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Bank size, capital, and systemic risk: Some international evidence

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ABSTRACT

This paper studies the significant variation in the cross-section of standalone and systemic risk of large banks during the recent financial crisis to identify bank specific factors that determine risk. We find that systemic risk grows with bank size and is inversely related to bank capital, and this effect exists above and beyond the effect of bank size and capital on standalone bank risk. Our results contribute to the ongoing debate on the merits of imposing systemic risk-based capital requirements on banks.

1. Introduction

The recent financial crisis has triggered a debate on bank size as a determinant of systemic risk. There are a number of reasons why this debate takes place now. First, large banks were at the center of the recent crisis. Second, the size of large banks has increased substantially over the last two decades (Fig. 1). Third, large banks tend to have lower capital ratios, less stable funding, and more exposure to potentially risky market-based activities (Figs. 2–4; see also Laeven et al., 2014).

This stylized evidence gives rise to a number of economic questions that are critical for formulating effective policy *vis-à-vis* large banks. First, what exactly is the source of risk in large banks? Is it low capital, unstable funding, market-based activities, size *per se*, or a combination of the above? Second, do these potential risk factors drive systemic risk through their effect on standalone bank risk (and can be addressed by traditional, micro-prudential regulation), or is there an effect on systemic risk that goes above and beyond that on standalone bank risk, suggesting a need for additional, macroprudential measures? Finally, which of the risk factors are robust across countries, so that targeting them could be part of international policy arrangements such as the Basel regulatory framework?

Answering these equations is paramount for informing the policy debate. Without that, policy may be imprecise and lack consensus. Indeed, the views in the ongoing policy debate on large banks differ substantially. Some, including the Basel Committee, advocate capital-based measures – such as an additional surcharge of up to 2.5% capital on large banks (e.g., International Monetary Fund, 2010; French et al., 2010). Others, such as the Volcker Rule as contained in the Dodd–Frank Act in the U.S., or the Vickers (2011) and Liikanen (2012) proposals in Europe, advocate restrictions on risky bank activities. And some advocate outright limits on the individual size of banks. Yet others argue that such restrictive regulations would distort the allocation of banks' resources, hurting the efficiency of capital allocation and imposing substantial costs to the real economy (Kashyap et al., 2010b; Aiyar et al., 2014). They propose to focus instead on reducing too big to fail subsidies through better resolution and contingent capital requirements (Farhi and Tirole, 2012; Kashyap et al., 2010a; Stein, 2013).

This paper studies the significant variation in the cross-section of systemic risk of large banks during the recent financial crisis in a broad sample of countries, with a view to identify bank specific factors that determine systemic risk. We use the crisis as a shock

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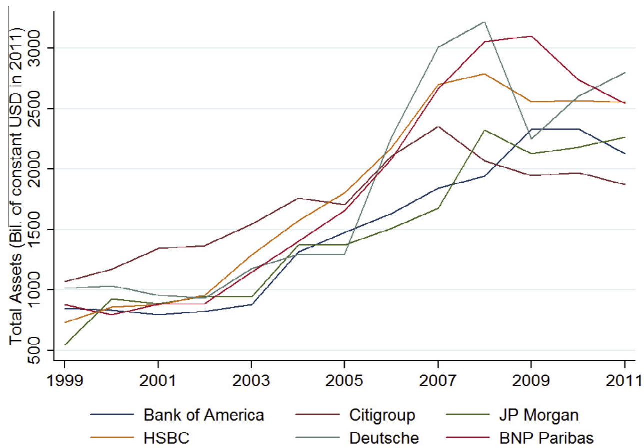

Fig. 1. Growth in size of the world's largest banks since late 1990s. Source: Bankscope and authors calculations.

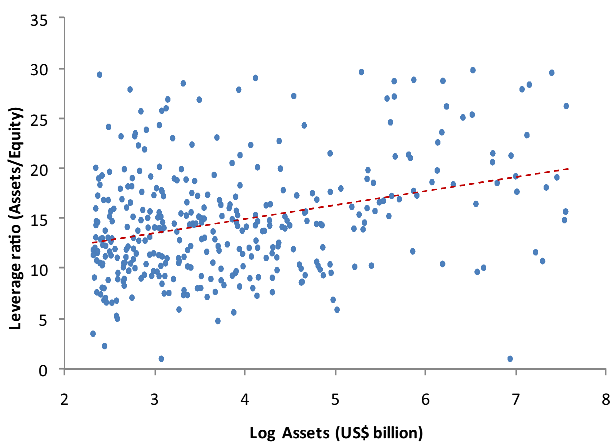

Fig. 2. Bank size and capital ratio. Source: Bankscope and authors calculations. Assets are in log billions of US dollars (log assets = 2 corresponds to US$ 7.4 billion, log assets = 5 to US$ 148 billion. Data are for the year 2011).

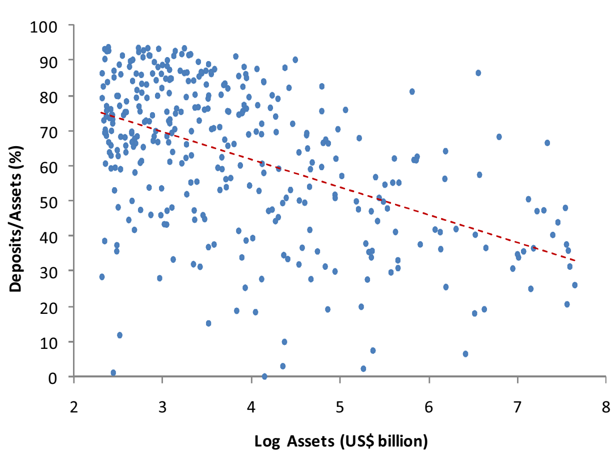

Fig. 3. Bank size and funding stability. Source: Bankscope and authors calculations. Assets are in log billions of US dollars (log assets = 2 corresponds to US$ 7.4 billion, log assets = 5 to US$ 148 billion. Data are for the year 2011).

to the banking system revealing the nature and size of systemic risk of individual banks. As proxies for systemic risk we use two recently developed measures of systemic risk, Adrian and

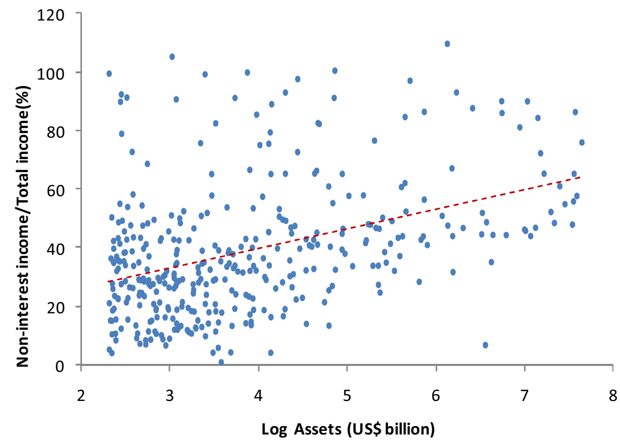

Fig. 4. Bank size and activities. Source: Bankscope and authors calculations. Assets are in log billions of US dollars (log assets = 2 corresponds to US$ 7.4 billion, log assets = 5 to US$ 148 billion. Data are for the year 2011).

Brunnermeier (2012)'s CoVaR and Brownlees and Engle (2012)'s SRISK. By simultaneously analyzing the role of banks size, capital, funding and activities, we are able to isolate the independent effects of these three key bank risk factors on systemic risk, and shed light on the ongoing debate on the merits of restricting bank size, imposing capital surcharges on large banks, and/or restricting their unstable funding and risky activities.

There are several theories supporting the view that large and complex banks contribute to systemic risk. According to one view, which we label the *unstable banking hypothesis*, large banks tend to engage more in risky activities (e.g., trading) and be financed more with short-term debt, which makes them more vulnerable to generalized liquidity shocks and market failures such as liquidity shortages and fire sales (Kashyap et al., 2002; Shleifer and Vishny, 2010; Gennaioli et al., 2013; Boot and Ratnovski, 2012).

According to another view, the *too-big-to-fail hypothesis*, regulators are reluctant to close or unwind large and complex banks, resulting in moral hazard behavior that leads banks to take on excessive risks in the expectation of government bailouts (e.g., Farhi and Tirole, 2012).

According to a third view, the *agency cost hypothesis*, large and complex banks that engage in multiple activities (e.g., combining lending and trading) suffer from increased agency problems and poor corporate governance that can translate into systemic risk (e.g., Bolton et al., 2007; Laeven and Levine, 2007). According to this view, banks have a natural tendency to take on excessive risks and to grow in size, while regulators, by focusing on microprudential regulation, did little to prevent the resulting build-up of systemic risk. As a result, large banks tend to share many of the risk factors that other theories have identified as being important drivers of systemic risk, such as high leverage, activity diversity, and interconnectedness.

Our analysis is not an attempt to test these theories, which are not mutually exclusive, but simply to identify the main drivers of systemic risk more generally. In the process, however, we also learn something about the relative merits of these theories in explaining variation in systemic risk.

We find strong evidence that systemic risk increases with bank size. Our results indicate that a one standard deviation increase in total assets increases the bank's contribution to systemic risk by about one-third its standard deviation when measured by ΔCoVaR, and by about half its standard deviation when measured by SRISK. These are large effects. We also find evidence that systemic risk is lower in better-capitalized banks, with the effects particularly pronounced for large banks. The significance of these results is robust to the sample, to the metric of systemic risk used, and to a range of controlled for bank attributes.

Our analysis also highlights the importance of using measures of systemic risk rather than traditional measures of bank performance to assess the drivers of systemic risk. For example, using measures of standalone bank risk, such as stock return and equity volatility, would significantly underestimate the influence of bank size on systemic risk.

The contribution of the paper is threefold. First, we analyze the determinants of systemic risk in a broad sample of countries, while the existing literature focuses primarily on the United States. This allows us to establish results that are robust across country samples, and to control for country factors that may influence the relation between bank size and systemic risk, such as macroeconomic conditions and deposit insurance. Second, we consider alternative measures of systemic risk while the literature typically focuses on one measure of systemic risk. Because these measures capture different aspects of systemic risk, their correlation is not always high. In fact, Billio et al. (2012) and Giglio et al. (2013) show that a combination of systemic risk measures has more predictive power in explaining bank performance during crisis events than a single measure of systemic risk. Therefore to guide policy it is critically important to consider alternative measures of systemic risk. Third, we analyze the determinants of systemic risk controlling for standalone bank risk, thus linking our analysis most closely to the macroprudential policy debate.

Our paper is closely related to recent literature on measuring and explaining systemic risk in banks. For example, Brunnermeier et al. (2013) relate ΔCoVaR to measures of a bank's reliance on non-interest income. However, unlike our paper, their sample is limited to US bank holding companies and they do not consider alternative measures of systemic risk. Beck and de Jonghe (2013) study how systemic risk is affected by lending concentration, Drehmann and Tarashev (2013) focus on the importance of interbank exposures as transmission channels for systemic risk, while Alessandri et al. (2014) link systemic risk to the Financial Stability Board's indicators of systemic importance. We focus on bank capital, funding, activities, and their interaction with bank size as the four most fundamental metrics that can drive bank risk.

In related work, Puzanova and Düllmann (2013) also study the systemic risk contributions of banks for an international sample of banks. However, the two approaches differ along several dimensions. We use a different measure of systemic risk. They use a novel credit risk modeling approach while we use two well established methods in the literature, CoVaR and SRISK. They focus on the time series and cross sectional dimensions of systemic risk while we focus on the change in systemic risk during the recent financial crisis (although we have also computed annual values). Finally, our sample is somewhat larger covering 412 banks from 56 countries compared to 54–86 banks, depending on the specification in their study. They find that both the cross sectional and time series dimensions of systemic risk matter. We find that in the cross section, bank size is an important determinant of the change in systemic risk during the crisis. Thus our results are complementary.

Other papers study bank stability through proxies other than systemic risk measures. Berger and Bouwman (2013) find that better capitalized banks are more likely to survive banking crises. Hovakimian and Kane (2000) show that banks extract substantial safety net subsidies from the presence of deposit insurance, thus boosting their market values. Beltratti and Stulz (2012), using crisis data, find that better capitalized banks performed better during the crisis, while Demirgüç-Kunt and Huizinga (2010) find that banks that rely to a larger extent on non-deposit funding and non-interest income are more profitable but also riskier.

Before turning to the analysis in this paper, a few caveats are in order. The measurement of systemic risk is still in its infancy (Hansen, 2014). We consider CoVaR and SRISK, and find the focus on them appropriate given that they are the two most widely used and established measures of systemic risk. Still, these measures will likely be refined and improved going forward, while other measures are being developed. For example, Tarashev et al. (2010) propose systemic risk measures based on Shapley values, and Huang et al. (2009, 2012) introduce measures of systemic risk based on the hypothetical price of insurance against financial distress (see also Guntay and Kupiec, 2014, for a discussion of shortcomings in the different measures of systemic risk). Further, our measures of systemic risk are based on stock prices. In the presence of expectations of government support (bailouts), market prices may inaccurately reflect systemic risk. Moreover, these measures will not capture the full social costs associated with the failure of financial institutions, including output losses and unemployment.

While we focus on the interaction of bank size with risk, other studies analyze the interaction between banks size and performance. One strand of the literature focuses on the role of competition and economies of scale in banking. For example, Hughes and Mester (2013) find that banks enjoy substantial economies of scale. Another strand of the literature focuses on economies of scope at banks. Here, Houston et al. (1997) find that diversified banks are better able to absorb liquidity shocks thanks to the presence of internal capital markets, while Laeven and Levine (2007) and Goetz et al. (2013) find that banks that diversify geographically or across product lines destroy value for their shareholders, consistent with the presence of agency costs in diversified firms. Other papers concentrate on the role of corporate governance, leverage, and regulation in influencing bank performance and risk. For example, using pre-crisis data, Caprio et al. (2007) find that banks with large owners are more highly valued, while Saunders et al. (1990) and Laeven and Levine (2009) find that such banks also take more risks.

The paper proceeds as follows. Section 2 presents the data used in this paper. Section 3 presents the results. Section 4 concludes.

2. Data

2.1. Sample

To construct the sample, we start from all publicly traded financial institutions in Bankscope with data on equity returns and total assets at the end of 2006. We exclude financial institutions that are not publicly traded because our measures of systemic risk are based on equity returns. We also exclude financial institutions that disappear before the end of our sample period in December 2008. This gives 1721 financial institutions. For the most part, we exclude non-bank financial institutions and focus on deposit-taking institutions (i.e., commercial banks and bank holding companies), reducing the sample to 1343 institutions. Our main analysis also focuses on large institutions that are more likely to be systemically important, limiting the sample to institutions with assets in excess of US$ 10 billion at the end of 2006.[1] The resulting sample consists of 412 deposit-taking institutions from 56 countries.

Table 1 reports the countries in our sample for which we have at least one large bank and for which we have country-level data on macroeconomic and bank regulatory variables (to be defined later). There are 32 countries in our sample that meet these criteria. There is much variation in the presence of large banks. A number of countries have only one large bank while 7 economies have

[1] Using an absolute cutoff is appropriate here because we focus on globally active banks. To capture domestic systemic importance, a cutoff based on bank size-to-GDP ratio could instead have been used.

Table 1
Country characteristics.

Country	Number of banks	Number of large banks	Log GDP per capita	Deposit insurance
Australia	8	5	10.53	0
Austria	4	3	10.58	1
Belgium	4	2	10.55	1
Brazil	4	2	8.66	1
Canada	8	6	10.60	1
China	7	5	7.63	0
Denmark	4	1	10.83	0
Finland	2	1	10.58	1
France	4	4	10.51	1
Germany	7	7	10.47	1
Greece	7	3	10.07	1
Hong Kong	9	2	10.24	1
India	14	2	6.69	1
Ireland	3	3	10.87	0
Israel	5	2	9.98	0
Italy	10	6	10.37	1
Japan	80	21	10.44	1
Korea, Rep. of	5	5	9.89	1
Luxembourg	1	1	11.41	1
Malaysia	8	1	8.71	1
Netherlands	4	3	10.63	0
Norway	1	1	11.20	1
Portugal	4	2	9.86	1
Singapore	3	3	10.37	1
South Africa	5	4	8.61	0
Spain	9	5	10.24	1
Sweden	3	3	10.69	1
Switzerland	7	2	10.90	1
Taiwan	18	6	9.71	1
Turkey	9	1	8.94	1
United Kingdom	10	8	10.61	1
United States	72	28	10.71	1
Total	339	148		

The sample includes publicly listed banks with assets in excess of US$ 10 billion as of December 2006. Large banks denote banks in the same sample with assets greater than US$ 50 billion at end-2006. Country characteristics are computed as of end-2006. Log GDP per capita is the log of real gross domestic product per capita in US dollars. Deposit insurance is a dummy variable equal to one when there is an explicit deposit insurance scheme from Demirgüç-Kunt et al. (2008).

more than five large banks (i.e., Canada, Germany, Italy, Japan, Taiwan, United Kingdom, and United States). The United States is the country in our sample with the largest number of large banks of 28 in total.

2.2. Bank-level systemic risk

Our main focus is on systemic risk from the middle of 2007 to the end of 2008, which we refer to as the crisis period. This is the period during which share prices of major U.S. financials collapsed and which included the failures of several large financial institutions such as Countrywide Financial Corporation, Northern Rock, and Lehman Brothers. Starting in July 2007, Countrywide Financial Corporation, which subsequently failed, warned of "difficult conditions" and Bear Stearns liquidated two hedge funds that invested in various types of mortgage-backed securities. And in August 2007 the American Home Mortgage Investment Corporation filed for Chapter 11 bankruptcy protection and BNP Paribas, France's largest bank, halted redemptions on three investment funds, evidence that the crisis had spread to the European continent. Our sample period then extends to the collapse of Lehman Brothers in September 2008 and its aftermath until the end of 2008, during which period the US and many European governments took extraordinary measures to support their financial systems, including through nationalizations and government recapitalizations of financial institutions. Our sample period also coincides with the crisis period considered in Beltratti and Stulz (2012), which simplifies comparison between the two studies.

Our systemic risk variables are ΔCoVaR and SRISK. The measure of ΔCoVaR follows Adrian and Brunnermeier (2012). It corresponds to the Value-at-Risk (VaR) of the market return conditional on some tail event observed for firm i:

$$\Pr\left(r_{m,t} \leqslant \mathrm{CoVaR}_{i,t}^{m|C(r_{i,t})} | C(r_{i,t})\right) = \alpha$$

where $r_{m,t}$ is the value-weighted return of the portfolio of all financial firms in the country we refer to it as the "market" portfolio, $C(r_{i,t})$ is the event observed for firm i, and α is the probability level of the conditional probability distribution. ΔCoVaR of firm i is defined as the difference between the VaR of the financial system conditional on firm i being in distress and the VaR of the system conditional on firm i being in its median state. That is,

$$\Delta\mathrm{CoVaR}_{i,t}(\alpha) = \mathrm{CoVaR}_{i,t}^{m|r_{i,t}=\mathrm{VaR}_{i,t}(\alpha)} - \mathrm{CoVaR}_{i,t}^{m|r_{i,t}=\mathrm{median}(r_{i,t})}$$

Following Adrian and Brunnermeier (2012) we set α equal to 0.05. Correspondingly, when calculating $\mathrm{CoVaR}_{i,t}^{m|r_{i,t}=\mathrm{VaR}_{i,t}(\alpha)}$, $C(r_{i,t})$ refers to the case when the individual firm stock return is at its bottom 5% probability level. And when calculating $\mathrm{CoVaR}_{i,t}^{m|r_{i,t}=\mathrm{median}(r_{i,t})}$, $C(r_{i,t})$ refers to the case when the individual firm stock return is at its medium level. In order to capture the variation in ΔCoVaR over time, we also control for a set of global state variables, as in Adrian and Brunnermeier (2012). These state variables include: the VIX index of stock market volatility, the change in the three-month Treasury bill rate, the liquidity spread between the three-month repo rate and the three-month T-bill rate, the change in the slope of the yield curve, and the change in the credit spread between BAA-rated bonds and the Treasury rate. In our analysis, we take the negative value of ΔCoVaR to translate it into an increasing measure of systemic risk.

Following Adrian and Brunnermeier (2012), we estimate ΔCoVaR using quantile regressions and using weekly data that covers both the pre-crisis and crisis period. Specifically, we estimate ΔCoVaR using weekly data from January 2000 to December 2012. Then in the analysis, we use the average of the predicted CoVaR for the period July 1, 2007 to December 31, 2008 as our dependent variable for ΔCoVaR during the crisis period.

We compute ΔCoVaR using weekly stock returns denominated in local currency to abstract from exchange rate effects. The rationale for using the local rather than the global market portfolio for the measure of the system VaR is that the primary effect of systemic risk is local since the financial firms have to be supported and bailed out by national governments. As an alternative, we computed a version of global ΔCoVaR where we set the market equal to the global portfolio of financial firms, thus incorporating global spillovers. The two versions of ΔCoVaR are highly correlated, with a correlation of 58 percent that is significant at the 1% level, and the results obtained with either measure are qualitatively similar once we include country fixed effects. We therefore report only results using the local ΔCoVaR.

The second measure of systemic risk is SRISK, based on Brownlees and Engle (2012) and Acharya et al. (2012). The SRISK index measures the expected capital shortage faced by a financial firm during a period of system distress when the market declines substantially. More precisely,

$$\mathrm{SRISK}_{i,t} = kD_{i,t} - (1-k)W_{i,t}\left(1 - \mathrm{LRMES}_{i,t+h|t}(C_{t+h|t})\right)$$

where k is the minimum fraction of capital as a ratio of total assets that each firm needs to hold (we set k equal to the prudential capital ratio of 8 percent), and $D_{i,t}$ and $W_{i,t}$ are the book value of its debt (total liabilities) and the market value of its equity, respectively.

Following Acharya et al. (2012), we set h in $C_{t+h|t}$ equal to 180 days and $C_{t+180|t}$ equal to −40 percent, and use the following approximation to compute long-run MES based on one-day MES:

$$\text{LRMES}_{i,t+180|t}(C_{t+180|t}) = 1 - \exp\left(-18 \times \text{MES}_{i,t+1|t}(C_{t+1|t})\right).$$

One-day MES is defined as the tail expectation of the firm's equity return conditional on a market decline: $\text{MES}_{i,t+1|t}(C_{t+1|t}) = -E_t(R_{i,t+1|t}|R_{m,t+1|t} < C)$, where $R_{i,t+1|t}$ and $R_{m,t+1|t}$ denote the one-day stock return for the firm and the market respectively, and C is the threshold of the decline in market index (−2 percent in this case).[2]

We construct SRISK by estimating the return model using daily data over the period January 2000 to December 2012. Then we compute SRISK using the average of the predicted values for MES over the period July 1, 2007 to December 31, 2008. Unlike Acharya et al. (2012), we do not limit SRISK from below to zero, allowing SRISK to take on negative values, with a view that highly capitalized banks with large buffers that can easily absorb systemic shocks subtract systemic risk from the financial system.[3] However, this modification does not qualitatively alter our results. All stock returns are computed in local currency terms.

For the purpose of our analysis, we winsorize each systemic risk measure at its 1st and 99th percentiles to remove the influence of outliers. ΔCoVaR is expressed as percentages and SRISK is expressed in billions of US dollars.

2.3. Bank characteristics

To identify the main drivers of systemic risk, we use several bank-specific variables, which proxy for the key risk factors highlighted in the earlier discussion: bank size, capital ratio, funding structure, and activities. Information on bank characteristics is obtained from Bankscope, and measured as of December 2006, i.e. prior to the crisis period (unless otherwise indicated).

Bank size is measured as the natural logarithm of the value of total assets in US dollars. Capital ratio is measured using Tier 1 ratio, which is the ratio of tier-1 capital to total risk-weighted assets. On the funding side, we examine the bank's reliance on deposit funding, captured as the ratio of deposits to assets. For bank activities, we use the ratio of loans to total assets to capture the bank's involvement in market-based activities.

In the extension of our analysis, we also control for country-specific variables: the presence of deposit insurance which previous research has shown can generate moral hazard on the part of banks using a dummy variable which equals 1 in countries that have explicit deposit insurance arrangements, and zero otherwise, using data from Demirgüç-Kunt et al. (2008), and GDP per capita.

2.4. Summary statistics

Table 2 reports the summary statistics of our two measures of systemic risk, winsorized at the top and bottom 1% level, together with the main explanatory variables used in our regression analysis. There, and in the analysis that follows, we use for each financial institution the simple average of institution-level systemic risk over the crisis period July 1, 2007 to December 31, 2008 as measure of systemic risk. The table reports summary statistics on those averages across our sample of financial institutions, together with our main explanatory variables. We find that ΔCoVaR ranges from a low of 0.08% to a low of 9.77%, and SRISK ranges from a low of US$ −9.07 billion to a high of US$ 69.43 billion. The difference in the number of observations between the two measures of systemic risk is due to missing information on balance sheet information for some financial firms.

Table 2
Summary statistics.

Variable	Obs	Mean	Std. Dev.	Min	Max
ΔCoVaR08 (%)	398	5.23	2.04	0.08	9.77
SRISK08 (US$ bn)	382	5.08	16.66	−9.07	69.43
Return08 (%)	404	−44.03	28.53	−99.18	54.43
Volatility08 (%)	400	7.18	3.35	1.03	25.40
ΔCoVaR06 (%)	400	2.95	1.16	0.08	6.09
SRISK06 (US$ bn)	395	1.78	9.37	−11.81	39.37
Return06 (%)	398	16.92	33.64	−50.78	152.29
Volatility06 (%)	400	3.58	1.41	1.02	9.91
Log assets	412	3.83	1.34	2.31	7.64
Tier 1 ratio (%)	341	10.18	4.37	3.68	48.47
Deposits/assets	391	0.63	0.21	0.00	0.94
Loans/assets	406	0.56	0.17	0.00	0.92
Deposit insurance	387	0.85	0.35	0	1
Log GDP per capita	56	9.96	1.07	6.68	11.41

This table reports summary statistics of the main regression variables for the sample of publicly listed banks around the world with assets greater than US$ 10 billion. ΔCoVaR08 is the ΔCoVaR computed over the period July 2007 to December 2008, expressed in percentages. SRISK08 is SRISK computed over the period July 2007 and December 2008, expressed in billions of US dollars. For details on the computation of ΔCoVaR and SRISK, see the main text. Volatility08 is the volatility of weekly equity returns computed over the period July 2007 to December 2008, expressed in percentages. Return08 is the cumulative stock return computed over the period July 2007 to December 2008, expressed in percentages. ΔCoVaR06, SRISK06, Volatility06, and Return06 are identical to their 08 counterparts but are calculated over the period January 2006 to December 2006. Log assets is the natural logarithm of total assets (in millions of US dollars). Tier 1 ratio is the ratio of Tier-1 capital to risk-weighted assets. Deposits/assets is the ratio of bank deposits to total assets. Deposit insurance is a dummy variable equal to one when there is an explicit deposit insurance scheme from Demirgüç-Kunt et al. (2008). Log GDP is the natural logarithm of per capital GDP.

Table 3 reports the correlations between our main variables, including the correlation between our two measures of systemic risk and their correlation with bank-level weekly stock return volatility and bank-level stock returns over the period from July 1, 2007 to December 31, 2008. The return and volatility variables are also winsorized at the 1st and 99th percentiles. The correlation table shows a strong but far from perfect correlation of about 40 percent between our two measures of systemic risk, suggesting that they each capture different aspects of systemic risk.

Moreover, the correlation between the two measures of systemic risk and returns and volatility is significant but low, especially in the case of SRISK, suggesting that systemic risk cannot simply be attributed to negative returns and high volatility, which have been the focus of most earlier studies of bank performance during the crisis (e.g. Beltratti and Stulz, 2012).

Table 3 also indicates that bank size is highly correlated with systemic risk, for both ΔCoVaR and SRISK. Moreover, both measures of systemic risk are negatively correlated with the Tier-1, the deposit, and the loan ratios.

Table 4 lists the names of the banks with the largest contribution to systemic risk, for global ΔCoVaR and SRISK measures in Panels A and B, respectively. The list prominently features large banks from both the US and Europe. The majority of institutions in this list received government support during the crisis, including in the form of capital injections and guarantees on assets or liabilities. Interestingly, the two lists are sufficiently different, which

[2] To ensure comparability with the established methods of calculating ΔCoVaR and SRISK, we use the same parameters and approximations as in the original studies whenever appropriate. This relates in particular to the 5% probability level in the calculation of ΔCoVaR, the 2% probability level in the calculation of SRISK, and the use of the daily return on the S&P 500 index as proxy for the market return in the calculation of SRISK.

[3] Acharya et al. (2012) limit SRISK from below to zero because they are interested in estimating capital shortages that by definition cannot take on negative values. For our purposes, negative values of SRISK are meaningful because they provide information on the relative contribution of the institution to systemic risk.

Table 3
Correlation matrix.

	ΔCoVaR08	SRISK08	Return08	Log assets	Tier 1 ratio	Deposits/assets	Loans/assets
ΔCoVaR08	1						
SRISK08	0.43*	1					
Return08	−0.37*	−0.30*	1				
Log assets	0.53*	0.75*	−0.31*	1			
Tier 1 ratio	−0.06	−0.19*	0.14*	−0.22*	1		
Deposits/assets	−0.34*	−0.39*	0.32*	−0.50*	−0.05	1	
Loans/assets	−0.22*	−0.31*	0.00	−0.29*	−0.44*	0.33*	1

This table reports the correlation matrix of the main regression variables for the sample of publicly listed banks around the world with assets greater than US$ 10 billion.
* denotes significance of pair-wise correlations at the 5% level.

Table 4
Financial institutions with the largest contribution to systemic risk, July 2007–December 2008.

Panel A: top 10 institutions by ΔCoVaR during the crisis		
1	UniCredit SpA	Italy
2	Citigroup Inc	USA
3	Standard Chartered Plc	UK
4	Wells Fargo & Company	USA
5	Barclays Plc	UK
6	BB&T Corporation	USA
7	Skandinaviska Enskilda Banken AB	Sweden
8	Bank of America Corporation	USA
9	Merrill Lynch & Co., Inc.	USA
10	Deutsche Bank AG	Germany
Panel B: Top 10 banks by SRISK during the crisis		
1	Royal Bank of Scotland Group Plc	UK
2	Deutsche Bank AG	Germany
3	Barclays Plc	UK
4	BNP Paribas	France
5	Crédit Agricole S.A.	France
6	Citigroup Inc	USA
7	JP Morgan Chase & Co.	USA
8	UBS AG	Switzerland
9	ING Groep NV	Netherlands
10	Bank of America Corporation	USA

The tables list the names and countries of origin of the top-10 financial institutions in terms of ΔCoVaR and SRISK, averaged over the period July 2007–December 2008.

points to different aspects of systemic risk being captured by ΔCoVaR and SRISK, and the usefulness of using multiple indicators in the analysis of systemic risk.[4]

3. Determinants of bank risk during the crisis

In this section, we estimate regressions to investigate the determinants of standalone and systemic bank risk. We use the following regression model to analyze the determinants of bank risk:

$$S_{ijt} = \alpha_j + \beta B_{ij,t-1} + \varepsilon_{ijt} \tag{1}$$

where S_{ijt} is a measure of risk of bank i in country j, computed over crisis period t, α_j is a country fixed effect, $B_{ij,t-1}$ is a vector of bank characteristics computed at time $t-1$, and ε_{ijt} is the error term.

We will examine three measures of bank risk over the period from July 2007 to December 2008: the standalone bank risk as measured by stock returns, and systemic risk as measured by ΔCoVaR and SRISK. In all regressions, bank risk is computed over the period July 2007–December 2008 for our full sample of banks with assets greater than US$ 10 billion. We further adjust these risk measures by subtracting their levels at year 2006 so as to control for potential omitted firm-level factors. All regressions include country fixed effects, with standard errors clustered at the country level.

3.1. Standalone bank risk

We first examine standalone bank risk as measured by stock returns. Table 5 reports regressions for the determinants of equity returns, which have been the key proxy of standalone bank risk during the crisis in earlier studies. In Column 1, we find that the stock return is significantly lower for banks with larger size. In Column 2, the stock return is higher for banks with larger Tier 1 ratio.[5] In Column 3, the interaction term of bank size and Tier 1 ratio is positive and significant at the 10% level. Therefore, higher capital ratio increases stock return, especially for large banks. In Column 4, we further include other bank characteristics such as deposit/asset and loan/asset ratios. We find that higher deposit ratio and lower loan/asset ratios are associated with higher stock returns. The interaction term of bank size and Tier 1 ratio is still positive, although not significantly different from zero.

The results offer a number of useful implications. First, bank size *per se* is a risk factor: larger banks performed worse during the crisis. Second, large banks with low capital performed especially poorly, highlighting that low capital in large banks is a major concern. (Here, the concern is micro-prudential, because we focus on the determinants of standalone bank risk.) The result that depository funding improves bank performance is consistent with the earlier literature highlighting bank wholesale funding as a major source of vulnerability (Huang and Ratnovski, 2009, 2011). The finding that banks with more loans performed worse can be explained by some smaller US banks holding large volumes of mortgages (that later became distressed) on balance sheet.

3.2. Systemic risk as measured by ΔCoVaR

Table 6 examines the determinants of ΔCoVaR, one of our measures of systemic risk. Column 1 focuses on bank size. We find that bank size is strongly associated with ΔCoVaR. The economic effect is substantial. Based on the coefficient estimates for the ΔCoVaR regressions, a one standard deviation increase in the log of total assets, which amounts to an increase in total assets of US$ 3.9 billion, would imply an increase in ΔCoVaR of 0.67 or 0.34 times its standard deviation, which is a substantial effect.

In Column 2 we consider the influence of bank capital, as measured by Tier 1 ratio. We find that systemic risk is significantly lower for well-capitalized banks, consistent with the hypothesis that banks with more capital find it more costly to take on risk, and have larger buffers that reduce the probability of bank failure and the implications of bank distress. In Column 3, we include the interaction term of bank size and Tier 1 ratio. There, the interaction

[4] This list excludes financial institutions that failed and were de-listed, since these are not included in our sample.

[5] Arguably, the Tier 1 capital ratio, by controlling both for the riskiness of assets and the quality of capital, is a more accurate measure of bank capital than the straight leverage ratio.

Table 5
Standalone risk regressions for July 2007–December 2008: return.

VARIABLES	(1)	(2)	(3)	(4)
Log Assets($)	−7.923***		−14.28**	−12.96**
	[2.696]		[6.166]	[6.403]
Tier 1 ratio		3.383**	−0.588	−1.450
		[1.316]	[2.808]	[2.516]
Tier 1 ratio*log assets			1.137*	1.099
			[0.667]	[0.705]
Deposits/assets				67.99***
				[16.13]
Loans/assets				−51.73***
				[14.24]
Country fixed effects	Y	Y	Y	Y
Observations	363	302	302	302
R-squared	0.577	0.609	0.623	0.645

This table reports regressions of the bank's stock return on a set of bank characteristics and includes country fixed effects. The dependent variable is the average stock return over the period July 2007 to December 2008, after subtracting the average return during the year 2006. Regressions are estimated using OLS. The sample includes publicly listed banks with assets greater than US$ 10 billion at end 2006. Standard errors, reported between brackets, are clustered at the country level. ***, **, and *denote statistical significance at the 1%, 5%, and 10% level, respectively.

term is negative, significantly different from zero at the 1% level. This means that higher capital ratio is particularly important for lowering the systemic risk for large banks.

In Column 4, we control for bank funding structure and activities, and find them not to be significant in explaining ΔCoVaR. However, the interaction of capital ratio and bank asset remains significant, both economically and statistically.

In the previous section we already pointed to the low correlation between standalone (as measured by stock returns) and systemic risk measures, suggesting that systemic risk cannot be captured simply through standalone bank risk, which has been the focus of most earlier studies of bank performance. In Column 5, we report regressions of systemic risk that control for the contemporaneous effect of equity returns and volatility, thus abstracting from the effects of banks size on systemic risk that operate through standalone bank risk. We find that bank size interacted with Tier 1 ratio remains significantly negative, suggesting that bank size contributes to systemic risk over and above its effect on the return level and its volatility. This also highlights the importance of using measures of systemic risk rather than traditional measures of bank performance in an analysis of the drivers of systemic risk. Using measures of individual bank risk, such as equity returns or volatility, would underestimate of the influence of bank size and capital on systemic risk.

3.3. Systemic risk as measured by SRISK

In Table 7, we repeat the same regressions for the SRISK measure of systemic risk. Column 1 focuses on bank size in December 2006, controlling for lagged values of SRISK. We find that bank size is strongly associated also with SRISK. In Column 2 we consider the influence of bank capital, as measured by Tier 1 ratio. Again, we find that SRISK is significantly lower for well-capitalized banks. In Column 3, we include the interaction term of bank size and Tier 1 ratio. There, the interaction term is negative, significantly different from zero at the 5% level. All these results are similar to those that were presented in Table 6 for ΔCoVaR.

In Column 4, we control for deposit over total assets and loan assets in total assets. We find that SRISK is not significantly associated with deposit/asset ratio, but negatively associated with loan/asset ratio. In Column 5, we report regressions of systemic risk that control for standalone bank risk measure such as equity returns and volatility. We find that none of them are significantly associated with SRISK. The interaction of capital ratio and bank asset remains significant at the 5% level throughout.

3.4. Discussion of results

Our results offer a number of interesting implications. The interaction between bank size and capital appears the single most robust variable in explaining systemic risk. A caveat is that, in principle, the SRISK measure of systemic risk would respond to higher bank size and lower bank capital by construction. However the fact that the interaction is also significant for ΔCoVaR (and also for bank returns) suggests that it captures more than a mechanical relationship. This result is consistent with the view that large banks enjoy too big to fail subsidies, making them pay less attention to the risks they take, and that they create externalities when they are distressed. The effects of the interaction between bank capital and size are consistent with the "skin-in-the-game" incentives (i.e., the risk reducing effect of increasing the investment at stake for equityholders that only share in the upside) and loss absorption role of bank capital (i.e., more capital allows banks to better absorb unexpected losses).

We find that the interaction between bank size and capital influences systemic risk over and above the effect that it has on standalone bank risk. This offers a clear justification for macroprudential policy. Traditional micro-prudential regulation would not give sufficient attention to low capital in large banks, because it would neglect the implications that it has for the risk in the financial system as a whole beyond its effect on individual banks.

The fact that insufficient bank capital is more significant than bank funding or activities in explaining systemic risk validates the Basel approach of addressing systemic risk of large banks through capital surcharges rather than trough systemic liquidity tools or activity restrictions. (Note that liquidity regulation would still be appropriate for micro-prudential purposes, as suggested by the results in Table 5 on standalone bank risk.) Our framework also suggests a way to estimate capital surcharges on large banks, which could compensate for the effect of their size on systemic risk. For example, the regression in Table 7 Column 5 suggests that a capital surcharge of 2.5 percent reduces the excess systemic risk of a large bank with US$ 1 trillion in assets over an otherwise similar bank with US$ 100 billion in assets by a quarter, a substantial amount.

With regards to market-based bank activities, which generate non-interest income, and which have been the focus of regulatory initiatives in U.S., UK and Europe, we find that they affect the SRISK measure of systemic risk but not the ΔCoVaR measure. This can be interpreted based on the differences between the two measures. Note that ΔCoVaR captures financial system performance conditional on a realization in the left tail of the distribution of bank

Table 6
Systemic risk regressions for July 2007–December 2008: ΔCoVaR.

Variables	(1)	(2)	(3)	(4)	(5)
Log assets ($)	0.471***		0.979***	0.982***	0.881***
	[0.122]		[0.202]	[0.203]	[0.174]
Tier 1 ratio		−0.0851**	0.136**	0.142**	0.116**
		[0.0377]	[0.0598]	[0.0583]	[0.0457]
Tier 1 ratio*log asssets			−0.0547***	−0.0547***	−0.0454***
			[0.0176]	[0.0179]	[0.0160]
Deposits/assets				−0.383	0.131
				[0.881]	[0.792]
Loans/assets				0.510	0.0886
				[0.619]	[0.741]
Return08					−0.00572*
					[0.00317]
Volatility08					0.0251
					[0.0513]
Country fixed effects	Y	Y	Y	Y	Y
Observations	358	298	298	298	298
R-squared	0.681	0.653	0.744	0.745	0.753

This table reports regressions of ΔCoVaR on a set of bank characteristics and includes country fixed effects. The dependent variable is the ΔCoVaR computed over the period July 2007 to December 2008, after subtracting the ΔCoVaR during the year 2006. Regressions are estimated using OLS. The sample includes publicly listed banks with assets greater than US$ 10 billion at end 2006. Standard errors, reported between brackets, are clustered at the country level. ***, **, and *denote statistical significance at the 1%, 5%, and 10% level, respectively.

Table 7
Systemic risk regressions for July 2007–December 2008: SRISK.

VARIABLES	(1)	(2)	(3)	(4)	(5)
Log assets	5.260***		9.964***	9.825***	9.261***
	[0.487]		[1.916]	[1.754]	[1.780]
Tier 1 ratio		−0.952**	1.159	1.042	0.897
		[0.357]	[0.767]	[0.736]	[0.657]
Tier 1 ratio*log assets			−0.487**	−0.491**	−0.431**
			[0.194]	[0.187]	[0.173]
Deposits/assets				2.779	3.766
				[4.101]	[3.830]
Loans/assets				−7.549**	−7.358**
				[3.358]	[3.292]
Return08					0.0170
					[0.0272]
Volatility08					0.534
					[0.347]
Country fixed effects	Y	Y	Y	Y	Y
Observations	340	285	285	285	285
R-squared	0.651	0.441	0.757	0.760	0.766

This table reports regressions of SRISK on a set of bank characteristics and includes country fixed effects. The dependent variable is the SRISK computed over the period July 2007 to December 2008, after subtracting the SRISK during the year 2006. Regressions are estimated using OLS. The sample includes publicly listed banks with assets greater than US$ 10 billion at end 2006. Standard errors, reported between brackets, are clustered at the country level. ***, **, and *denote statistical significance at the 1%, 5%, and 10% level, respectively.

returns, while SRISK captures bank performance conditional on the left tail of system returns. Thus, ΔCoVaR can be seen as a measure more closely capturing contagion risks, while SRISK as more closely capturing the exposure to common shocks that affect the whole financial system. It would then appear that market-based activities make banks more exposed to common shocks (consistent with that market-based exposures are relatively more correlated across banks than, say, lending exposures), but are not material in increasing the risk of contagion from a distressed bank.

3.5. Systemic risk, bank characteristics, and country characteristics

So far we have used country fixed effects to control for country factors that could potentially correlates with systemic risk. Now we focus on a country trait which has entered the debate on financial structure, i.e., the presence of deposit insurance. We focus on the influence of deposit insurance, with a view that the pre-existence of a deposit insurance scheme captures the implicit support of the government to support large banks. Theoretically, the impact of deposit insurance could go either ways. On the one hand, one may expect deposit insurance to reduce the probability of bank run and hence systemic risk. On the other hand, one may expect the presence of deposit insurance, by inducing moral hazard when underpriced, to increase system risk. We also control for GDP per capita interacted as a proxy for the government's ability to support the financial system when it is in distress. To examine which effects dominate for large banks, we include an interaction of deposit insurance dummy in 2006 and GDP per capital with log bank assets.

The results are shown in Table 8. Column 1 reports the regression for ΔCoVaR, Column 2 for SRISK, and Column 3 for stock return. We find that deposit insurance and higher GDP per capital interacted with log assets are significantly positive for SRISK, but not for ΔCoVaR. Recalling that ΔCoVaR captures more scope for contagion while SRISK exposure to common shocks, the results appear consistent with the theoretical arguments that when banks expect to be bailed out in a crisis they choose to take more correlated risk (Farhi and Tirole, 2012), increasing SRISK, but that at the

Table 8
Systemic and individual risk regressions with country characteristics.

Variables	ΔCoVaR (1)	SRISK (2)	Return (3)
Log assets($)	1.815*	−14.83*	−2.634
	[0.977]	[7.937]	[16.04]
Tier 1 ratio	0.131**	1.270**	−2.189
	[0.0601]	[0.569]	[1.896]
Tier 1 ratio*log assets	−0.0528***	−0.497***	0.846
	[0.0182]	[0.157]	[0.631]
Deposits/assets	−0.446	2.414	63.33***
	[0.879]	[4.036]	[15.80]
Loans/assets	0.475	−5.888*	−50.13***
	[0.630]	[3.219]	[12.81]
Deposit insurance*log assets	0.0590	4.288***	−6.117
	[0.161]	[1.515]	[3.805]
Log GDP per capita*log assets	−0.0867	2.019***	−0.212
	[0.0962]	[0.738]	[1.525]
Country fixed effects	Y	Y	Y
Observations	291	281	300
R-squared	0.742	0.800	0.453

This table reports regressions of ΔCoVaR, SRISK, and the average stock return on a set of bank characteristics and includes interactions between the bank's log assets and country characteristics, such as deposit insurance and log GDP per capita. The ΔCoVaR regression is reported in column 1, the SRISK regression in column 2, and the regression with the average stock return as dependent variable is reported in column 3. The dependent variables are computed over the period July 2007 to December 2008, after subtracting their year 2006 values. Deposit insurance is a dummy variable equal to one when there is an explicit deposit insurance scheme from Demirgüç-Kunt et al. (2008). Log GDP is the natural logarithm of per capital GDP. Regressions include country fixed effects. Standard errors, reported between brackets, are clustered at the country level. ***, **, and *denote statistical significance at the 1%, 5%, and 10% level, respectively.

Table 9
Systemic and individual risk regressions for OECD countries only.

Variables	ΔCoVaR (1)	SRISK (2)	Return (3)
Log assets($)	1.035***	9.736***	−13.50**
	[0.223]	[1.380]	[5.468]
Tier 1 ratio	0.151**	0.644	−3.600**
	[0.0586]	[0.556]	[1.623]
Tier 1 ratio*log assets	−0.0620***	−0.433***	1.184*
	[0.0195]	[0.136]	[0.640]
Deposits/assets	−0.402	6.432	57.40***
	[0.998]	[4.515]	[17.82]
Loans/assets	0.841	−8.269**	−51.56***
	[0.606]	[3.450]	[13.38]
Country fixed effects	Y	Y	Y
Observations	223	211	230
R-squared	0.731	0.768	0.415

This table examines systemic and individual risk regressions for OECD countries only. The regression in column 1 reports results for ΔCoVaR, the regression in column 2 for SRISK, and the regression in column 3 for the average stock return. The dependent variables are computed over the period July 2007 to December 2008, after subtracting their year 2006 values. Regressions include bank-specific control variables and country fixed effects. Standard errors, reported between brackets, are clustered at the country level. ***, **, and *denote statistical significance at the 1%, 5%, and 10% level, respectively.

same time the prospect of government support to banks reduces the risk of contagion (Dell'Ariccia and Ratnovski, 2013), mitigating the effect on ΔCoVaR.

In Table 9, we look at the banks in OECD countries only and find similar results. That is, the interaction of size and capital ratio is significantly negative for ΔCoVaR and SRISK, while significantly positive for stock returns.

We also re-estimate our main regressions in Tables 5–9 for a longer sample period, the period July 2007 until December 2009. The rationale for doing this is that systemic risk in many European countries became elevated only in 2009 when sovereign risk pressures were coming to the fore in the periphery countries of Europe. Our explanatory variables remain computed for the end of 2006. We continue to find that the interaction of Tier 1 ratio and log assets is significantly negative for ΔCoVaR and SRISK, albeit insignificant (still positive) for stock returns. Therefore, our earlier results carry over to the longer sample period.

4. Conclusions

We find strong evidence that systemic risk increases with bank size. Our results indicate that a one standard deviation increase in total assets increases the bank's contribution to systemic risk by about one-third its standard deviation when measured by ΔCoVaR, and by about half its standard deviation when measured by SRISK. These are large effects. These effects might moreover underestimate the true systemic risk of large banks, because market values of bank equity during the crisis may be boosted by expectations of government support, and because they do not account for the social costs associated with large bank failures (e.g., output losses and unemployment). We also find some evidence that systemic risk is lower in more-capitalized banks, with the effects particularly more pronounced for large banks. The significance of these results is robust to the sample, to the metric of systemic risk used, and to a range of controlled bank attributes.

Taken at face value, these results lend support to the views that large banks pose excessive systemic risk, and could be seen as evidence in support of calls to limit the size or activities of banks. However, such calls should come with much caution because our empirical tests do not identify the optimal size of banks. In particular, while large banks may increase systemic risk, they may also offer efficiency gains, for instance by being better able to offer certain financial services that require economies of scale. Indeed, many would argue that the increased competition in banking following deregulation has increased the efficiency of banks. The balance between these two considerations is a complex trade off.

Finally, and most importantly, even if we could conclude that large banks are excessively large it is not clear what to do about it. Quantity restrictions such as size and activity limits may be distortive if they are not set at optimal levels, which seems hard to do in practice, and may be easy to circumvent by large, complex banking organizations that are generally active internationally. For these reasons, some have argued in favor of tightening capital requirements, which can be seen as less intrusive and could easily be varied over time should this be deemed desirable (e.g. Stein, 2013). And there is scope to reduce too-big-to-fail subsidies though better resolution rules, although it is doubtful whether these subsidies can ever be fully eliminated. While our results underpin the importance of the debate on whether banks are too large and complex, more research is needed to guide policy in this important policy area.

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References

Acharya, Viral, Engle, Robert, Richardson, Matthew, 2012. Capital shortfall: a new approach to ranking and regulating systemic risks. American Economic Review 102 (3), 59–64.

Adrian, Tobias, Brunnermeier, Markus K., 2012. CoVaR. Mimeo, Princeton University, <http://scholar.princeton.edu/markus/files/CoVaR.pdf>.

Aiyar, Shekhar, Calomiris, Charles W., Wieladek, Tomasz, 2014. Does macro-prudential regulation leak? evidence from a UK policy experiment. Journal of Money, Credit and Banking 46 (1), 181–214.

Alessandri, Piergiorgio, Masciantonio, Sergio, Zaghini, Andrea, 2014. Everything you always wanted to know about systemic importance (but were afraid to ask). CFS Working Paper 463.

Beck, Thorsten, De Jonghe, Olivier, 2013. Lending concentration, bank performance and systemic risk: exploring cross-country variation. World Bank Policy Research Working Paper 6604.

Beltratti, Andrea, Stulz, Rene, 2012. The credit crisis around the globe: why did some banks perform better? Journal of Financial Economics 105, 1–17.

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

Billio, Monica, Getmansky, Mila, Lo, Andrew W., Pelizzon, Loriana, 2012. Econometric measures of connectedness and systemic risk in the finance and insurance sectors. Journal of Financial Economics 104 (3), 535–559.

Bolton, Patrick, Freixas, Xavier, Shapiro, Joel, 2007. Conflicts of interest, information provision and competition in financial service industry. Journal of Financial Economics 85 (2), 297–330.

Boot, Arnoud W.A., Ratnovski, Lev, 2012. Banking and Trading. IMF Working Paper No. 12/238. Washington, DC, International Monetary Fund.

Brownlees, Christian, Engle, Robert, 2012. Volatility, Correlation and Tails for Systemic Risk Measurement. Mimeo, Pompeu Fabra.

Brunnermeier, Markus K., Dong, Gang, Palia, Darius, 2013. Banks' Non-Interest Income and Systemic Risk. Mimeo, Princeton University, <http://scholar.princeton.edu/markus/files/paper_2012_01_31.pdf>.

Caprio, Gerard, Laeven, Luc, Levine, Ross, 2007. Governance and bank valuation. Journal of Financial Intermediation 16, 584–617.

Dell'Ariccia, Giovanni, Ratnovski, Lev, 2013. Bailouts and Systemic Insurance. IMF Working Paper 13/233.

Demirgüç-Kunt, Asli, Huizinga, Harry, 2010. Bank activity and funding strategies: the impact on risk and return. Journal of Financial Economics 98, 626–650.

Demirgüç-Kunt, Asli, Kane, Edward J., Laeven, Luc, 2008. Determinants of deposit-insurance adoption and design. Journal of Financial Intermediation 17 (3), 407–438.

Drehmann, Matthias, Tarashev, Nicola, 2013. Measuring the systemic importance of interconnected banks. Journal of Financial Intermediation 22 (4), 586–607.

Farhi, Emmanuel, Tirole, Jean, 2012. Collective moral hazard, maturity mismatch and systemic bailouts. American Economic Review 12 (1), 60–93.

French, Kenneth R., Baily, Martin N., Campbell, John Y., Cochrane, John H., Diamond, Douglas W., Duffie, Darrell, Kashyap, Anil, Mishkin, Frederic S., Rajan, Raghuram G., Scharfstein, David S., Shiller, Robert J., Shin, Hyun Song, Slaughter, Matthew J., Stein, Jeremy C., Stulz, Rene M., 2010. Squam Lake Report: Fixing the Financial System. Princeton University Press, Princeton, NJ.

Gennaioli, Nicola, Shliefer, Andrei, Vishny, Robert W., 2013. A model of shadow banking. Journal of Finance 68 (4), 1331–1363.

Giglio, Stefano, Kelly, Bryan, Pruitt, Seth, Qiao, Xiao, 2013. Systemic risk and the macroeconomy: an empirical evaluation. Mimeo, Booth School of Business,University of Chicago.

Goetz, Martin, Laeven, Luc, Levine, Ross, 2013. Identifying the valuation effects and agency costs of corporate diversification: evidence from the geographic diversification of U.S. banks. Review of Financial Studies 26 (7), 1787–1823.

Guntay, Levent, Kupiec, Paul, 2014. Taking the Risk out of Systemic Risk Measurement. Working Paper.

Hansen, Lars Peter, 2014. Challenges in Identifying and Measuring Systemic Risk. In: Brunnermeier, M.K., Krishnamurthy, A. (Eds.), Risk Topography: Systemic Risk and Macro Modeling, Chapter 1, University of Chicago Press.

Houston, Joel, James, Christopher, Marcus, David, 1997. Capital market frictions and the role of internal capital markets in banking. Journal of Financial Economics 46, 135–164.

Hovakimian, Armen, Kane, Edward, 2000. Effectiveness of capital regulation at U.S. commercial banks, 1985 to 1994. Journal of Finance 55 (1), 451–468.

Huang, Rocco, Ratnovski, Lev, 2009. Why are Canadian Banks More Resilient? IMF Working Paper 09/152.

Huang, Rocco, Ratnovski, Lev, 2011. The dark side of bank wholesale funding. Journal of Financial Intermediation 20 (2), 248–263.

Huang, Xin, Zhou, Hao, Zhu, Haibin, 2009. A framework for assessing the systemic risk of major financial institutions. Journal of Banking and Finance 33 (11), 2036–2049.

Huang, Xin, Zhou, Hao, Zhu, Haibin, 2012. Systemic risk contributions. Journal of Financial Services Research 42 (1–2), 55–83.

Hughes, Joseph P., Mester, Loretta, 2013. Who Said large banks don't experience scale economies? evidence from a risk-return-driven cost function. Journal of Financial Intermediation 22 (4), 559–585.

International Monetary Fund, 2010, Global Financial stability report, April, Chapter 2. Systemic Risk and the Redesign of Financial Regulation. Washington, DC, International Monetary Fund.

Kashyap, Anil K., Rajan, Raghuram, Stein, Jeremy C., 2002. Banks as liquidity providers: an explanation for the coexistence of lending and deposit-taking. Journal of Finance 57 (1), 33–74.

Kashyap, Anil K., Rajan, Raghuram, Stein, Jeremy C., 2010a. Rethinking capital regulation. In: Federal Reserve Bank of Kansas City Symposium on Maintaining Stability in a Changing Financial System, 2008. Federal Reserve Bank of Kansas City, Kansas City, pp. 431–471.

Kashyap, Anil K., Stein, Jeremy C., Hanson, Samuel G., 2010. An analysis of the impact of substantially heightened capital requirements on large financial institutions. Working Paper, Harvard University.

Laeven, Luc, Levine, Ross, 2007. Is there a diversification discount in financial conglomerates? Journal of Financial Economics 85, 331–367.

Laeven, Luc, Levine, Ross, 2009. Bank governance, regulation, and risk taking. Journal of Financial Economics 93, 259–275.

Laeven, Luc, Ratnovski, Lev, Tong, Hui, 2014. Bank Size and Systemic Risk. IMF Staff Discussion Note 14/04.

Liikanen, Erkki (Chair), 2012. The High-Level Expert Group on Reforming the Structure of the EU Banking Sector: Final Report.

Puzanova, Natalia, Düllmann, Klaus, 2013. Systemic risk contributions: a credit portfolio approach. Journal of Banking and Finance 37 (4), 1243–1257.

Saunders, Anthony, Strock, Elizabeth, Travlos, Nikolaos G., 1990. Ownership structure, deregulation, and bank risk taking. Journal of Finance 45, 643–654.

Shleifer, Andrei, Vishny, Robert W., 2010. Unstable banking. Journal of Financial Economics 97 (3), 306–318.

Stein, Jeremy, 2013. "Regulating Large Financial Institutions", Speech at the "Rethinking Macro Policy II", conference. International Monetary Fund, Washington, D.C.

Tarashev, Nikola, Borio, Claudio, Tsatsaronis, Kostas, 2010. Attributing Systemic Risk to Individual Institutions. Bank for International Settlements Working Paper 308.

Vickers, John (Chair), 2011. Final Report of the Independent Commission on Banking.