Determinants of Systemically Important Banks: The Case of Europe[*]

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Abstract

We investigate the drivers of systemic risk and contagion among European banks from 2007 to 2012. First, we derive a systemic risk measure from the concepts of MES and CoVaR analysing tail co-movements of daily bank stock returns. We then run panel regressions for our systemic risk measure using idiosyncratic bank characteristics and a set of country and policy control variables. Our results comprise highly significant drivers of systemic risk in the European banking sector with important implications for banking regulation.

Keywords: too big to fail; systemic risk; determinants; financial crisis; bank; SIFI; Europe

JEL classification: G01; G21; G28

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1 Introduction

Which factors determine the systemic importance of European banks? With the most recent financial crises, interest in the concept of systemic risk has grown. In this paper, we investigate the drivers of systemic risk[1] in the European financial sector as well as contagion[2] among banks. To this end, we propose a novel measure of systemic risk – the Systemic Risk Index (*SRI*) –to capture the impact a single financial institution has on the financial sector and vice versa. The topic of our paper is f considerable interest for regulators and economists, because our results offer new insights into the drivers of financial instability and provide implications for the macroprudential regulation of banks.

Financial systems as a whole tend toward instability. This is due to the fragile nature of their players, especially banks. Because of their role as a financial intermediary (or delegated monitor), their opaqueness, their interconnectedness, and the typical characteristics of their lenders, banks are particularly prone to infecting other banks with financial distress – or to being infected by them. This in particular holds for those banks that almost certainly and rather quickly could destabilise the system as a whole: so-called systemically important financial institutions (SIFIs). Consequently, the identification of drivers of systemically important banks (SIBs) is of vital importance. Recent papers on systemic risk of banks produced substantial findings. Existing literature in this field, however, is comparably young and leaves questions unanswered: (1) First, it is unclear how to identify systemically important banks. (2) Second, there is no consensus on how to measure their potential negative

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1 Systemic risk is the risk "that cumulative losses will accrue from an event that sets in motion a series of successive losses along a chain of institutions or markets comprising a system… That is, systemic risk is the risk of a chain reaction of falling interconnected dominoes" (Kaufman, 1995). Essentially, we follow this idea by measuring the contagion from banks to the financial system and vice versa. The European Systemic Risk Board/European Commission (2010) defines systemic risk as the risk of disruption in the financial system with the potential to have serious negative consequences for the internal market and the real economy. Similarly to this idea, Acharya et al. (2011) and Adrian and Brunnermeier (2011) quantify systemic risk by measuring a bank's (risk) contribution to the overall financial system. For a list of further possible definitions of systemic risk in the literature, see Prokopczuk (2009).

2 Banking contagion, concentrating on the transmission of a bank shock to other banks or the financial system, lies at the heart of systemic risk. Long before the recent financial crises, Bagehot (1873) diagnoses as follows: "In wild periods of alarm, one failure makes many, and the best way to prevent the derivative failures is to arrest the primary failure which causes them".

impact on the system. (3) Third, it is unknown which macroprudential regulations for systemically important banks are most effective without hampering free market forces. We contribute to the closing of the research gaps by using innovative key indicators for systemic risk. The remainder of this paper is organised as follows:

Section 2 offers a review of related literature on systemic risk (of European banks) as our background and starting point. The subsequent section 3 explains our sample selection. Section 4 depicts the design of our research. The presentation of our results follows in section 5, while section 6 concludes our findings.

2 Related literature

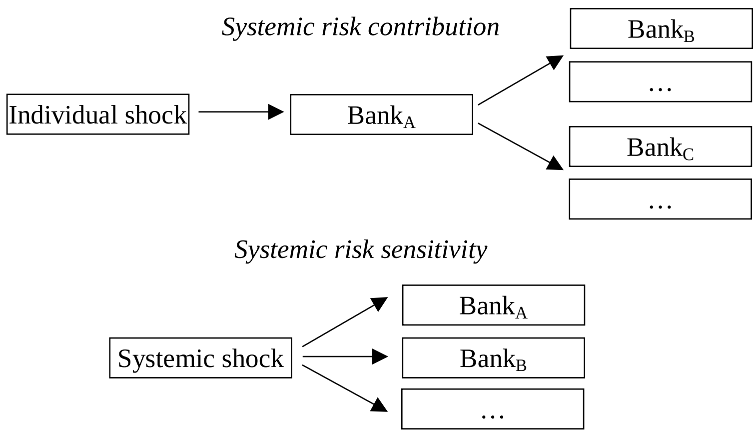
In this section, we briefly discuss the related theoretical and empirical literature on drivers of systemic risk in the European banking sector.

The first step for the identification of drivers of systemic risk is the assessment of systemic risk levels. The number of measures for systemic risk has grown rapidly in recent years[3]. The literature can be divided into the streams of (1) *systemic risk contribution* and (2) *systemic risk sensitivity* (see e.g. Prokopczuk, 2009) as illustrated in Figure 1. Approaches for *systemic risk contribution* try to determine systemic importance by measuring a single institution's contribution to systemic risk. Those measures assess how one institution affects others. According to this understanding, it is of particular interest to avoid and mitigate contagion effects. Conversely designed measures dealing with the (2) *systemic risk sensitivity* try to determine systemic importance by measuring the extent to which a single institution is affected in the case of a systemic event. The overall functioning of the financial system and individual institutional resilience is the focus of this approach. Table 1 summarises a selection of popular systemic risk measures for financial institutions from both streams. Considering both approaches, we combine a measure for systemic risk contribution (related to ΔCoVar by

[3] Bisias et al. (2012) provide a survey of systemic risk measures.

Adrian and Brunnermeier, 2011) and a measure for the systemic risk sensitivity (related to MES by Acharya et al., 2011) based on banks' stock returns as presented in section 4.1.

Figure 1. Systemic risk contribution and sensitivity



This figure illustrates the two different contagion channels of systemic risk

The second step for the identification of drivers of systemic risk is to run panel regression analyses with different potential factors from the micro or macro level that may affect systemic risk. Previous papers arrive at the following findings: Applying the *ΔCoVar* (*systemic risk contribution)* approach, Bori et al. (2012) find that market-based variables are strong predictors for systemic risk in Europe. Their results show that institutional factors like size and leverage contribute significantly to banks systemic risk. Furthermore, the concentration of the banking system increases systemic risk. Following a *ΔCoVar*-related approach, Hautsch et al. (2014) find that unlike leverage and funding risk (measured by maturity mismatch), size is not a dominant factor among European banks.

Based on the *SRISK* measure (*systemic risk sensitivity approach*), Engle et al. (2012) find that banks account for approximately 80% of the systemic risk in Europe, with UK and French institutions bearing the highest levels of systemic risk. With an enhanced version of the *MES* and hand-collected data of European banks, Acharya and Steffen (2014) find that banks' sovereign debt holdings are major contributors to systemic risk. Based on contingent claims

Table 1. Systemic risk sensitivity and systemic risk contribution: Measures of systemic risk

Systemic risk contribution How does a single institution contribute to systemic risk?		*Systemic risk sensitivity* To what extent is a single institution affected by systemic risk?	
ΔCoVar	captures the marginal contribution of a particular institution (in a non-causal sense) to the overall systemic risk by applying quantile regressions (Adrian and Brunnermeier, 2011)	*Marginal Expected Shortfall (MES)*	determines the level of systemic risk by measuring an institution's losses (in terms of negative index returns) when the (financial) system as a whole is doing poorly (Acharya et al., 2011)
Co-Risk	analyses the tails of the default distributions for pairs of institutions, or − to put it simply − it analyses how the default risk of an institution affects the default risk of another institution (Chan-Lau, 2010)	*SRISK*	is an index formed by the leverage, size and the MES of a firm (Brownlees and Engle, 2012)
Granger Causality	measures the directionality of relationships or causality of price movements of securities issued by financial institutions (Billio et al., 2012)	*Lower Tail Dependence (LTD)*	is a measure of the propensity of a single financial institution to experience joint extreme adverse effects (measured in price returns) with the market (Weiß et al., 2014)
Principal Component Analysis (PCA)	is a technique to decompose asset returns of a sample of financial institutions into linkages between those institutions (León and Murcia, 2013)	*Contingent Claims Analysis (CCA)*	measures systemic solvency risk based on market-implied expected losses of financial institutions by generating aggregate estimates of the joint default risk of multiple institutions as a conditional tail expectation (Jobst and Gray, 2013)

This table summarises a selection of common systemic risk measures for financial institutions from the *systemic risk sensitivity* and *systemic risk contribution* streams.

analysis, Vallascas and Keasey (2012) find several key drivers of systemic risk of European banks like high leverage, low liquidity, size, and high non-interest income. Using a comparable methodology, Varotto and Zhao (2014) confirm the positive impact of size and leverage on systemic risk for a set of European banks. Black et al. (2013) propose a sensitivity-related risk measure for systemic risk, and find significant correlations with accounting- and market-based bank-specific measures of European banks: They confirm that systemic risk increases with bank size. Interestingly, they also find that European banks with a more traditional lending business and more liquid assets are less likely to increase systemic risk. Lastly, they find that bank profitability has no impact on systemic risk, and that the market-to-book ratio has an influence on banks' systemic risk in Europe that can be either positive or negative.

3 Sample selection

We start by selecting a representative sample of European banks. To obtain a testable sample of systemically relevant banks in the European Union, we use the 2014 European Banking Authority (EBA) EU-wide stress-test sample of banks (European Banking Authority 2014), as it includes quantitative and qualitative selection criteria. The bank selection is based on asset value, importance for the economy of the country, scale of cross-border activities, and whether the bank requested/received public financial assistance[4]. This initial EBA sample contains 123 banks/bank holdings from 22 countries[5]. In order to calculate our systemic risk proxy, we collect share-price data of the publicly listed banks from the EBA sample from *Thomson Reuters Financial Datastream*. However, for a variety of reasons, many European banks are not publicly listed, or are listed but not traded in actuality. Hence, their stocks exhibit constant prices over long periods and trading volumes slightly above zero. After

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4 The newer, but slightly shorter European Central Bank list of "significant" supervised entities from September 2014 is equal to the EBA 2014 list – with a few exceptions (European Central Bank 2014). We do not use this list since it does not include UK banks.

5 Namely Australia, Belgium, Cyprus, Denmark, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Luxemburg, Malta, the Netherlands, Norway, Poland, Portugal, Slovenia, Spain, Sweden, and the United Kingdom.

excluding those bank shares with more than 25% zero daily returns for the analysed periods, approx. 60 banks remain for each observed year. Lacking or inconsistent accounting data necessitate the exclusion of a further number of banks,[6] so that we finally produce a full sample (unbalanced panel) of 334 bank observations for the period from 2007 to 2012 (see Table 2). Our sample includes 14 of the 24 European banks that failed the EBA stress test at the end of Oct. 2014 (see European Banking Authority, 2014 and Appendix Table 6). The full bank sample as a balanced panel with 294 observations is used for robustness checks (Appendix Table 3).

Table 2. Bank sample distribution

Year	2007	2008	2009	2010	2011	2012	2013	Total
Banks	56	58	56	57	54	55	53	334

The table presents the distribution of European banks we analyse in our sample. The distribution per country is reported in Appendix Table 5. Appendix Table 6 provides the names of all banks included in the sample.

4 Research design

To measure systemic risk in the European banking system, we combine the *contribution* and *sensitivity* approach used by recent literature (Guerra et al., 2013; Bongini and Nieri, 2014)[7] and propose a new risk measure, the *systemic risk index* (*SRI*), to capture both equally. From the point of view of the method of first measuring the systemic risk of a bank, our paper is most closely related to Adrian and Brunnermeier (2011) and Acharya et al. (2011). Second, to analyse determinants on systemic risks, we make use of the approaches elaborated by Acharya and Steffen (2014) and Weiß et al. (2014).

6 We manually check missing accounting values, finding and adding most of them. In some cases, however, we do not find the necessary data, which may bias our results since balance sheet composition may affect the bank opacity, see Flannery et al. (2013). In a recent paper on bank opaqueness, Mendonça et al. (2013) find that a decrease in bank opaqueness fosters an environment favourable to the development of a sound banking system and the avoidance of financial crises.

7 The variety of systemic risk measures is growing fast: Bisias et al. (2012) and Billio et al. (2012) provide overviews of systemic risk measures in the finance literature.

4.1 Systemic Risk Index – measuring system risk

When the banking system is in distress, losses and liquidity shortages spread from one bank to others, finally affecting the system as a whole (Hauptmann and Zagst 2011). To analyse the role of a single bank in closely knit and, thus, contagious networks, Adrian and Brunnermeier (2011) propose the $CoVaR$, which is the value at risk (VaR) of the banking system conditional on an institution being in distress. The $CoVaR$ follows the *systemic risk contribution approach*: It is meant to capture the bank-specific potential for spreading financial distress from a single institution *i* across the banking system *Sys* by gauging the tail co-movement of the financial system with the institution's stock (Adrian and Brunnermeier, 2011). The $CoVaR$, however, does not satisfactorily capture the tail co-movement of the banking system and a single bank, since it ignores observed values within the tail.[8] Conceptually, we follow the $CoVaR$ approach to a large extent, but avoid its shortcomings by proposing the measure SRC – the systemic risk contribution – which considers the co-movement of the banking system returns and individual bank returns within tails. Recall that VaR_q^i − the value at risk of an institution's stock with the return r^i − is implicitly defined as the q-quantile: $P\left(r^i \leq VaR_q^i\right) = q$. It measures the minimum return r^i of an institution's stocks within the $1 - q\%$ confidence interval within a certain period of time (usually one year).

By the systemic risk contribution – SRC_q^i – we denote the average return of a banking system relative to an institution return i conditional on the institution's return r^i being below its value at risk $\left(VaR_q^i\right)$:

$$SRC_q^i := E\left[\frac{r^{Sys}}{r^i}\middle| r^i \leq VaR_q^i\right] = E\left[\frac{r^{Sys}}{r^i}\middle| {r^i}_{q=5\%}\right], \tag{1}$$

with r^{Sys} denoting the return of the banking system.[9]

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[8] This criticism is similar to the general criticism of the VaR.

[9] Theoretically, r^i could be equal to zero and, for that case, formula (1) would not work. This case is, however, hardly possible in practice as an average of the worst stock return observations is unlikely to be zero.

Generally defined, the SRC_q^i measures the reaction of the banking system at the q% worst days of a certain bank's stocks within one year.[10] . In other words, an $SRC_{5\%}^i$ of 0.5 would mean that the average return of the banking system r^{Sys} would be positively associated with a coefficient of 0.5 with an institution's stock returns r^i, when the respective institution's losses exceeds their VaR limit.To put it simply: When the institution's stocks decline by e.g. 6% on average during the worst 5% of days within one year, we expect the banking system's stocks to decline by 3% on those days.

The SRS (systemic risk sensitivity) measure follows the *systemic risk sensitivity approach*: It captures the banking systems' return r^{Sys} when a single institution *i* is in distress. The *SRS* we propose is very closely related to the marginal expected shortfall (MES) employed by Acharya et al. (2011). Instead of measuring absolute values, we put the banking system's losses in relation to the institution's losses. Finally, since we use average values we improve the explanatory power of the MES by better capturing the tail co-movement of a single institution and the banking system. Analogously to SRC_q^i, we denote by systemic risk sensitivity, SRS_q^i, the average return of a bank i relative to a banking system return conditional on the banking system's return r^{Sys} falling below its value at risk $\left(VaR_q^{Sys}\right)$[11]:

$$SRS_q^i := E\left[\frac{r^i}{r^{Sys}}\middle| r^{Sys} \leq VaR_q^{Sys})\right] = E\left[\frac{r^i}{r^{Sys}}\middle| r^{Sys}{}_{q=5\%}\right]. \tag{2}$$

An $SRS_{5\%}^i$ of 0.5 would mean that the respective institution's mean stock return r^i would be positively associated with the banking system's return r^{Sys}, with a coefficient of 0.5 when the banking system's losses exceed their VaR limit. In other words, when the banking system's stocks decline by, e.g. 6% on average during the worst 5% of days within one year, we would expect the institution's stocks to decline by 3% on those days.

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[10] We derived the *SRC* from the *CoVaR* measure proposed by Adrian and Brunnermeier (2011).

[11] We derive the *SRS* from the *MES* measure proposed by Acharya et al. (2011).

At the final stage, we average the SRC_q^i and SRS_q^i to obtain our *systemic risk index* SRI_q^i for financial institutions, which considers both directions of risk transmission and contagion equally[12]:

$$SRI_q^i := \frac{SRC_q^i + SRS_q^i}{2}. \tag{3}$$

For the remainder of the paper, for q we will use the 5% quantile and simplify the notation to SRI^i. The *systemic risk index* SRI^i is a good convention for approximating the practical requirements of regulators and theoretical models on the systemic importance of financial institutions. It demonstrates both how a single bank affects the financial system and how it can be affected by that system. Furthermore, SRI is based on well-known statistical measures of risk, and the results – expressed in natural units – allow for an interpretation from an economic point of view. To demonstrate that the value at risk is not equal to our systemic risk index, we plot VaR^i (with reverse signs) against the SRI^i for our sample of European banks (see Figure 2): It illustrates that there is only a very weak link between the individual (idiosyncratic) risk of the institutions we analyse, measured by VaR^i (abscissa), and the institutions' systemic risk, measured by SRI^i (ordinate). There is only a weak, statistically insignificant correlation between the VaR^i and SRI^i of -0.0322 (p-value <0.583). The observed SRI^i is also more stable since its mean coefficient of variation (0.201) is lower than in the case of the VaR^i (0.380). Finally, the issue of choosing an appropriate index for calculating our *SRI* measure is not trivial (Benoit, 2014). As our aim is to estimate systemic risk in the European financial sector, we use the *MSCI Europe Financials Index*. This value-weighted equity index captures around 100 large and mid-cap entities across 15 countries in

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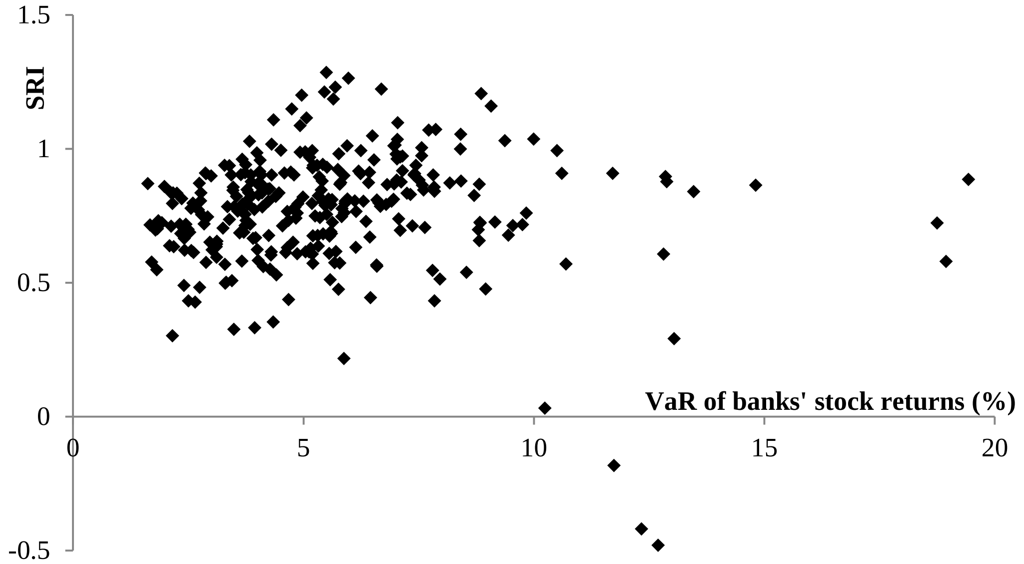
12 Since we understand the *SRI* as an index, we use equal weighting of *SRC* and *SRS*. Instead of the arithmetic, other weightings like the geometric mean could also be applied. We believe, however, that the economic interpretation of the *SRI* would not benefit from this.

Europe from the banking, financial services, insurance, and real estate sectors.[13] We provide a robustness check for our results using the *EU Datastream Banks Index* (Appendix Table 4).

Figure 2. VaR of banks' stock returns (in %) and SRIs (2007-2012).



The figure presents a comparison of the value at risk (*VaR*) and the systemic risk index (*SRI*) for the sample of European banks.

4.2 Bank characteristics as determinants of systemic risk

The purpose of our study is to identify sources for systemic risk of banks in Europe. With this paper, we investigate the extent to which panel regressions could explain why some banks have a higher influence on financial market stability than others.[14] With this objective in mind, we collect a dataset on idiosyncratic bank characteristics as well as information concerning countries' regulatory environments and macroeconomic conditions. The data on banks' cash flows, balance sheets, and profit or loss statements is obtained from *Thomson Reuters Worldscope* (for a full variable definition, see Appendix Table 1). Where available, we fill data gaps manually with data from banks' websites.

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13 The *MSCI Europe Financials Index* (Datastream code: M1URFNE) offers the best available coverage for the European financial sector. We also create our own indices by value weighting the stock returns of all banks in our samples (as proposed by e.g. Weiß et al., 2014), leading to the same core results for our regression. However, as we are more interested in analysing the determinants for systemic risk in the European financial sector as a whole, those results are not presented in this paper.

14 Interestingly and in contrast to most of the literature, Dungey et al. (2012) find cases where firm characteristics make little difference to the systemic risks of banks.

Our first explanatory variable is *SIZE*, which is defined as the decimal logarithm of a bank's total assets. Large banks may be better diversified and carry less *individual* (idiosyncratic) risk. However, large banks are more closely connected to and within the financial system through interbank liabilities and other exposures to the financial system, making them particularly hard to replace (Basel Committee on Banking Supervision, 2013)[15]. Additionally, banks deemed "too big to fail" are thought to receive implicit state guarantees, so that subsequent bailout expectations increase the risk appetite of banks enjoying this governmental support, as protected actors feel less incentivised to apply market discipline (Gropp et al., 2014; Kleinow and Horsch, 2014). Therefore, we expect bank size to have a positive influence on systemic risk.

To describe the type of business a bank is mainly engaged in on the asset side and the level of revenue diversification, we obtain data on banks' share of total loans to total assets (*LOAN*) – loan ratio – and the share of non-interest income to total income (*NON_INT*). Although employing different approaches, both are indicators for the banks' dependency on – riskier – non-commercial-banking activities such as investment banking or trading. In contrast, it is also argued and empirically supported in the literature that low ratios of total loans to total assets and relatively high non-interest incomes are an indicator of innovative business models, better diversification and, as a consequence, lower systemic risk exposures (see e.g., Laeven and Levine, 2007; Demsetz and Strahan, 1997; Morgan and Stiroh, 2005). However, for the case of small banks in countries with more private/asymmetric information, De Jonghe et al. (2014) show that the "bright side of innovation" disappears – a situation that is less likely in Europe. Consequently, from literature we cannot derive a clear hypothesis of the impact of *LOAN* and *NON_INT* on systemic risk. To control for the influence of a bank's loan portfolio quality (credit risk), we use *NON_PERF* – the share of loan loss provisions to the total book value of loans – as an explanatory variable in our regression. We assume that *NON_PERF* captures the risk level of a bank's loan portfolio, and we expect banks with riskier loan portfolios to affect the financial system more negatively than others.

[15] The BCBS uses exposures (a method comparable to our *SIZE*) as an indicator of systemic importance.

In order to measure the influence of banks' capital structure, we include *LEVERAGE* and *DEPOSIT* in our regression. For *LEVERAGE*, i.e. the ratio of debt to equity, we expect a clear positive relationship with the systemic risk a bank poses on the financial system, because higher leverage means higher default risks due to a smaller cushion that could absorb losses, as well as a higher ratio of fixed expenses. As a proxy for the banks' liability portfolio and business type, we utilise *DEPOSIT*, i.e. the ratio of total deposits to total liabilities. Traditional commercial banks with a focus on non-securitised savings and loan business usually have high deposit ratios. In particular, banks with high deposit ratios are financed less via securities or by the capital market in general. Therefore, they are less connected to other banks or other institutional investors. For these reasons, we expect *DEPOSIT* to have a negative influence on banks' systemic risk.

A further variable we use is the regulatory measure *TIER1* ratio (or Basel core capital ratio), which is the ratio of core equity capital to total risk-weighted assets, measuring the capacity of loss absorption. According to bank regulators, a high *TIER1* ratio indicates that the bank is in a solid state. In this scenario, we would expect a negative impact on a bank's systemic risk. On the contrary, banks that are forced to have a higher regulatory coverage ratio may also be incentivised to take even more risk, because they do not internalise the negative realisations of tail risk projects (Perotti et al., 2011).

Another bank-specific variable we consider for our panel regression is *LIQUIDITY* (the ratio of cash and tradable securities to total deposits). A large portion of cash and security reserves is probably advantageous at times of negative shocks in the financial system, when interbank markets easily dry out and liquidity becomes scarce (e.g. Brunnermeier, 2009). According to this account, *LIQUIDITY* is expected to decrease systemic risk. *FIN_POW*, the ratio of net cash flow of operating activities to total liabilities, is also a proxy for liquidity risks and indicates the time banks need to settle their total liabilities with their operating cash flow. Similarly to *LIQUIDITY*, we expect a negative influence on systemic risk.

Next, we control for the influence of banks' profitability on systemic risk by employing the operating profit margin – *OP_MARG* – (the ratio of operating income to net sales) and the rather capital-oriented return on invested capital (*ROIC*). In principle, as Weiß et al. (2014) argue, both measures could be coincident with stability or risk: High values of *OP_MARG* or *ROIC* could shield from the risk of defaulting, so that those banks could be a pillar of stability. Higher profitability, on the other hand, could also be the result of extended yet successful engagement in risky lending/non-lending activities, which may suddenly cause or contribute to the bank's – as well as general systemic – instability. Therefore, we expect an undirected effect on systemic risk. The same is true for *INCOME*, the annual growth of income (mainly consisting of interest and fees – for a full variable definition, see Appendix Table 1). We consider it a good proxy for bank activity growth, since it is comparatively less vulnerable to accounting manipulations.

Next, we employ the ratio of the market capitalisation to the book value of the bank's common equity: market-to-book ratio – MBR. A high MBR can be an indicator of disproportionately high expectations for earnings prospects on the side of investors. High earning prospects are normally associated with higher risks. In most cases, this development is intensified by bank managers ("empire building"), since they are incentivised toward excessive risk taking in order to increase firm value to form a "glamour bank", as Weiß et al. (2014) argue. Following a different line of thought, Demsetz et al. (1996) argue that a high market-to-book ratio helps to reduce excessive risk taking, because banks have a great deal to lose if a risky business strategy leads to insolvency. However, this may not or may less strongly apply to banks deemed "too big to fail" due to their increased appetite for risk. Overall, we expect the MBR ratio to affect systemic risk, even though the direction is indecisive. The last bank-specific variable we consider is the banks' long-term rating (LTR). Due to data gaps in bank rating histories, we first collect the long-term ratings from Moody's and fill missing values with hand-collected rating data from S&P's and Fitch. We use an 18-notch rating scale. For numerical reasons, values from 0 to 1 in steps of $\frac{1}{18}$ are assigned, with

0 denoting AAA (the highest rating) and 1 denoting D (default)[16]. The mean LTR value of 0.276 *in* Table 3 therefore indicates the relatively high mean rating of A for the banks in the sample. We expect (the assessment of) individual banks' default probability to have an increasing effect on systemic risk, and so LTR should positively affect systemic risk.

Table 3: Summary statistics for bank characteristics

Variable	Exp. influence	Symbol	Obs.	Mean	Median	Std.dev.	Min	Max
Size	+	*SIZE*	334	11.160	11.094	0.680	9.530	12.483
Loan ratio	+/-	*LOAN*	334	0.640	0.670	0.152	0.110	0.909
Non-interest income ratio	+/-	*NON_INT*	334	0.452	0.381	0.351	-0.157	2.807
Non-performing loan ratio	+	*NON_PERF*	334	0.010	0.007	0.011	-0.006	0.100
Leverage ratio	+	*LEVERAGE*	334	6.922	6.635	16.797	-231.857	99.737
Deposit ratio	-	*DEPOSIT*	334	0.459	0.444	0.184	0.038	0.964
Tier 1 ratio	+/-	*TIER1*	334	0.102	0.100	0.031	-0.073	0.189
Liquidity ratio	-	*LIQUIDITY*	334	0.969	0.693	0.952	0.048	9.077
Financial power	-	*FIN_POW*	334	0.064	0.043	0.073	0.002	0.545
Operating margin	+/-	*OP_MARG*	334	0.064	0.092	0.203	-1.670	0.440
Return on invested capital	+/-	*ROIC*	334	0.025	0.023	0.048	-0.294	0.354
Income growth	+/-	*INCOME*	334	0.186	0.016	2.761	-0.798	50.221
Market-to-book ratio	+/-	*MBR*	334	0.934	0.780	0.698	-2.350	4.410
Long-term rating	+	*LTR*	334	0.276	0.222	0.179	1.000	0.889

The table presents descriptive statistics for bank-specific financial data (from balance sheets and profit or loss statements) used in the panel regressions. Bank-specific data are taken from the databases *Thomson Worldscope* and *Thomson Reuters Financial Datastream*. Further variable definitions and data sources are provided in Appendix Table 1.

4.3 Country controls as determinants of systemic risk

To control for the impact of different macroeconomic conditions and regulations among the European Union jurisdictions, we include another five country-related variables. Differences in (capital) regulation are of special interest, because stricter regulations and powerful supervisors could limit systemic risks. The data we use is provided by the *World Bank* or *Eurostat* databases (Appendix Table 1 provides detailed definitions and data sources).

[16] The ratings transition matrix is provided in Table 7.

The first index we employ from the *World Bank Worldwide Governance Indicators* database is political stability (*POLITIC_STAB*): It is designed as an indicator of the likelihood that a government will be destabilised or overthrown by unconstitutional or violent means (e.g. political violence or terrorism). We expect high instability to increase banks' (systemic) risk, as demonstrated by Uhde and Heimeshoff (2009). The second index from the World Bank is regulatory quality (*REGULATION*): It captures the ability of the government to formulate and implement sound policies and regulations that permit and promote private system development. We expect *REGULATION* to decrease systemic risks of European banks.

Furthermore, we analyse how the concentration of the banking industry affects the stability of the financial system (*CONCENTRATION*: the sum of assets of the three largest national commercial banks as a share of total commercial banking assets). Prior research disagrees regarding the influence of concentration on the stability of a banking system. To extend this argumentation, Blundell-Wignall et al. (2011) and Carletti and Hartmann (2002) find that the trade-off between banking concentration and stability does not generally hold. In this case, we would expect high banking concentration to increase stability. However, there are also theoretical justifications and relevant empirical indications that defend the opposing view of fragility increasing with concentration, such as e.g. Beck et al. (2013). Supporting this theory, Kleinow et al. (2014) argue that this appears particularly plausible for SIFIs that have incentives to increase risk taking. Therefore, we hypothesise that *CONCENTRATION* has the effect of increasing systemic risk.

To control for the country's indebtedness we use the government debt ratio (*DEBT*), which is the government gross debt in relation to the respective gross domestic product (GDP). Policy makers in countries with high levels of debt have lower chances to bail out banks since financial resources are scarce. We therefore expect high government debt ratio levels to increase domestic banks' systemic risk. Finally, to capture the influence of inter-relations between a country and its domestic banking sector, we use the claims of the institutions on their respective central government (as a percentage of GDP) as another variable (*BANK_CL*).

If the domestic banking sector holds a relatively high share of its government's public debt, this should increase the systemic risk of banks in the financial system. Table 4 provides univariate statistics for all country and regulatory controls of our panel regressions. Further information on the evolution of all variables is reported in Appendix Table 5.

Table 4. Summary statistics for country controls

Variable	Exp. influence	Symbol	Obs.	Mean	Median	Std.dev.	Min	Max
Political stability	-	*POLITIC_STAB*	334	0.620	0.631	0.438	-0.466	1.495
Regulatory quality	-	*REGULATION*	334	1.262	1.213	0.402	0.498	1.924
Bank concentration	+	*CONCENTRATION*	334	0.705	0.712	0.140	0.422	0.999
Government debt ratio	+	*DEBT*	334	0.799	0.746	0.323	0.249	1.703
Bank claim ratio	+	*BANK_CL*	334	0.177	0.181	0.118	-0.129	0.431

The table presents descriptive statistics for country-specific data used in the panel regressions. Data are taken from the *World Bank* or *Eurostat* database. Further variable definitions and data sources are provided in Appendix Table 1.

5 Results

In this section, we first present the results for the estimates of banks' systemic risk, and then turn to the panel regressions of the dependent systemic risk measure for our sample of 334 bank observations during 2007 and 2012.

5.1 Systemic risk of European banks

We first compute the *SRI* for all banks in the sample. The distribution results (see Table 5) demonstrate that, possibly due to monetary and supervisory interventions, median values of *SRC* spreading from one bank to the financial system were highest in 2008 but declined till 2012 (with the exception of 2010). The *SRC* shows that European banks are becoming less "influential". The other side of the coin, however, indicates an increasing *SRS* between 2007 and 2012 (with the exceptions of 2008 and 2011). This shows that contagiosity between banks is increasing, possibly due to the increasing alertness of banks' stockholders.

The statistics on *SRI* demonstrate that the highest systemic risk levels can be observed for the period during the Eurozone crisis from 2010 to 2012. Looking at the standard deviation

(Std.dev.) and the Min/Max values, we also find evidence that there is an increasing inequality among banks with respect to systemic risk, i.e. some are becoming less systemically relevant while others are becoming more systemically relevant. We provide the names of the top 5 banks in the sample in the systemic risk ranking for each year in Appendix Table 7.

Table 5. Summary statistics for the systemic risk of European banks

		Syst. risk contribution (*SRC*)				Systemic risk sensitivity (*SRS*)				Systemic risk index (*SRI*)			
Year	Banks	Median	Std.dev.	Min	Max	Median	Std.dev.	Min	Max	Median	Std.dev.	Min	Max
2007	56	0.528	0.213	0.015	0.949	0.853	0.341	0.001	2.074	0.743	0.196	0.054	1.104
2008	58	0.580	0.228	0.134	1.265	0.914	0.345	0.120	1.830	0.755	0.160	0.127	1.049
2009	56	0.482	0.271	0.096	1.033	0.838	0.457	0.251	2.194	0.765	0.222	0.242	1.207
2010	57	0.542	0.219	-0.259	0.924	1.086	0.364	0.069	1.670	0.804	0.236	-0.076	1.072
2011	54	0.450	0.243	-0.017	0.877	1.004	0.386	0.119	2.009	0.775	0.230	0.156	1.223
2012	53	0.352	0.174	-0.028	0.737	1.280	0.710	-0.951	2.215	0.820	0.393	-0.480	1.286

The table presents descriptive statistics for the systemic risk contribution (*SRC*), the systemic risk sensitivity (*SRS*) as well as the banks' systemic risk index (*SRI*) used in the panel regressions. Further variable definitions are provided in Section 4.1.

5.2 Determinants of systemic risk

Turning to our main research question, we try to identify the drivers of systemic risk for our sample of European banks. To this end, we estimate several linear panel regression models using *SRI* and its components *SRC* and *SRS* as the dependent variables as well as our bank-specific and country-/policy-specific explanatory variables: Table 6 presents the results of our main regressions for the full period of 334 bank observations, while results of numerous robustness checks and panel data tests/diagnostics are reported in the appendix.

The random effects estimator is used to account for time-invariant bank-specific influences, and guarantees consistent coefficient estimates. However, the Hausmann (1978) specification test indicates that the random effects estimator is only consistent for the baseline regression (Appendix Table 2). Therefore, we use the fixed effects estimator model for the other panel regressions. The assumption behind the fixed effects model is that, unlike the random effects model, variation across entities is neither random nor uncorrelated with the predictor or independent variables included in the model. All estimation results of the linear panel regression models are based on heteroskedasticity-consistent Huber-White (1980) standard errors because unreported results confirm the presence of heteroskedasticity in our regressions. Further results of various test diagnostics (random effects, fixed effects, cross sectional dependence, autocorrelation) are reported in Appendix Table 2.

The panel regression models in Table 6 present the interesting result that numerous explanatory variables have a significant effect on systemic risk as measured by the *SRC*, *SRS*, and *SRI*. Most resulting significant coefficients, however, match closely with our estimated direction of influence.

To start with *SIZE*, the coefficient indicates that bank size is significant for *SRI*: The larger banks are, the larger the probability that they infect others should they get into financial problems. Analogously observed from a macroeconomic view, a system is more vulnerable if it relies to a large extent on a small number of larger banks, as it makes them being rescued or replaced by a competitor more unlikely. We confirm the findings of Haq and Heaney (2012), Black et al. (2013), and Varotto and Zhao (2014) for European banks. For *SRC* as the dependent variable, however, we find that the largest European banks did not increase systemic risks, but had a calming effect on the system. This may be due to their implicit “too big to fail” insurance. In this case, regulation of banks’ size may simply be counterproductive in mitigating systemic risks.

The proxy for the asset structure – loan ratio (*LOAN*) – and the proxy for income structure – non-interest income (*NON_INT*) – show a clear positive relation to systemic risk. Hence, the result for *LOAN* indicates that high volumes of loans can be a signal for deficits in risk diversification and increase the systemic risk of banks, while *NON_INT* (indicating a positive correlation of non-interest income business and systemic risk) indicates that the “bright side of innovation” (Beck et al., 2013) cannot be observed for European banks during the sample period. Our results for the non-performing loan (NON_PERF), leverage (LEVERAGE), and deposit ratio (DEPOSIT), however, show only insignificant coefficients. In particular, the insignificance of LEVERAGE is interesting. Regulators include this measure in Basel III, whereas we cannot empirically support an enhancing influence on systemic risk.

Table 6. Unbalanced panel regressions of banks' systemic risk index

Dependent variable:		Expected influence	Systemic Risk Contribution (*SRC*)	Systemic Risk Sensitivity (*SRS*)	Systemic Risk Index (*SRI*)
			Fixed effects		Random effects
Size	*SIZE*	+	**-0.313***	0.328	**0.197*****
			(0.098)	(0.307)	(0.000)
Loan ratio	*LOAN*	+/-	0.077	0.601	**0.501*****
			(0.696)	(0.247)	(0.000)
Non-interest income ratio	*NON_INT*	+/-	0.016	**0.192*****	**0.156*****
			(0.579)	(0.009)	(0.000)
Non-performing loan ratio	*NON_PERF*	+	-2.861	5.367	1.261
			(0.111)	(0.307)	(0.594)
Leverage ratio	*LEVERAGE*	+	0.001	0.002	0.001
			(0.264)	(0.438)	(0.579)
Deposit ratio	*DEPOSIT*	-	0.298	0.982	0.271
			(0.243)	(0.129)	(0.110)
Tier 1 ratio	*TIER1*	+/-	-0.292	**2.568****	**0.981***
			(0.449)	(0.037)	(0.066)
Liquidity ratio	*LIQUIDITY*	-	0.023	**0.251*****	**0.050****
			(0.271)	(0.004)	(0.025)
Financial power	*FIN_POW*	-	-0.231	**-3.692*****	-0.590
			(0.569)	(0.005)	(0.291)
Operating margin	*OP_MARG*	+/-	-0.049	**0.426****	**0.187***
			(0.668)	(0.041)	(0.055)
Return on invested cap.	*ROIC*	+/-	0.239	**-2.577****	**-1.735*****
			(0.638)	(0.017)	(0.001)
Income growth	*INCOME*	+/-	**0.045***	0.015	**-0.006*****
			(0.092)	(0.833)	(0.000)
Market-to-book ratio	*MBR*	+/-	-0.034	**0.253****	0.012
			(0.287)	(0.013)	(0.839)
Long-term rating	*LTR*	+	**-0.528*****	0.063	**0.351*****
			(0.000)	(0.845)	(0.005)
Political stability	*POLITIC_STAB*	-	-0.093	**0.514*****	**0.140*****
			(0.153)	(0.001)	(0.000)
Regulatory quality	*REGULATION*	-	**0.487*****	**-0.808*****	**-0.174****
			(0.000)	(0.002)	(0.010)
Bank concentration	*CONCENTRATION*	+	**-0.569****	**1.119****	-0.136
			(0.040)	(0.028)	(0.238)
Government debt ratio	*DEBT*	+	0.115	**-0.952****	**-0.361*****
			(0.496)	(0.031)	(0.000)
Bank claim ratio	*BANK_CL*	+	0.011	**1.968****	**0.703*****
			(0.958)	(0.024)	(0.001)
Observations			334	334	334
Groups			60	60	60
R^2			within 0.462	within 0.362	overall 0.478

The table presents the results of the panel regression (random and fixed effects) of banks' systemic risk on the European banking sector. For the estimation of the linear panel regression model, we use heteroskedasticity-robust Huber-White (1980) standard errors. The *p*-values are denoted in parentheses. */**/*** indicate coefficient significance at the 10%/5%/1% levels. Variable definitions and sources are provided in Appendix Table 1.

The coefficient of *TIER1* has a significantly positive impact on the *SRS* and the *SRI*. It means that for European banks, our counterintuitive finding – that high regulatory capital ratios drive systemic risk – confirms theoretical and empirical literature on regulatory disincentives, as explained in Section 4.2 (Perotti et al., 2011; Black et al., 2013). Furthermore, most coefficients demonstrate consistent and equal signs within the three observed systemic risk measures. For example, *LIQUIDITY* demonstrates consistently positive coefficients whereas the cash flow-based *FIN_POW* has negative coefficients in all regression models (see Table 6). Both liquidity-related measures indicate different influences: The first means that liquidity of banks would increase systemic risks – an outcome that literature and theory do not support. One explanation could be that a higher pool of cash indicates a lower profitability due to less-efficient allocation of capital. The negative impact of *FIN_POW* on systemic risk is more reasonable, as solvent banks are able to endow sufficient capital and current asset reserves, i.e. cushions against losses or liquidity shortages, making them resistant against financial distortions.

The significant coefficients for the ratio of operating income to net sales (*OP_MARG)* and the return on invested capital (*ROIC)* provide very interesting results, illustrating both a risk-enhancing and a risk-reducing effect of profitability: In the short run, banks may successfully engage in risky lending/non-lending activities. This high profitability would shield from the risk of defaulting, and lower systemic risk. In the long run, however, risk exposure may prove to be the other side of the profitability-coin. The annual growth of bank income (*INCOME*) does not have a clear significant influence on systemic risk and, therefore, basically confirms our hypotheses from theory and empirical literature. Our results also support the positive correlation of systemic risk and *MBR* with significant results for *SRS* – and thus support the results of Brunnermeier et al. (2011), Varotto and Zhao (2014), as well as Weiß et al. (2014). Our proxy for bank creditworthiness *(LTR)* shows significant, though contrary impacts of financial creditworthiness on systemic risk. A high *LTR* measure denotes a low creditworthiness. Therefore, the result suggests that banks with better/higher ratings have a higher *SRC*, but that their *SRI* is lower.

Our country controls are insightful too: The measure for political stability of a country (*POLITIC_STAB)* demonstrates an influence that is different from what the literature proposes and from what we would expect: Political stability and the absence of violence significantly increase the systemic risk of European banks. One possible explanation is that in a stable system actors found, operate, and interconnect financial institutions beyond the level that the institutional framework reliably provides. This is in contrast to political instability, in which links between financial units may disappear and, as a result (and somewhat paradoxically), reduce the systemic risk and the possibility of contagion.

REGULATION, capturing the World Bank's assessment of ability of a government to formulate and implement sound policies and regulations, seems to exert significant influence on systemic risk for all periods. For both the *SRI* and the *SRS*, we find a negative correlation to systemic risk, i.e. that banks headquartered in countries that promote sound policies and private system development have less systemic risk. For the *SRC*, however, we see an inverse relationship of regulation and systemic risk that could stem from reactions to blind action-taking national regulators. One outcome that we did not expect is the significant negative correlation of government debt ratio (*DEBT*) and systemic risk. We explain this with the high government debt ratios in western European countries with the most stable and best-developed financial markets, i.e. in countries with such institutional frameworks, higher debt ratios are not inducing a higher systemic risk of banks. Finally, *BANK_CL* (the banks' claims against national governments) demonstrates a significant positive influence on the systemic risk index. We also provide evidence that this is especially the case for banks' *SRS*. Large government bond/loan exposures of banks indicate the strong interconnectedness of the financial and governmental systems, making the transfer of (financial) problems between them more likely. A higher volume of those assets can also be interpreted as a particular diversification failure, as the government is already a source of political/regulatory/legal risk, and now adds credit and market price risk.

5.3 Robustness checks

We perform numerous checks to examine the robustness of our results to alternate model specifications and different data (e.g. explanatory variables and the equity index as a proxy for the financial system).[17] Robustness check specification I (Appendix Table 3) provides results for the fixed effects regression of the full (unbalanced and balanced) sample. We can assume that the results of the baseline regressions depend neither on insignificant explanatory variables nor on the unbalanced nature of our panel data, nor on the choice of a fixed or random panel regression model. Robustness check specification II (Appendix Table 4) provides results for the baseline regressions (Table 6) using another bank equity index (*EU Datastream Banks Index*) as a proxy for the financial system. This supports the assumption that our results do not depend on the bank equity index we chose. Additionally, we estimate alternative specifications of the panel regressions using different sets of explanatory variables. We find that the results from our baseline regressions are not substantially affected. To conclude, our robustness checks generally suggest that the findings obtained in the baseline specifications are robust.

6 Conclusion

In this study, we analyse the major drivers for systemic risk of banks in Europe. In particular, we identify why some banks are expected to contribute more to systemic events in the European financial system than others. In our panel regressions, we find empirical evidence supporting existing literature on systemically important financial institutions, identifying bank size, asset and income structure, loss and liquidity coverage, profitability, and several macroeconomic conditions as drivers of systemic risk. We also find that simple approaches in measuring systemic risk – as proposed by Rodríguez-Moreno and Peña (2013) – would not be suitable because systemic risk contribution may be driven by different factors than systemic risk sensitivity.

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[17] The regression diagnostics for the robustness checks are not reported in order to save space, but are available upon request.

Regulators have to consider a broad variety of indicators for assessing systemic risks. Although we propose different measures for systemic risk, we empirically support the urgency of recent regulatory approaches to identify systemically important banks in Europe by using a broad set of financial indicators (Basel Committee on Banking Supervision, 2013). Macroprudential regulation is essential to prevent systemic risk crises in the banking system. We provide evidence that existing microprudential-oriented rules for liquidity, liable equity capital, and leverage are less effective, and that policymakers may consider new measures like asset diversification to mitigate systemic risks in the banking system.

However, some limitations of our research remain: Even though our systemic risk measures avoid the shortcomings of existing approaches, the assessment of the tail co-movement of security prices excludes a number of (admittedly, "smaller") institutions without publicly listed securities.[18] The second shortfall is that we do not assess the systemic impact of other financial institutions, such as insurers, investment funds, and players from the growing shadow banking system. Finally, to confirm our findings in the long run, future research could try to make use of financial and country data over longer periods.

[18] The most useful measures of systemic risk may be ones that have yet to be tried because they require proprietary data only regulators can obtain, see Bisias et al. (2012).

Appendix

Appendix Table 1. Definitions and data sources of explanatory variables

Variable	Symbol	Definition	Data source
Dependent variable			
Systemic risk index	*SRI*	For detailed definition see section 4.1. *SRI* measures systemic risk of banks by considering both directions of risk transmission and contagion: A single institution affecting the banking system, and the banking system affecting a single institution.	Own calculations with daily bank stock return data from Datastream
Independent variables bank characteristics			
Size	*SIZE*	log(total assets)	Worldscope WC02999
Loan ratio	*LOAN*	$\frac{\text{total loans}}{\text{total assets}}$	WC02271, WC02999
Non-interest income ratio	*NON_INT*	$\frac{\text{non} - \text{interest income}}{\text{total interest income}}$	WC01021, WC01016
Non-performing loan ratio	*NON_PERF*	$\frac{\text{loan loss provisions}}{\text{total loans}}$	WC01271, WC02271
Leverage ratio	*LEVERAGE*	$\frac{\text{long } + \text{ short term debt \& } current\ portion\ of\ long - term\ debt}{\text{common equity}}$	WC08231
Deposit ratio	*DEPOSIT*	$\frac{\text{total deposits}}{\text{total liabilities}}$	WC03019, WC03351
Tier 1 ratio	*TIER1*	$\frac{\text{Basel III Tier 1 capital}}{\text{risk} - \text{weighted assets}}$	WC18157
Liquidity ratio	*LIQIDITY*	$\frac{\text{cash \& } securities}{\text{deposits}}$	WC15013
Financial power	*FIN_POW*	$\frac{\text{net cash flow operating activities}}{\text{total liabilities}}$	WC04860, WC03351
Operating margin	*OP_MARG*	$\frac{\text{operating income}}{\text{net sales}}$	WC08316
Return on invested capital	*ROIC*	$\frac{\text{net income – bottom line } + \text{ (interest expense on debt } - \text{ interest capitalised)} \times (1 - \text{tax rate})}{\text{average of last and current year's (total capital } + \text{ short term debt } current\ portion\ of\ long - term\ debt)}$	WC08376
Income growth	*INCOME*	$\frac{\text{operating income present year}}{\text{operating income last year}}$	WC01001
Market-to-book ratio	*MBR*	$\frac{\text{market capitalisation}}{\text{book value common equity}}$	WC09704
Long-term rating	*LTR*	LT Issuer Ratings are opinions of the ability of entities to honour senior unsecured financial obligations and contracts. As our primary source we use Moody's long-term issuer ratings (or, alternatively, the long-term deposit ratings). In case of neither being existent, we take S&P's long-term issuer (foreign currency) ratings for banks or, alternatively, Fitch's long term issuer ratings as a last resort. Higher values indicate a higher default probability, i.e. a lower rating.	Rating history online database (Moody's, S&P's, Fitch); annual report, investor relations website (in case of missing data)

The table provides definitions and data sources for the variables that are used in the panel regressions.

Appendix Table 1. Definitions and data sources of explanatory variables (continued)

Variable	Symbol	Definition	Data source
Independent variables country controls			
Political stability	*POLITIC_STAB*	Political Stability and Absence of Violence/Terrorism captures perceptions of the likelihood that the government will be destabilised or overthrown by unconstitutional or violent means, including politically-motivated violence and terrorism. Estimate gives the country's score on the aggregate indicator, in units of a standard normal distribution, i.e. ranging from approximately -2.5 to 2.5, whereby high numbers stand for high political stability.	Worldwide Governance Indicators PV.EST
Regulatory quality	*REGULATION*	Regulatory Quality captures perceptions of the ability of the government to formulate and implement sound policies and regulations that permit and promote private system development. Estimate gives the country's score on the aggregate indicator in units of a standard normal distribution, i.e. ranging from approximately -2.5 to 2.5.	Worldwide Governance Indicators RQ.EST
Bank concentration	*CONCENTRATION*	Assets of the three largest commercial banks as a share of total commercial banking assets.	Global Financial Development GFDD.OI.01
Government debt ratio	*DEBT*	The indicator is defined (in the Maastricht Treaty) as consolidated general government gross debt at nominal value, outstanding at the end of the year in the following categories of government liabilities (as defined in ESA95) in relation to the respective GDP. Basic data are expressed in national currency, and converted into euro using year-end exchange rates for the euro provided by the European Central Bank (ECB).	Eurostat tsdde410
Bank claim ratio	*BANK_CL*	Banks' claims on central government as a percentage of GDP include loans to central government institutions net of deposits.	World Development Indicators FS.AST.CGOV.GD.ZS

The table provides definitions and data sources for the variables that are used in the panel regressions.

Appendix Table 2. Panel data tests/diagnostics

Test/diagnostic	2007-2012 Unbalanced panel	2007-2012 Balanced panel
Time-fixed effects	Prob>F=0.240	Prob>F=0.560
Random effects		
LM test	Prob>chi^2=0.000	Prob>chi^2=0.230
Hausman test	Prob>chi^2=1.000	Prob>chi^2=0.029
Cross sectional dependence		
Breusch-Pagan-LM test	Not enough obs.	Not enough obs.
Pesaran test	Not enough obs.	Pesran: Pr. 1.666
Friedman test	Not enough obs.	Frees: 0.769
Frees test	Not enough obs.	Friedman: Pr. 1.000
Autocorrelation (Wooldridge test)	Prob>F=0.308	Prob>F=0.687
Heteroskedasticity	We use heteroskedasticity-robust standard error estimates (Huber/White) to account for heteroskedasticity.	

The table provides results of 8 tests for time-fixed/random effects, cross-sectional dependence, and autocorrelation for all shown panel regressions. There are no time-fixed effects, but only random effects. We are able to reject cross-sectional dependence only for the balanced panel. Although autocorrelation is not a problem in panels with few years, we test it anyway. Tests do not indicate autocorrelation. To account for heteroskedasticity, we use heteroskedasticity-robust standard errors estimates (Huber/White-estimators).

Appendix Table 3. Robustness check specification I - panel regressions (fixed effects) of banks' systemic risk index

Dependent variable:	Systemic risk index (*SRI*)			
	Unbalanced fixed effects	Unbalanced fixed effects	Balanced fixed effects	Balanced fixed effects
SIZE	0.007		0.001	
	(0.968)		(0.994)	
LOAN	0.306		0.253	
	(0.189)		(0.232)	
NON_INT	**0.105***	**0.121***	**0.112***	**0.125***
	(0.004)	(0.002)	(0.004)	(0.003)
NON_PERF	1.269		1.225	
	(0.581)		(0.611)	
LEVERAGE	0.001		**0.006***	0.002
	(0.228)		(0.000)	(0.161)
DEPOSIT	**0.638**	**0.691***	**0.586**	**0.814***
	(0.013)	(0.003)	(0.022)	(0.001)
TIER1	**1.179**	0.900	**1.477***	0.593
	(0.042)	(0.113)	(0.007)	(0.285)
LIQUIDITY	**0.137***	**0.116***	**0.064**	**0.126***
	(0.001)	(0.001)	(0.019)	(0.008)
FIN_POW	**-1.955***	**-2.185***	**-0.979***	**-0.850***
	(0.001)	(0.001)	(0.003)	(0.000)
OP_MARG	**0.185*	0.134	**0.175*	0.138
	(0.066)	(0.202)	(0.087)	(0.222)
ROIC	**-1.187*	**-1.153**	**-1.749***	**-1.105*
	(0.060)	(0.038)	(0.009)	(0.060)
INCOME	0.031		0.029	
	(0.280)		(0.337)	
MBR	**0.108**	**0.129**	0.026	
	(0.018)	(0.017)	(0.409)	
LTR	0.239		0.194	
	(0.120)		(0.190)	
POLITIC_STAB	**0.211***	**0.186**	**0.169**	**0.198***
	(0.009)	(0.017)	(0.025)	(0.009)
REGULATION	-0.163		-0.107	
	(0.203)		(0.383)	
CONCENTRATION	0.270		0.392	
	(0.330)		(0.122)	
DEBT	**-0.413*	**-0.507**	**-0.559***	**-0.680***
	(0.051)	(0.024)	(0.006)	(0.001)
BANK_CL	**0.962**	**0.991**	**1.039**	**1.189***
	(0.026)	(0.019)	(0.020)	(0.004)
Observations	334	334	294	294
Groups	60	60	49	49
R^2	within 0.323	within 0.297	within 0.391	within 0.281

This table shows that our results from the baseline regressions depend on neither insignificant explanatory variables, nor on the unbalanced nature of our panel data, nor on the choice of a fixed or random panel regression model. For the estimation of the linear panel regression model, we use heteroskedasticity-robust Huber-White (1980) standard errors. The *p* values are denoted in parentheses. */**/*** indicate coefficient significance at the 10%/5%/1% levels. Variable definitions and sources are provided in Appendix Table 1.

Appendix Table 4. Robustness check specification II - unbalanced panel regressions of banks' systemic risk index using an alternative index (EU Datastream Banks Index) as a proxy for the banking system

Dependent variable:	Systemic Risk Contribution (*SRC*)	Systemic Risk Sensitivity (*SRS*)	Systemic risk index (*SRI*)
	Fixed effects		Random effects
SIZE	-0.213	0.416	**0.198*** **
	(0.280)	(0.162)	(0.000)
LOAN	-0.010	0.658	**0.504*** **
	(0.961)	(0.177)	(0.000)
NON_INT	0.029	**0.167** **	**0.142*** **
	(0.404)	(0.012)	(0.000)
NON_PERF	-2.023	3.380	0.834
	(0.276)	(0.439)	(0.685)
LEVERAGE	0.000	0.001	0.000
	(0.308)	(0.485)	(0.716)
DEPOSIT	0.275	0.860	0.223
	(0.296)	(0.129)	(0.160)
TIER1	0.020	**2.118* **	**0.910* **
	(0.958)	(0.050)	(0.054)
LIQUIDITY	0.017	**0.241*** **	**0.047** **
	(0.432)	(0.007)	(0.025)
FIN_POW	-0.208	**-3.337*** **	-0.618
	(0.572)	(0.005)	(0.233)
OP_MARG	0.019	0.145	0.109
	(0.873)	(0.421)	(0.233)
ROIC	0.183	**-1.597* **	**-1.316*** **
	(0.701)	(0.090)	(0.009)
INCOME	0.033	0.009	**-0.006*** **
	(0.197)	(0.893)	(0.000)
MBR	-0.036	**0.229** **	0.014
	(0.230)	(0.015)	(0.806)
LTR	**-0.580*** **	0.046	**0.385*** **
	(0.000)	(0.882)	(0.001)
POLITIC_STAB	-0.041	**0.494*** **	**0.137*** **
	(0.502)	(0.001)	(0.000)
REGULATION	**0.477*** **	**-0.924*** **	**-0.187*** **
	(0.001)	(0.000)	(0.006)
CONCENTRATION	-0.393	0.884*	-0.184
	(0.134)	(0.059)	(0.114)
DEBT	0.228	**-1.056** **	**-0.349*** **
	(0.204)	(0.016)	(0.000)
BANK_CL	0.062	**1.419* **	**0.579*** **
	(0.778)	(0.073)	(0.005)
Observations	334	334	334
Groups	60	60	60
R^2	within 0.396	within 0.325	overall 0.494

To prove our results do not depend on the bank equity index we chose for our baseline regression, this table presents the results of the panel regression of banks' systemic risk on the European banking sector using another bank equity index. For the estimation of the linear panel regression model, we use heteroskedasticity-robust Huber-White (1980) standard errors. The *p* values are denoted in parentheses. */**/*** indicate coefficient significance at the 10%/5%/1% levels. Variable definitions and sources are provided in Appendix Table 1

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Appendix Table 5. Sample description

Country (banks)	2007	2008	2009	2010	2011	2012	Sum	Variables (mean values)	2007	2008	2009	2010	2011	2012
AUT	1	1	1	1	1	1	6	*SRI*	0.723	0.737	0.725	0.766	0.756	0.732
BEL	2	2	2	2	1	1	10	*SIZE*	11.149	11.151	11.158	11.151	11.180	11.174
CYP	1	2	2	2	1	0	8	*LOAN*	0.633	0.649	0.650	0.639	0.637	0.631
DNK	2	3	3	3	3	3	17	*NON_INT*	0.414	0.266	0.514	0.567	0.449	0.511
ESP	5	5	5	5	5	5	30	*NON_PERF*	0.003	0.006	0.013	0.011	0.013	0.014
FIN	1	1	1	1	1	1	6	*LEVERAGE*	9.924	6.335	7.625	7.643	6.672	3.126
FRA	3	3	3	3	3	3	18	*DEPOSIT*	0.429	0.443	0.471	0.470	0.452	0.489
GBR	4	4	4	4	4	4	24	*TIER1*	0.083	0.085	0.104	0.108	0.111	0.121
GER	6	6	5	5	5	3	30	*LIQUIDITY*	1.113	1.141	0.878	0.873	0.910	0.890
GRC	4	4	4	4	4	4	24	*FIN_POW*	0.119	0.047	0.064	0.058	0.043	0.055
HUN	1	1	1	1	1	1	6	*OP_MARG*	0.163	0.080	0.068	0.072	0.009	-0.013
IRL	3	3	3	3	3	3	18	*ROIC*	0.050	0.039	0.022	0.023	0.001	0.014
ITA	10	11	11	11	11	11	65	*INCOME*	0.243	0.077	-0.121	-0.056	0.062	0.955
MLT	1	1	0	1	0	1	4	*MBR*	1.884	0.774	0.905	0.797	0.594	0.630
NED	2	1	1	1	1	1	7	LTR	0.160	0.186	0.225	0.271	0.372	0.458
POL	3	3	3	3	3	4	19	*POLITIC_STAB*	0.681	0.665	0.503	0.597	0.649	0.626
PRT	3	3	3	3	3	3	18	*REGULATION*	1.328	1.324	1.284	1.267	1.193	1.165
SWE	4	4	4	4	4	4	24	*CONCENTRAT.*	0.692	0.707	0.700	0.713	0.714	0.705
Sum	56	58	56	57	54	53	334	*DEBT*	0.638	0.680	0.786	0.850	0.907	0.946
								BANK_CL	0.135	0.127	0.164	0.206	0.208	0.228

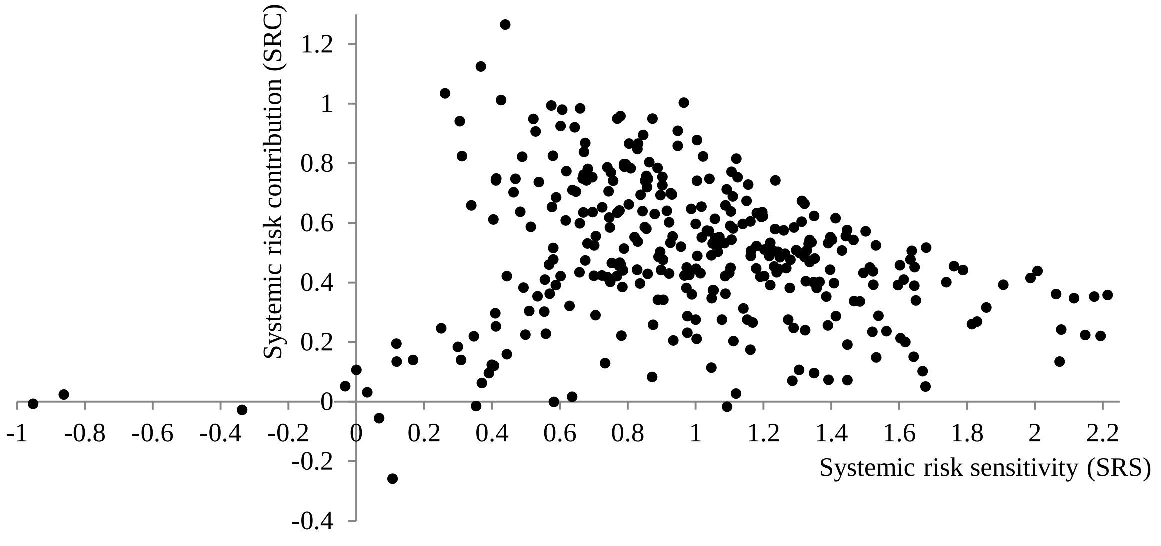
The table provides the number of banks in the sample selected for each country. We additionally report the evolution of the mean values of the variables used in our empirical investigation. Variable definitions and sources are provided in Appendix Table 1.

Appendix Table 6. Bank sample constituents

Country	Bank name	Country	Bank name
Austria	Erste Group Bank AG	Italy	Banca Popolare di Sondrio SpA*
Belgium	Dexia NV	Italy	Banco Popolare SC*
Belgium	KBC Group NV	Italy	Credito Emiliano SpA
Cyprus	Bank of Cyprus Public Company Ltd	Italy	Intesa Sanpaolo SpA
Cyprus	Hellenic Bank Public Company Ltd *	Italy	Mediobanca SpA
Denmark	Danske Bank	Italy	UniCredit SpA
Denmark	Jyske Bank	Italy	Unione Di Banche Italiane SpA
Denmark	Sydbank	Malta	Bank of Valletta plc
Finland	OP-Pohjola Group	Netherlands	ABN AMRO Bank NV
France	BNP Paribas	Netherlands	ING Bank NV
France	Groupe Crédit Agricole	Poland	BANK BPH SA
France	Société Générale	Poland	Bank Handlowy w Warszawie SA
Germany	Aareal Bank AG	Poland	Getin Boble Bank SA
Germany	Commerzbank AG	Poland	PKO Bank Polski
Germany	Deutsche Bank AG	Portugal	Banco BPI SA
Germany	Hypo Real Estate Holding AG	Portugal	Banco Comercial Português SA*
Germany	IKB Deutsche Industriebank AG	Portugal	Espírito Santo Financial Group SA
Germany	Landesbank Berlin Holding AG	Spain	BBVA SA
Greece	Alpha Bank SA	Spain	Banco de Sabadell SA
Greece	Eurobank Ergasias SA*	Spain	Banco Popular Español SA
Greece	National Bank of Greece SA*	Spain	Banco Santander SA
Greece	Piraeus Bank SA*	Spain	Bankinter SA
Hungary	OTP Bank Ltd	Sweden	Nordea Bank AB (publ)
Ireland	Allied Irish Bank plc	Sweden	Skandinaviska Enskilda B. AB (SEB)
Ireland	Bank of Ireland	Sweden	Svenska Handelsbanken AB (publ)
Ireland	Permanent TSB plc*	Sweden	Swedbank AB (publ)
Italy	Banca Carige SpA*	UK	Barclays plc
Italy	B. Monte dei Paschi di Siena SpA*	UK	HSBC Holdings plc
Italy	B. Piccolo Credito Valtellinese SC*	UK	Lloyds Banking Group plc
Italy	B. Pop. Dell'Emilia Romagna SC*	UK	Royal Bank of Scotland Group plc
Italy	Banca Popolare Di Milano SC*		

The table provides the full list of banks in the sample including the names of the countries where the respective bank is headquartered. Banks that failed the EBA stress test at the end of Oct. 2014 are denoted with *.

Appendix Figure 1. Banks' systemic risk contribution (SRC) and sensitivity (SRS)



The table reports the two systemic risk measures we use to construct the systemic risk index: *SRS* and *SRC*.

Appendix Table 7. Systemic risk ranking (mean values for 2007-2012)

Measure	Ranking	Value	Country	Bank name
Systemic risk contribution (*SRC*)	1	0.822	United Kingdom	Lloyds Banking Group plc
	2	0.750	Spain	Banco de Sabadell SA
	3	0.750	Spain	Banco Santander SA
	4	0.731	Spain	BBVA SA
	5	0.686	Italy	Banca Carige SpA
Systemic risk sensitivity (*SRS*)	1	1.501	France	Société Générale
	2	1.496	Poland	PKO Bank Polski
	3	1.469	United Kingdom	HSBC Holdings plc
	4	1.450	Belgium	KBC Group NV
	5	1.421	France	Groupe Crédit Agricole
Systemic risk index (*SRI*)	1	1.011	France	Société Générale
	2	0.996	France	Groupe Crédit Agricole
	3	0.964	United Kingdom	HSBC Holdings plc
	4	0.952	Italy	UniCredit SpA
	5	0.947	France	BNP Paribas

The table provides the systemic risk ranking of the banks in the sample according to the systemic risk measures *SRC*, *SRS* and *SRI* presented in Section 4.1

Table 7:Rating transition matrix for explanatory variable LTR

S&P's	Moody's	Fitch	Scale	*LTR*
AAA	Aaa	AAA	18	0.000
AA+	Aa1	AA+	17	0.056
AA	Aa2	AA	16	0.111
AA-	Aa3	AA-	15	0.167
A+	A1	A+	14	0.222
A	A2	A	13	0.278
A-	A3	A-	12	0.333
BBB+	Baa1	BBB+	11	0.389
BBB	Baa2	BBB	10	0.444
BBB-	Baa3	BBB-	9	0.500
BB+	Ba1	BB+	8	0.556
BB	Ba2	BB	7	0.611
BB-	Ba3	BB-	6	0.667
B+	B1	B+	5	0.722
B	B2	B	4	0.778
B-	B3	B-	3	0.833
CCC	Caa1	CCC		
CCC	Caa2	CCC	2	0.889
CCC	Caa3	CCC		
CC	Ca	CC	1	0.944
CC	Ca	C		
SD	C	DDD		
D	C	DD	0	1.000
D	C	D		

The table provides the transmission of ratings to numbers (*LTR*) for using them in our panel regression. We use an 18-notch rating scale. For numerical reasons, values from 0 to 1 in steps of 1/18 are assigned, with 0 denoting AAA (the highest rating) and 1 denoting D (default).

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