t;[14] $R_{m,k,t}$ is the daily logarithmic excess stock market returns from the broad stock market index m for country k; $R_{e,k,t}$ is the real estate stock market index for each country,[15] and the term $\varepsilon_{i,k,t}$ is a bank-specific residual. For each bank i, we calculate the real estate beta ($\gamma_{i,k,t}$) by running separate regressions on daily data for every quarter q from 2007Q4 to 2009Q4. We then calculate the average real estate beta for each individual bank during the crisis period. Overall, after excluding banks for which no observation was available, we managed to compute the real estate beta for 757 banks.

2.2.2. Size

As in our literature review we also include a variable accounting for size, measured as the average natural logarithm of total assets of the consolidated institution before the crisis. We also calculate a dummy variable (Sifi) to measure whether the institution was categorized as a systemically important according to the national supervisory authorities or the Bank for International Settlements.

We include the other variables into main groups:

[11] 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.

[12] 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 larger institutions.

[13] The final EDF value, expressed as a percentage, represents the implied risk of default and is constructed by combining companies' financial statements with stock market information and a proprietary default database maintained by Moody's KMV. Compared to other measures of expected bank risk, the KMV methodology has various advantages. First, it is not based on ratings which might be biased indicators of corporate risk due to conflicts of interest. Second, unlike measures of default risks derived exclusively from accounting information—such as Z-scores—, EDF is not a backward-looking indicator of risk. Third, despite their simplifying assumptions, EDF estimations of default risk show strong robustness to model misspecifications (Jessen and Lando, 2015). Finally, during the recent financial crisis and compared to other measures of default risk, the EDF has done relatively well as a predictor of firms' risk on a cross-sectional perspective. That is, the relative positions of firms ranked according to their EDF levels in the year before the crisis were good predictors of rank ordering of default risk during the crisis (Munves et al. 2009).

[14] We calculate excess returns as the difference between stock market returns and the 10-year government bond yield for the country concerned.

[15] No index is available for Ireland.

2.2.3. Capital structure

We approximate bank capital by using a ratio of Tier I capital to total risk-weighted 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 percent) to account for possible non-linear effects for less-capitalized banks. We also construct a total capital ratio (broader definition of bank capital), as well as a core capital to total assets ratio.

2.2.4. 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 on securitization has been constructed by combining data from three different sources (Bondware, Home Mortgage Disclosure Act and Standard and Poor's) and has been matched with balance sheet information from individual banks. Then it has been 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.[16] We also distinguish between mortgage-backed and other forms of securitization.

2.2.5. 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.

2.2.6. 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.[17]

2.3. Additional controls

As part of our robustness tests, we also include a number of additional controls. First, some of our specifications incorporate a group of macroeconomic controls 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 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 Bankscope as the sum of the squared values of the percentage of equity held by each individual shareholder. Third, 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.

3. 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 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.

3.1. Baseline results

Table 3 provides the estimates of the baseline specification for different measures of bank risk. 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 (VI) contain the coefficients of OLS regressions where distress is measured by systematic, systemic, central bank liquidity and two measures of idiosyncratic risks as described in the previous section.[18]

The results are quite stark and strongly suggest that bank characteristics are highly predictive of the broader measures of bank risk (i.e. systemic, systematic, rescue and central bank liquidity). In contrast the predictive power of bank characteristics on the idiosyncratic measures of bank risk is very mild.

With the exception of the idiosyncratic risk variable, the results are remarkably consistent across most columns, both in terms of sign and statistical significance.[19] 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 different models due to data availability). Our results remain robust to the inclusion of additional controls (see next section).

Focusing on the results for the non-idiosyncratic measures of bank risk (columns I to IV), bank size is actually the only variable whose sign changes across the models. It is positively related to measures of bank risk in the first three columns. The positive sign is consistent with the view that large banks were significantly riskier during the recent crisis. Large banks might have also been considered as "too big to fail", thus inducing governments to rescue them more often (Huang et al. 2012; Demirgüç-Kunt and Huizinga, 2010; Tarashev et al. 2009). The apparently contradictory negative sign for size in column (IV) 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

[16] 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.

[17] We also disaggregate non-interest income into two broad categories: (1) Securities income which arises from fees, commissions and other non-interest banking services such as investment banking, and (2) Trading income undertaken on banks' on behalf.

[18] 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.

[19] 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.

Table 3
Bank Characteristics and Risk.
This table reports the results from regressions of several measures of bank risk on bank characteristics. Column (I) reports the results of the probit regression using government support as a measure of bank risk. Columns (II) to (VI) contain the coefficients of OLS regressions where bank risk is measured as Systematic risk, Systemic risk, Central bank liquidity and two measures of Idiosyncratic risk. See Section 2 for further details and Table 1 for variables' definitions. The dependent variables in column I is calculated as a dummy for the crisis period (2007Q4 to 2009Q4). The dependent variables in columns II to VI are calculated as averages of quarterly data for individual banks during the crisis period (2007Q4 to 2009Q4) except for the variable 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 as 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 (I)	Systematic risk (II)	Systemic risk (III)	Central bank liquidity (IV)	Idiosyncratic risk1 (V)	Idiosyncratic risk2 (VI)
	Size	0.0409***	0.1090***	0.6949***	−0.2979***	0.0006***	0.0948**
		(0.003)	(0.032)	(0.134)	(0.023)	(0.000)	(0.042)
Capital structure	Capital ratio	−0.0207***	−0.0097	−0.0349	−0.1814***	−0.0001	−0.0002
		(0.001)	(0.007)	(0.036)	(0.053)	(0.000)	(0.011)
	Undercapitalized	−0.0415***	−0.0811***	−0.1116***	−0.0097	−0.0008***	−0.0051
		(0.008)	(0.017)	(0.040)	(0.020)	(0.000)	(0.019)
Asset structure	Loans to total assets	0.0047***	0.0061***	0.0356***	0.0781***	0.0000	−0.0028
		(0.001)	(0.002)	(0.013)	(0.004)	(0.001)	(0.003)
	Securitization	−0.0103***	−0.2076***	−0.5671***	−0.6012***	0.0005***	0.0566
		(0.001)	(0.054)	(0.189)	(0.143)	(0.000)	(0.071)
Funding structure	Short-term market funding	0.0071***	0.0097***	0.0494*	0.1483***	0.0001*	−0.0021
		(0.001)	(0.003)	(0.025)	(0.006)	(0.000)	(0.004)
	Deposit funding	−0.0103***	−0.0201***	−0.0655***	−0.0759***	−0.0002	−0.0117***
		(0.001)	(0.003)	(0.016)	(0.014)	(0.001)	(0.004)
Income structure	Excessive loan growth	0.0385***	0.1597***	0.2765***	0.4453***	0.0004***	−0.0230
		(0.005)	(0.027)	(0.075)	(0.008)	(0.000)	(0.037)
	Non-interest income	−0.0034***	−0.0043**	−0.0099	−0.2350***	−0.0001	−0.0046*
		(0.000)	(0.002)	(0.011)	(0.001)	(0.005)	(0.003)
	Constant	−2.8028***	−1.3420***	−5.9516***	2.9702***	−0.0074***	−0.3538
		(0.391)	(0.257)	(1.258)	(0.143)	(0.001)	(0.362)
	No. of observations	852	483	483	83	483	483
	R^2	0.111	0.517	0.378	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					

variable, higher size is mechanically associated with lower liquidity/size ratio. It could be that larger banks were considered as too-big-to-fail by the financial markets and access to the private short-term liquidity markets was more open for them than for smaller institutions and require, as a result, less central bank liquidity. We next discuss the impact of the different balance sheet structures.

3.1.1. 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 (Bank for International Settlements, 2010). Empirically, it is also consistent with recent empirical results by Gropp et al. (2016) and Behn et al. (2016) that show that the effects of higher capital ratios are stronger for weakly capitalized banks.

3.1.2. 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 (Knaup and Wagner, 2012).

3.1.3. Funding structure

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 et al. 2013) and proposals to strengthen anticyclical liquidity regulations such as the use of liquidity charges (see for instance, Brunnermeier et al. 2012a; Perotti and Suarez, 2011).

3.1.4. Income structure

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 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. It also informs the regulatory debate going forward (Reinhart and Rogoff, 2009). Results on non-interest income are more blurred and appear to be relevant for some of the specifications only.[20]

[20] In additional specifications we distinguished between two major sources of non-interest income: Securities income (including revenues from fees, commissions and other non-interest related banking services such as investment banking) and

Table 4
Quantile Estimates Bank Characteristics and Systematic Risk.
This table reports the quantile results from regressions of Systematic risk on bank characteristics. See Table 1 for variables' definitions. Columns (I) to (V) contain the coefficients of quantile estimates regressions for the 10, 25, 50, 75 and 90 percent quantiles of bank systematic risk calculated as averages of quarterly data during the crisis period (2007Q4 to 2009Q4). The variables accounting for Size, Capital structure, Asset structure, Funding structure and Income structure are calculated as 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 (IV)	Q75 (V)	Q90 (VI)	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 ratio	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*
	Constant	−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	

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). To do this we classify and rank banks during the crisis by quantiles according to their realized levels of bank risk.

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 characteristics and risk by estimating quantile regressions.[21]

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 2.1, $X_{i,\,b}$ contains the same set of regressors as in Eq. (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 percent quantiles are presented in Table 4. 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.[22]

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. Funding via bank deposits buttress bank stability particularly for the riskier banks whereas 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.

Overall, this section shows that certain bank characteristics—fast loan growth, size and unstable funding—prior to the crisis were consistently related to systematic risk and that their impact was non-lineal. 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.

3.2. Real estate developments

Since bank characteristics seem to predict the systemic dimensions of bank risk, it would be logical to understand whether there

Trading income. The new results (available upon request) do not show any major differences across the main sources of non-interest income.

[21] 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).

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

Table 5
Real Estate Beta and Bank Risk.
This table reports the results from regressions of several measures of bank risk on real estate beta and other bank characteristics. Column (I) reports the results of the probit regression using Government support as a measure of bank risk. Columns (II) to (V) contain the coefficients of regressions where bank risk is measured as Systematic and Systemic risk as well as two measures of Idiosyncratic risk respectively. See Section 2 for further details and Table 1 for variables' definitions. The dependent variables in column I is calculated as a dummy for the crisis period (2007Q4 to 2009Q4). Columns II to V are calculated as averages of quarterly data for individual banks during the crisis period (2007Q4 to 2009Q4). The variables accounting for Real estate beta, Size, Capital structure, Asset structure, Funding structure and Income structure are calculated as 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 (I)	Systematic risk (II)	Systemic risk (III)	Idiosyncratic risk1 (IV)	Idiosyncratic risk2 (V)
	Real estate beta	0.0662**	1.0971***	2.3576***	0.0042	0.0963
		(0.028)	(0.080)	(0.804)	(0.003)	(0.062)
	Size	0.0841***	0.1037**	0.5094***	0.0006	0.0873*
		(0.018)	(0.040)	(0.185)	(0.001)	(0.045)
Capital structure	Capital ratio	−0.0147***	−0.0136*	0.0210	−0.0003	−0.0084**
		(0.002)	(0.007)	(0.055)	(0.000)	(0.004)
	Undercapitalized	−0.0784**	−0.1082***	−0.1993	−0.1993	0.0156
		(0.033)	(0.023)	(0.148)	(0.001)	(0.035)
Asset structure	Loans to total assets	0.0072***	0.0033	0.0256**	0.0000	−0.0055
		(0.002)	(0.003)	(0.012)	(0.000)	(0.008)
	Securitization	−0.0077***	−0.1545	−0.0990	−0.0002	0.0101
		(0.002)	(0.111)	(0.221)	(0.003)	(0.089)
Funding structure	Short-term market funding	0.0084***	0.0068***	0.0363**	0.0001	−0.0032
		(0.003)	(0.002)	(0.017)	(0.000)	(0.006)
	Deposit funding	−0.0124***	−0.0139***	−0.0391*	−0.0003	−0.0249
		(0.002)	(0.004)	(0.021)	(0.001)	(0.021)
Income structure	Excessive loan growth	0.0445***	0.1336***	0.2727**	0.0004	0.0045
		(0.011)	(0.018)	(0.129)	(0.001)	(0.023)
	Non-interest income	−0.0033***	−0.0029	0.0012	−0.0002**	−0.0117
		(0.000)	(0.002)	(0.010)	(0.000)	(0.012)
	Constant	−2.5073***	−0.2926	−1.1668	0.0047	0.6502
		(0.879)	(0.323)	(1.340)	(0.008)	(0.905)
	No. of observations	483	483	483	483	483
	R^2	0.167	0.603	0.453	0.129	0.113
	Percent true positives/negatives	66.20/76.61				
	Percent correctly classified	74.8				
	Hosmer–Lemeshow test	7.83				
	Hosmer–Lemeshow test *p*-value	0.450				

is a major systemic driver leading to those bank characteristics. A natural candidate would be real estate developments which have been historically connected to the majority of systemic crises.

For this reason Table 5 incorporates to our baseline regression real estate beta as an additional bank characteristic. In fact real estate developments seem to be an important part of the narrative as this variable is strongly related to the systemic dimensions of bank risk and takes away some of the predictive power of other bank characteristics although size, excessive loan growth and unstable funding continue to predict realized bank risk.

Clearly real estate developments would also be expected to interact with bank characteristics as banks alter their business models to take advantage of profitable opportunities on the real estate business. Table 6 builds on Table 5 but also includes, progressively, the interactions between real estate beta and three key variables: excessive loan growth, deposit funding and capital ratio. Columns IV to VI add the interactions of real estate beta, excessive real estate loan growth, mortgage-backed securitization and capital ratio. It shows that excessive lending growth augments the impact of real estate betas on bank risk. That is, banks that "ride the real estate cycle" by lending more aggressively would typically end up with higher materialized risk. Mortgage-backed securitization seems to have a similar impact on bank risk when interacted with real estate betas. Interestingly the variable excessive loan growth continues to be a predictor of bank risk also by itself—i.e. not interacted with real estate. This suggests a key role for this variable as a central predictor of bank risk. As expected, concentrations on real estate business as measured by the real estate beta becomes a risk factor only during instances of housing bubbles (Table 7). During these periods, traditional excessive loan growth also seems to become a strong factor forecasting systemic risk. In short, loan growth and real estate exposure seem to be the two key variables that ought to be monitored by supervisors, particularly during housing bubbles.

3.3. Size

Larger institutions might benefit from an implicit guarantee as they might be considered "too-big-too fail" by supervisors. They probably have, as a result, an incentive to take on more risks than smaller institutions. In fact, most of our results (Tables 3 to 7) show a clear link between size and realized risk. Table 8 considers further the role of size by individuating the effect of systemically important banks as designated by supervisory authorities. It also assesses whether the effect of size on bank risk becomes stronger as exposure to real estate developments increases.

In Table 8 we interact the variable real estate beta with bank size (column I) to assess whether the role of too-big-to-fail on bank risk changes as real estate exposure changes. We also interact real estate beta with Sifi—a dummy variable designing systemically important financial institutions—(column II) as well as a triple interaction of real estate beta, Sifi and bank size (column III). Again the idea is to see if the designation of an institution as Sifi—which is closer to the concept accounting for Too-big-to-fail status than size—might lead to riskier strategies in connection to real estate developments and whether this connection changes as the size of the institution increases.

Columns IV, V and VI interact the variable Sifi with our usual key determinants of bank risk: Excessive loan growth, deposit funding and capital ratio. Systemic institutions designated as Sifis

Table 6
Real Estate Beta and Bank Characteristics.
This table reports the results from regressions of Systematic risk on real estate beta – also interacted with some key bank characteristics –, and bank characteristics. See Table 1 for variables' definitions. Columns (I) to (III) contain the coefficients of estimates of real estate beta interacted progressively with Excessive loan growth, Deposit funding and Capital. Columns (IV) to (VI) contain the coefficients of estimates of Real estate beta interacted progressively with Excessive real estate loan growth, Mortgage-backed securitization and Capital. The dependent variable in columns I to VI are calculated as averages of quarterly data for individual banks during the crisis period (2007Q4 to 2009Q4).The variables accounting for Real estate beta, Size, Capital structure, Asset structure, Funding structure, Income structure, Excessive real estate loan growth and Mortgage-backed securitization are calculated as 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.

		Bank risk					
		Systematic risk (I)	Systematic risk (II)	Systemic risk (III)	Systematic risk (IV)	Systematic risk (V)	Systematic risk (VI)
	Real estate beta * Excessive loan growth	0.1124***	0.1934***	0.2827***			
		(0.021)	(0.069)	(0.082)			
	Real estate beta * Deposit funding		−0.0066	−0.0126**			
			(0.005)	(0.006)			
	Real estate beta * Capital ratio			−0.3036**			
				(0.153)			
	Real estate beta * Excessive real estate loan growth				0.0188***	0.0180***	0.0198***
					(0.003)	(0.003)	(0.004)
	Real estate beta *Mortgage-backed securitization					0.0511**	0.0503**
						(0.021)	(0.021)
	Real estate beta * Capital ratio						−0.1852
							(0.132)
	Real estate beta	0.2318**	0.2893***	0.2927***	0.3829***	0.3469***	0.3538***
		(0.114)	(0.095)	(0.094)	(0.094)	(0.096)	(0.096)
	Size	0.0373	0.0347	0.0280	0.0849*	0.0941*	0.0950*
		(0.049)	(0.049)	(0.049)	(0.051)	(0.050)	(0.050)
Capital structure	Capital ratio	−0.0096	−0.0103	−0.0096	−0.0246**	−0.0217*	−0.0220*
		(0.011)	(0.011)	(0.011)	(0.012)	(0.012)	(0.012)
	Undercapitalized	−0.1049***	−0.1004***	−0.0923***	−0.1252***	−0.1169***	−0.1157***
		(0.026)	(0.027)	(0.027)	(0.026)	(0.026)	(0.026)
Asset structure	Loans to total assets	0.0019	0.0022	0.0017	0.0028	0.0026	0.0024
		(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
	Securitization	−0.1691	−0.1941	−0.2133	−0.1547	−0.1749	−0.1700
		(0.133)	(0.136)	(0.135)	(0.133)	(0.132)	(0.132)
Funding structure	Short-term market funding	0.0059	0.0063	0.0055	0.0077*	0.0064	0.0060
		(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
	Deposit funding	−0.0143***	−0.0140***	−0.0139***	−0.0150***	−0.0151***	−0.015***
		(0.004)	(0.004)	(0.004)	(0.005)	(0.004)	(0.004)
Income structure	Excessive loan growth	0.1919***	0.1914***	0.1922***	0.1546***	0.1425***	0.1410***
		(0.042)	(0.042)	(0.042)	(0.044)	(0.044)	(0.044)
	Non-interest income	−0.0031	−0.0034	−0.0034	−0.0030	−0.0027	−0.0029
		(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
	Constant	−0.5373	−0.5523	−0.5320	−0.5320	−0.1931	−0.1551
		(0.375)	(0.374)	(0.372)	(0.387)	(0.383)	(0.384)
	No. of observations	483	483	483	483	483	483
	R^2	0.580	0.586	0.593	0.576	0.587	0.590

might be able to operate riskier business models characterized by aggressive loan growth, less stable funding and a weaker capital position.

As expected the variable size is connected to systemic risk and its effect becomes larger as real estate beta increases. Yet, somewhat surprisingly, the designation of banks as systemically important financial institutions (Sifi) seems to add little predictive power to forecast realized risk. Also when interacted with some key bank characteristics. In fact, the value of the Sifi coefficient is negative at times.

3.4. Results before the crisis

The results for our baseline estimations also hold when our measures for bank risk are calculated before the crisis takes place. Specifically, 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. That is a year before the crisis erupted. The variables accounting for bank characteristics—including the real estate beta—are calculated as averages of quarterly data for individual banks during the 2003Q4 to 2005Q4 period. The idea is to ascertain whether the predictability of certain bank characteristics on bank risk also holds *before* a crisis takes place so that remedial measures could be taken before crises erupted. The use of pre-crisis information of all variables would also contribute to add consistency to our empirical findings as it is possible that divergences in the findings of the empirical literature might be due to the use of samples which might be subject to banking crises.

Interestingly, the new estimations suggest that bank characteristics clearly predicted bank risk also prior to the crisis and were particularly relevant to forecast the systemic and systematic components of risk.[23] The findings also hold the variable real estate beta is included on the analysis (Table 9). Hence bank characteristics are good at predicting 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 this line also, as systemic risks mostly induced in our case by real estate betas is probably the dimension of risk with the strongest importance from a supervisory standpoint, our findings strongly suggests that supervisors would need to be particularly watchful at taming risks for

[23] Results are available upon request.

Table 7
Housing Bubble, Bank Characteristics and Risk.
This table reports the results from regressions of Systematic risk on Housing Bubble interacted with some bank key characteristics, and bank characteristics. See Table 1 for variables' definitions. Columns (I) to (III) include the coefficients of Housing bubble interacted with Excessive loan growth, Deposit funding and Capital ratio. Columns (IV) to (V) include the interactions of Housing Bubble and Real estate beta. The dependent variable is calculated as averages of quarterly data for individual banks during the crisis period (2007Q4 to 2009Q4). The variables accounting for Size, Capital structure, Asset structure, Funding structure and Income structure are calculated as 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.

		Bank Risk				
		Systematic risk (I)	Systematic risk (II)	Systematic risk (III)	Systematic risk (IV)	Systematic risk (V)
	Housing bubble * Excessive loan growth	0.0570***	0.0534***	0.0519***		
		(0.007)	(0.015)	(0.015)		
	Housing bubble * Deposit funding		0.0005	0.0005		
			(0.002)	(0.002)		
	Housing bubble * Capital ratio			−0.0036		
				(0.010)		
	Housing bubble *Real estate beta				1.2592***	1.2858***
					(0.209)	(0.229)
	Real estate beta					−0.0262
						(0.070)
	Size	0.0891**	0.0867**	0.0867**	0.1364***	0.1389***
		(0.037)	(0.038)	(0.040)	(0.040)	(0.044)
Capital structure	Capital ratio	−0.0326***	−0.0330***	−0.0337***	−0.0203*	−0.0205*
		(0.010)	(0.010)	(0.010)	(0.011)	(0.011)
	Undercapitalized	−0.0320*	−0.0316*	−0.0332*	−0.0870***	−0.0870***
		(0.017)	(0.018)	(0.018)	(0.025)	(0.025)
Asset structure	Loans to total assets	−0.0013	−0.0015	−0.0016	−0.0019	−0.0019
		(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
	Securitization	−0.2339***	−0.2305***	−0.2323***	−0.1456	−0.1458
		(0.068)	(0.075)	(0.070)	(0.119)	(0.120)
Funding structure	Short-term market funding	0.0042	0.0041	0.0042	0.0065*	0.0065*
		(0.003)	(0.003)	(0.003)	(0.004)	(0.004)
	Deposit funding	−0.0114***	−0.0110***	−0.0113***	−0.0120***	−0.0119***
		(0.003)	(0.004)	(0.003)	(0.004)	(0.004)
Income structure	Excessive loan growth	0.1120***	0.1167***	0.1181***	0.0983***	0.0960**
		(0.031)	(0.036)	(0.037)	(0.034)	(0.039)
	Non-interest income	−0.0035	−0.0033	−0.0034	−0.0043	−0.0043
		(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
	Constant	−0.6402**	−0.6566**	−0.6482**	−0.9415***	−0.9494***
		(0.270)	(0.308)	(0.265)	(0.326)	(0.333)
	No. of observations	483	483	483	483	483
	R2	0.556	0.556	0.556	0.617	0.617

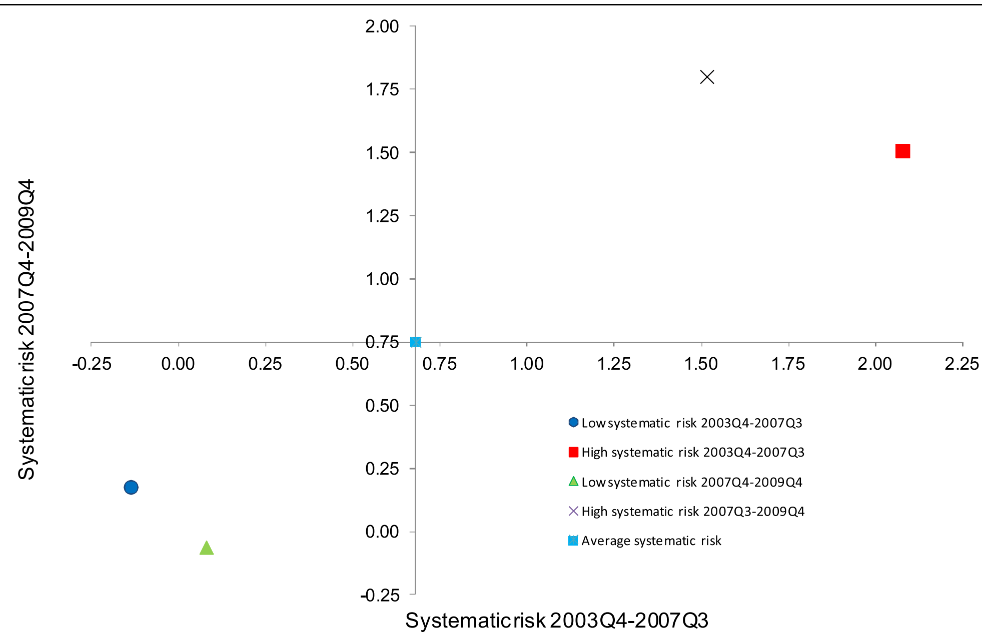

Fig. 2. Scatter plots of the systematic risk levels for the pre-and post-crisis periods.
On the X axis, the diagram below shows the 5 (i.e. low systematic risk) and 95 (i.e. high systematic risk) percentile values for the systematic risk variable during the pre-crisis period (2003Q4 to 2007Q3). Systematic 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).

Table 8
Real Estate Beta and Size.
This table reports the results from regressions of Systematic risk on real estate beta – also interacted with some key bank characteristics –, and bank characteristics. See Table 1 for variables' definitions. Columns (I) to (III) contain the coefficients of estimates of real estate beta interacted progressively with Excessive loan growth, Deposit funding and Capital. Columns (IV) to (VI) contain the coefficients of estimates of Real estate beta interacted progressively with Excessive real estate loan growth, Mortgage-backed securitization and Capital. The dependent variable in columns I to VI are calculated as averages of quarterly data for individual banks during the crisis period (2007Q4 to 2009Q4).The variables accounting for Real estate beta, Size, Capital structure, Asset structure, Funding structure, Income structure, Excessive real estate loan growth and Mortgage-backed securitization are calculated as 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.

		Bank Risk					
		Systematic risk (I)	Systematic risk (II)	Systematic risk (III)	Systematic risk (IV)	Systematic risk (V)	Systematic risk (VI)
	Real estate beta * Size	0.2750***					
		(0.091)					
	Real estate beta *Sifi		−1.3387*				
			(0.750)				
	Real estate beta * Sifi * Size			−0.2354*			
				(0.127)			
	Sifi * Excessive loan growth				0.0123		
					(0.042)		
	Sifi * Deposit funding					0.0050	
						(0.004)	
	Sifi * Capital ratio						0.0188
							(0.041)
	Real estate beta	0.9652***	0.6925***	0.6559***			
		(0.229)	(0.204)	(0.211)			
	Sifi				−0.3266*	−0.7371***	−0.4185***
					(0.178)	(0.247)	(0.135)
	Size	0.0752*	0.0830	0.0883*	0.1742***	0.2025***	0.1589***
		(0.042)	(0.052)	(0.053)	(0.034)	(0.033)	(0.034)
Capital structure	Capital ratio	−0.0117**	−0.0255**	−0.0246**	−0.0226***	−0.0258***	−0.0220**
		(0.006)	(0.012)	(0.012)	(0.006)	(0.009)	(0.009)
	Undercapitalized	−0.0959***	−0.1127***	−0.1120***	−0.0604***	−0.0739***	−0.0640***
		(0.023)	(0.027)	(0.028)	(0.013)	(0.019)	(0.019)
Asset structure	Loans to total assets	0.0032	−0.0027	−0.0008	0.0041*	−0.0002	0.0028
		(0.003)	(0.004)	(0.003)	(0.002)	(0.003)	(0.003)
	Securitization	−0.1960	0.0178	−0.0301	−0.1397	−0.2681***	−0.2132***
		(0.133)	(0.111)	(0.115)	(0.089)	(0.067)	(0.054)
Funding structure	Short-term market funding	0.0068***	0.0012	0.0038	0.0080***	0.0032	0.0065**
		(0.003)	(0.004)	(0.004)	(0.001)	(0.003)	(0.003)
	Deposit funding	−0.0133***	−0.0166***	−0.0154***	−0.0232***	−0.0290***	−0.0240***
		(0.004)	(0.005)	(0.005)	(0.003)	(0.003)	(0.003)
Income structure	Excessive loan growth	0.1487***	0.1393***	0.1402***	0.1061*	0.1309***	0.1411***
		(0.026)	(0.046)	(0.046)	(0.055)	(0.027)	(0.029)
	Non-interest income	−0.0032*	−0.0001	−0.0001	−0.0030**	−0.0038*	−0.0045**
		(0.002)	(0.003)	(0.003)	(0.001)	(0.002)	(0.002)
	Constant	−0.3962	0.1413	−0.0422	−0.1305	0.1678	−1.2532***
		(0.350)	(0.441)	(0.401)	(0.393)	(0.282)	(0.261)
	No. of observations	483	483	483	483	483	483
	R2	0.604	0.522	0.592	0.470	0.525	0.519

banks with certain characteristics. In a way, our findings provide supportive evidence at the microeconometric level to the Reinhart and Rogoff's (2009) macroeconomic results.

An important practical implication of our findings is that banks with high systemic and systematic risk prior to the crisis would also be those institutions with relatively high materialized risk during the crisis. Fig. 2 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 percent (i.e. low systematic risk) and 95 percent (i.e. high systematic risk) percentiles. On the Y axis, the diagram shows the 5 percent (i.e. low systematic risk) and 95 percent (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. A similar picture appears when real estate beta is used instead of systematic risk vouching for the predictability of stock-market based indicators of systemic crisis related to real estate developments.

4. Robustness

Strictly speaking, the results presented in earlier sections are 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 have characteristics linked to a riskier profile, 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 to policy makers, 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 correctly 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

Table 9
Before the Crisis: Real Estate Beta and Bank Risk.
This table reports the results from regressions of several measures of bank risk before the 2007–2009 crisis on real estate beta and other bank characteristics. Columns (I) to (V) contain the coefficients of regressions where bank risk is measured as Systematic, Systemic risk, Structural Credit risk as well as two measures of Idiosyncratic risk. See Section 2 for further details and Table 1 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 Real estate beta, Size, Capital structure, Asset structure, Funding structure and Income structure are calculated as 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.

		Bank Risk			
		Systematic risk (I)	Systemic risk (II)	Idiosyncratic risk1 (III)	Idiosyncratic risk2 (IV)
	Real estate beta	0.6114**	0.6981*	0.0061	0.0231
		(0.286)	(0.394)	(0.028)	(0.027)
	Size	0.1645***	0.2736***	−0.0092	0.0109***
		(0.026)	(0.017)	(0.008)	(0.003)
Capital structure	Capital ratio	−0.0308**	−0.0450***	0.0018	0.0016
		(0.014)	(0.010)	(0.001)	(0.001)
	Undercapitalized	−0.1111***	−0.0089	0.0043	−0.0076
		(0.024)	(0.036)	(0.005)	(0.005)
Asset structure	Loans to total assets	0.0079*	0.0052***	−0.0001	−0.0001
		(0.004)	(0.002)	(0.001)	(0.000)
	Securitization	−0.1846*	−0.1083	0.0111	−0.0042
		(0.100)	(0.255)	(0.025)	(0.014)
Funding structure	Short-term market funding	0.0162***	0.0137***	−0.0001	−0.0004
		(0.005)	(0.004)	(0.001)	(0.000)
	Deposit funding	−0.0170***	−0.0180***	0.0011	−0.0004
		(0.005)	(0.005)	(0.001)	(0.000)
Income structure	Excessive loan growth	0.0269*	0.0182	−0.0020	0.0000
		(0.014)	(0.012)	(0.002)	(0.001)
	Non-interest income	−0.0015	−0.0048	0.0004	−0.0005
		(0.003)	(0.004)	(0.000)	(0.000)
	Constant	−0.8781*	−1.0554***	0.1010*	−0.0943***
		(0.496)	(0.231)	(0.055)	(0.028)
	No. of observations	483	483	483	483
	R^2	0.261	0.382	0.111	0.227

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 monitored by supervisors and eventually asked to reduce their overall level of risk.

These considerations notwithstanding, we address endogeneity concerns by including additional control variables in the main regressions additional variables capturing banks' profitability, corporate governance, and major macroeconomic variables (GDP, house prices, stock market returns) and results are qualitatively similar to our baseline specification.[24]

Analogously, further estimations also vouch for the robustness of the results for the estimations including information on bank risk for the pre-crisis period. We also account for the possible (lurking) effect of possible long-lived risk-taking preferences of individual banks on our findings that affect both banks' characteristics 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).[25]

An alternative strategy to tackle endogeneity concerns is to split the sample 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. There is evidence suggesting that 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 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.[26]

As an additional robustness test we ran an instrumental variable regression for systematic risk, using as instruments the average balance sheet variables of other banks in the country, as suggested by Laeven and Levine (2009).[27] 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. We find that our results remained unaffected. Finally our results were also robust to the use of the variable *EDF* as an alternative measure of bank risk (described in detail in Section 2.1).[28]

5. Conclusion

In the years prior to the 2007–2009 crisis, most forward-looking indicators of bank risk clustered and suggested an unusually benign outlook. 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 following aggressive credit expansion policies, with unstable funding and large size in the years before the crisis experienced more troubles after Lehman's default. We also show that the impact of these characteristics consistently predicts systemic but not idiosyncratic bank risk.

Exposure to real estate developments seems to be a major driver of bank risk: We consistently find that that banks with high levels of real estate beta exhibited higher levels of realized risk during the financial crisis. We also show that the link between real estate beta and risk is stronger for larger banks that undertook ag-

[24] Results are available upon request.
[25] 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.
[26] Results are available upon request.
[27] Results are available upon request. For US banks we have considered a breakdown at state level.
[28] Results are available upon request.

gressive credit growth policies in the presence of housing bubbles. We also find that those bank characteristics that were related to risk as materialized during the crisis were useful to predict bank risk also before the financial crisis erupted.

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