Bank Size, Capital Requirements, and Systemic Risk: Some International Evidence

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Abstract: This paper studies the significant variation in the cross-section of individual and systemic risk of large banks during the recent financial crisis to identify bank specific factors that determine risk. The results indicate that individual and systemic risk grows with bank size and is inversely related to bank capital, consistent with the presence of agency conflicts in large organizations and too big to fail considerations. Our results contribute to the ongoing debate on the merits of imposing systemic risk-based capital requirements on banks.

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Introduction

The recent financial crisis has triggered a debate on the optimal size and structure of banks. This is not only because banks that combine lending and trading activities were at the center of the recent crisis, but also because the size of large banks and the degree of their engagement in market-based activities have increased substantially over the last two decades.

The views in this debate differ. Some, including the Basel Committee, advocate incremental measures – such as an additional surcharge of up to 2.5% capital on large banks (e.g., International Monetary Fund, 2010; and 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 outright restrictions on risky bank activities – prohibiting proprietary trading or segregating non-domestic and non-lending bank operations into ring-fenced subsidiaries. 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, Stein, and Hanson, 2010; Aiyar, Calomiris, and Wieladek, 2013). They propose to focus instead on the existence of too big to fail subsidies, which have encouraged banks to grow in size and take on excessive risks, and could be reduced through better resolution and contingent capital requirements (Farhi and Tirole, 2012; Kashyap, Rajan, and Stein, 2010; and Stein, 2013).

Much of this debate is taking place without detailed analysis of the main drivers of systemic risk in banks. The academic literature on the performance of banks has focused primarily on measures of individual bank performance and risk taking, rather than on the contribution of individual banks to systemic risk, i.e., the risk of the financial system as a whole. This distinction is important because relatively stable but highly interconnected banks may pose significant systemic risk if they become jointly distressed. Measures of individual bank risk may therefore present a poor guide to assessing the systemic risk of banks.

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 those bank specific factors that determine systemic risk. We use the crisis as a shock to the banking system revealing the nature and size of systemic risk of individual banks. As proxies for systemic risk we use recently developed measures of systemic risk, including Adrian and Brunnermeier (2012)'s CoVaR and Brownlees and Engle (2012)'s SRISK. By simultaneously analyzing the role of banks size, activity diversity, and funding structures, we are able to isolate the independent effects of these bank factors on systemic risk, and shed light on the ongoing debate on the merits of restricting bank size and/or 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, Shleifer, and Vishny, 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, Freixas, and Shapiro, 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 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.

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 individual 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 at least twofold. 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 control for country factors that may influence the relation between bank size, activities, 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. To guide policy it is therefore critically important to consider alternative measures of systemic risk.

Our paper is related to a large literature studying the performance and riskiness of banks. 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, James, and Marcus (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, Laeven, and Levine (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. And Berger and Bouwman (2013) find that better capitalized banks are more likely to survive banking crises. Hovakimian and Kane (1990) 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.

Our paper is also closely related to recent literature on measuring and explaining systemic risk in banks. For example, Brunnermeier, Dong, and Palia (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. Billio et al. (2012) considers alternative measures of systemic risk to infer their ability to predict periods of financial stress, while Giglio et al. (2013) considers alternative measures of systemic risk but focuses on their predictive power in terms of macroeconomic outcomes, and does not consider the role of bank-specific factors such as size and activity in driving systemic risk.

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, 2012). While we use the two most widely used measures of systemic risk, these measures will likely be refined and improved going forward while other measures are being developed. Moreover, these measures of systemic risk capture only certain aspects of systemic risk. Indeed, work by Giglio et al. (2013) shows that use a combination of systemic risk measures significantly improves their predictive power. The measures of systemic risk we use rely on market prices and therefore can only capture systemic risk inasmuch it is reflected in market 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.

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

1. Data

2.1. Sample

To construct the sample, we start from the sample of 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 1,721 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 1,343 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. The resulting sample consists of 412 deposit-taking institutions from 56 countries. Within this sample, we define a large bank as a deposit-taking institution with assets in excess of US$ 50 billion at the end of 2006. In robustness tests, we also report results for the broader sample that includes smaller institutions and/or non-bank financial institutions.

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 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:

$$\Pr(r_{m,t} \leq CoVaR_{i,t}^{m|C(r_{i,t})} \mid C(r_{i,t})) = \alpha$$

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 quantile of the conditional probability distribution. The $\Delta CoVaR$ 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,

$$\Delta CoVaR_{i,t}(\alpha) = CoVaR_{i,t}^{m|r_{i,t}=VaR_{i,t}(\alpha)} - CoVaR_{i,t}^{m|r_{i,t}=median(r_{i,t})}$$

Following Adrian and Brunnermeier (2012) we set α equal to 0.05. Correspondingly, when calculating $CoVaR_{i,t}^{m|r_{i,t}=VaR_{i,t}(\alpha)}$, $C(r_{i,t})$ refers to the case when the individual firm stock return is at its bottom 5% quantile. And when calculating $CoVaR_{i,t}^{m|r_{i,t}=median(r_{i,t})}$, $C(r_{i,t})$ refers to the case then 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 $\Delta CoVaR$ 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 ΔCoVaR where we set the market equal to the US 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. 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, Engle, and Richardson (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,

$$SRISK_{i,t} = kD_{i,t} - (1-k)W_{i,t}(1 - LRMES_{i,t+h|t}(C_{t+h|t}))$$

where k is the minimum fraction of capital (expressed as a ratio of total assets) each firm needs to hold, 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.

MES is defined as the tail expectation of the firm's equity return conditional on a market decline:

$$MES_{i,t+h|t}(C) = -E_t(R_{i,t+h|t} \mid R_{m,t+h|t} < C)$$

where $R_{i,t+h|t}$ and $R_{m,t+h|t}$ denote the stock return for the firm and the market between period t and $t+h$, and C is the threshold of the decline in market index. Following Acharya et al. (2012), we take the daily return on the S&P 500 index as proxy for the market return. We set h equal to 1 day, with t measured in days, and C equal to -2 percent, so that MES is the one-day loss expected if market returns are less than −2 percent. To construct MES, we estimate the return model using daily data over the period January 2000 to December 2012. Then we compute MES for the crisis period as the average of the predicted values for MES over the period July 1, 2007 to December 31, 2008.

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:

$$LRMES_{i,t+180|t}(C_{t+180|t}) = 1 - \exp(-18 \times MES_{i,t+1|t}(C_{t+1|t})),$$

where $C_{t+1|t}$ is -2 percent. Moreover, as in Acharya et al. (2012), we set k equal to the prudential capital ratio of 8 percent. As with MES, 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.[1] 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. $\Delta CoVaR$ is expressed as percentages and SRISK is expressed in billions of US dollars.

[1] 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.

2.3 Bank size, activity, funding structure, and other bank characteristics

To identify the main drivers of systemic risk, we use several bank-specific and country-specific variables. The bank-specific variables we create are proxies for the various risk factors that the earlier mentioned theories focus on, i.e., bank size, capital ratio, funding structure, and activity diversity. Information on bank characteristics is obtained from the Bankscope database, measured as of December 2006, 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. On the activity side, we use the ratio of loans to total assets to capture the bank's involvement in market-based activities.

We also control for the presence of deposit insurance which previous research has shown can generate moral hazard on the part of banks using a dummy variable, Deposit Insurance, which equals 1 in countries that have explicit deposit insurance arrangements, and zero otherwise, using data from Demirgüç-Kunt, Karacaovali, and Laeven (2005).

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 $\Delta CoVaR$ 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 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 1^{st} and 99^{th} 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 $\Delta CoVaR$ 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, ranked in terms of SRISK (but showing also the $\Delta CoVaR$ measure). Contrary to Tables 2 and 3, Table 4 reports the unwinsorized values of the systemic risk variables. The list prominently features large financial institutions from both the US and Europe (as well as US government-sponsored entities

Fannie Mae and Freddie Mac). 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.[2] Interestingly, the top-5 contributors to SRISK and $\Delta CoVaR$ are all European banks.

2. Determinants of systemic risk during the crisis

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

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

where S_{ijt} is a measure of systemic 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, which includes $S_{ij,t-1}$, and ε_{ijt} is the error term.

2.1 Systemic risk as measured by ΔCoVaR

We start with regressions of systemic risk computed over the period July 2007 – December 2008 for our full sample of banks with assets greater than US$ 10 billion. All regressions include country fixed effects and control for lagged pre-crisis values of systemic risk measured in 2006. Standard errors are clustered at the country level. Results are presented in Table 5 for CoVaR and in Table 6 for SRISK.

Column 1 of Table 5 controls for lagged values of systemic risk and for bank size using the logarithm of total assets (expressed in US dollars) in December 2006. We find that bank size is strongly associated with ΔCoVaR. This is consistent with the view that large banks enjoy too big to fail subsidies, making them pay less attention to the risks they take, but also to the view

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

that large banks tend to have different business models with less traditional banking activities that make them more interconnected with the rest of the financial system.

The economic effect of this 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 0.62 or 0.30 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.[3] Our prior is that a more highly capitalized bank will pose less threat to the financial system, thereby reducing systemic risk. A bank with more capital will find it more costly to take on risk, and has larger buffers should the bank fail, reducing the probability of bank failure. Consistent with our priors, we find that systemic risk 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. This means that higher capital ratio is particularly important for lowering the systemic risk for large banks.

In Column 4, we further control for other bank characteristics related to funding structure and activities of the bank. Funding structure is captured by deposit over total assets. One may argue that banks that finance themselves largely with deposits are more stable than banks that fund themselves in repo markets and other short-term debt markets. To capture bank activities, we include the fraction of loan assets in total assets. One may argue that banks that engage more in trading and other non-interest earning activities increase systemic risk because the income stream of these activities is inherently more volatile than that of traditional lending activities and because banks with trading activities have become increasingly interconnected by funding

[3] 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.

themselves in short-term repo markets to fund trading activities. Moreover, compensation contracts in trading operations of banks are particularly perverse in generating steep incentives for traders to take on risks without paying attention to potential spillovers they may create for other parts of the financial system. In Column 4, we find that ΔCoVaR is not significantly associated with either deposit/asset ratio or loan/asset ratio. More importantly, 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 stock returns and volatility and our measures of systemic risk, suggesting that systemic risk cannot be captured simply by returns and volatility, which have 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 return and volatility. (As we shall present, bank size is positively associated with equity volatility and negatively associated with equity returns.) We find that bank size interacted with Tier 1 ratio remains significantly negative, after controlling for the contemporaneous effect of return and volatility, 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 volatility, would underestimate of the influence of bank size on systemic risk.

3.2 Systemic Risk as measured by SRISK

Column 1 of Table 6 controls for lagged values of SRISK and for bank size in December 2006. We find that bank size is strongly associated with SRISK. This is consistent with the view that large banks enjoy too big to fail subsidies, making them pay less attention to the risks they take. The economic effect of this effect is also substantial. Based on the coefficient estimates for size, one standard deviation increase in the log of total assets would translate in an increase in SRISK of US$ 8.17 billion or 0.49 its standard deviation.

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. Hence higher capital ratio is particularly important for lowering the systemic risk for large banks.

In Column 4, we further 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. More importantly, the interaction of capital ratio and bank asset remains significant at the 5% level.

In Column 5, we report regressions of systemic risk that control for equity returns and volatility. We find that stock return is not significantly associated with SRISK, but return volatility is significantly associated with SRISK at the 10% level. More importantly, bank size interacted with Tier 1 ratio remains significantly negative, after controlling for the contemporaneous effect of return and volatility.

3.3 Individual bank risk

In Tables 7 and 8, we report regressions for equity returns and volatility, which have been the focus of earlier studies of bank performance.

Table 7 reports the result for equity returns. 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. In Column 3, the interaction term of bank size and Tier 1 ratio is positive, 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.

Table 8 reports the result for volatility. In Column 1, we find that the volatility is significantly higher for banks with larger size. In Column 2, we do not find a significant correlation between capital ratio and volatility. In Column 3, the interaction term of bank size and Tier 1 ratio is negative, significant at the 10% level. Therefore, higher capital ratio reduces volatility for large banks. In Column 4, we further include deposit/asset and loan/asset ratios. Higher deposit ratio and lower loan/asset ratios are associated with lower stock return volatility. Moreover, the interaction term of bank size and Tier 1 ratio is still negative at the 10% level.

3.4 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 impacts 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.

To examine which effects dominate for large banks, we therefore include an interaction of deposit insurance dummy in 2006 and log assets. Table 9 examine whether deposit insurance has disproportional effects on large banks in terms of their systemic and individual risks. Column 1 reports the regression for ΔCoVaR, Column 2 for SRISK, Column 3 for stock return, while Column 4 for return volatility. There, we also control for potential disproportional effect of economic development by including an interaction of GDP per capita (log) and log assets. We find that deposit insurance interacted with log assets is significantly positive for SRISK. Hence large banks are disproportionally associated with SRISK in countries with deposit insurance.

3.5. Longer sample period

Now we re-estimate our main regressions in Tables 5 to 8 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. The results are presented in Table 10.

We continue to find that the interaction of Tier 1 ratio and log assets is significantly negative for ΔCoVaR, SRISK and return volatility, albeit insignificant (still positive) for stock return. 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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Table 1. Country characteristics

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, Kane, and Laeven (2008).

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		

Table 2. Summary statistics

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. DCoVaR08 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 CoVaR 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. DCoVaR06, 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, Kane, and Laeven (2008). Log GDP is the natural logarithm of per capital GDP.

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	412	9.96	1.07	6.68	11.41

Table 3. Correlation matrix

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. Asterisks denote significance of pair-wise correlations at 5% level.

	∆CoVaR08	SRISK08	Return08	Volatility08	Log Assets	Tier 1 Ratio	Deposits/Assets	Loans /Assets
∆CoVaR08	1							
SRISK08	0.43*	1						
Return08	-0.37*	-0.30*	1					
Volatility08	0.35*	0.27*	-0.57*	1				
Log Assets	0.53*	0.75*	-0.31*	0.17*	1			
Tier 1 Ratio	-0.06	-0.19*	0.14*	0.02	-0.22*	1		
Deposits/Assets	-0.34*	-0.39*	0.32*	-0.10	-0.50*	-0.05	1	
Loans/Assets	-0.22*	-0.31*	0.00	0.00	-0.29*	-0.44*	0.33*	1

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

This table lists the top-20 financial institutions in terms of SRISK, averaged over the period July 2007 – December 2008, together with their ΔCoVaR and MES estimates, the average and volatility of their equity returns, their total assets, country of origin, and specialization. Government support indicates whether or not the firm received support from the government in the form of capital injections, guarantees on assets or liabilities, or outright nationalization. Information on government support is from Laeven and Valencia (2012).

Company Name	Country	Specialization	Total assets in 2006 (US$bn)	Total assets in 2008 (US$bn)	SRISK (US$bn)	ΔCoVaR	Volatility	Stock Return	Government support?
Royal Bank of Scotland	United Kingdom	Bank holding company	1710.6	3501.1	258.2	8.97	10.06	-91.35	Yes
Deutsche Bank	Germany	Commercial bank	2070.0	3065.1	216.4	7.18	8.97	-74.72	No
Barclays	United Kingdom	Bank holding company	1956.7	2992.8	210.6	10.76	9.24	-77.03	No
BNP Paribas	France	Commercial bank	1896.9	2888.5	170.1	10.33	7.06	-64.92	Yes
Credit Agricole	France	Cooperative bank	1660.1	2300.8	149.1	8.32	7.77	-69.43	Yes
Citigroup	United States	Bank holding company	1884.3	1938.5	146.1	8.69	17.31	-85.93	Yes
JPMorgan Chase	United States	Bank holding company	1351.5	2175.1	127.6	7.61	9.00	-36.41	Yes
UBS	Switzerland	Commercial bank	1922.8	1894.2	114.1	9.11	9.06	-78.81	Yes
ING Groep	Netherlands	Bank holding company	1615.0	1853.3	108.4	12.16	9.13	-76.24	Yes
Bank of America Corp	United States	Bank holding company	1459.7	1817.9	104.6	8.77	10.33	-69.85	Yes
Societe Generale	France	Commercial bank	1260.2	1572.6	94.5	8.64	8.40	-73.82	Yes
HSBC Holdings	United Kingdom	Bank holding company	1860.8	2527.5	87.8	8.02	4.76	-25.78	No
HBOS	United Kingdom	Bank holding company	1161.7	1005.8	72.1	7.84	12.96	-92.64	Yes
Fannie Mae	United States	Government-sponsored entity	843.9	912.4	69.8	4.34	42.65	-98.82	Yes
Mizuho	Japan	Bank holding company	1227.1	1495.3	69.4	5.61	8.50	-69.17	No
Unicredit	Italy	Commercial bank	1084.3	1455.2	69.1	10.47	6.48	-73.70	No
Merrill Lynch	United States	Investment bank	841.3	667.5	67.3	7.73	15.01	-85.67	Yes
Freddie Mac	United States	Government-sponsored entity	804.9	851.0	63.1	3.82	42.59	-98.74	Yes
Mitsubishi UFJ	Japan	Bank holding company	1519.0	1824.4	62.6	7.57	7.70	-58.18	No
Morgan Stanley	United States	Bank holding company	1120.6	658.8	60.9	7.43	16.73	-79.10	Yes

Table 5. Systemic risk regressions for July 2007 – December 2008: ΔCoVaR

This table reports regressions of ΔCoVaR on a set of bank characteristics and includes country fixed effects. 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.

VARIABLES	(1)	(2)	(3)	(4)	(5)
ΔCoVaR06	1.08***	1.39***	1.13***	1.14***	1.12***
	[0.14]	[0.15]	[0.16]	[0.15]	[0.15]
Log Assets($)	0.46***		0.90***	0.90***	0.80***
	[0.14]		[0.20]	[0.19]	[0.17]
Tier 1 Ratio		-0.070*	0.13**	0.14**	0.11**
		[0.040]	[0.060]	[0.060]	[0.046]
Tier 1 Ratio*Log Assets			-0.048**	-0.048**	-0.039**
			[0.020]	[0.020]	[0.018]
Deposits/Assets				-0.47	0.061
				[0.88]	[0.76]
Loans/Assets				0.63	0.21
				[0.68]	[0.82]
Return08					-0.0061
					[0.0037]
Volatility08					0.023
					[0.051]
Country fixed effects	Y	Y	Y	Y	Y
Observations	358	298	298	298	298
R-squared	0.776	0.758	0.809	0.810	0.816

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

This table reports regressions of SRISK on a set of bank characteristics and includes country fixed effects. 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.

VARIABLES	(1)	(2)	(3)	(4)	(5)
SRISK06	0.94***	1.34***	0.90***	0.88***	0.84***
	[0.16]	[0.28]	[0.22]	[0.22]	[0.21]
Log Assets($)	6.11***		11.6***	11.6***	11.1***
	[1.34]		[2.69]	[2.48]	[2.31]
Tier 1 Ratio		-0.76**	1.40*	1.28	1.09
		[0.34]	[0.79]	[0.77]	[0.65]
Tier 1 Ratio*Log Assets			-0.56**	-0.57**	-0.51**
			[0.25]	[0.24]	[0.20]
Deposits/Assets				3.61	4.22
				[4.79]	[4.13]
Loans/Assets				-7.26**	-7.17**
				[3.14]	[3.02]
Return08					0.041
					[0.037]
Volatility08					0.72*
					[0.40]
Country fixed effects	Y	Y	Y	Y	Y
Observations	340	285	285	285	285
R-squared	0.826	0.708	0.843	0.844	0.847

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

This table reports regressions of return on a set of bank characteristics and includes country fixed effects. 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.

VARIABLES	(1)	(2)	(3)	(4)
Return06	-0.030	0.0092	0.026	0.036
	[0.084]	[0.10]	[0.11]	[0.10]
Log Assets($)	-5.55***		-11.7**	-10.8**
	[1.33]		[4.61]	[5.12]
Tier 1 Ratio		2.34***	-0.94	-1.78
		[0.81]	[1.69]	[1.72]
Tier 1 Ratio*Log Assets			0.95*	0.92
			[0.52]	[0.58]
Deposits/Assets				58.0***
				[19.1]
Loans/Assets				-50.7***
				[12.8]
Country fixed effects	Y	Y	Y	Y
Observations	363	302	302	302
R-squared	0.322	0.356	0.381	0.431

Table 8. Systemic risk regressions for July 2007 – December 2008: Volatility

This table reports regressions of volatility on a set of bank characteristics and includes country fixed effects. 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.

VARIABLES	(1)	(2)	(3)	(4)
Volatility06	0.85**	0.76**	0.85***	0.80**
	[0.34]	[0.30]	[0.31]	[0.33]
Log Assets($)	0.53***		1.87**	1.86**
	[0.16]		[0.82]	[0.86]
Tier 1 Ratio		-0.012	0.56	0.64
		[0.094]	[0.38]	[0.43]
Tier 1 Ratio*Log Assets			-0.17*	-0.17*
			[0.094]	[0.100]
Deposits/Assets				-5.56*
				[2.79]
Loans/Assets				6.21*
				[3.57]
Country fixed effects	Y	Y	Y	Y
Observations	360	299	299	299
R-squared	0.456	0.450	0.493	0.540

Table 9. Systemic and individual risk regressions with country characteristics

This table includes the interactions between log assets and country characteristics, such as deposit insurance and log GDP per capita. Deposit insurance is a dummy variable equal to one when there is an explicit deposit insurance scheme from Demirgüç-Kunt, Kane, and Laeven (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.

	ΔCoVaR	SRISK	Return	Volatility
VARIABLES	(1)	(2)	(3)	(4)
Dependent variable in 2006	1.132***	0.814***	0.00320	0.765**
	[0.176]	[0.196]	[0.0990]	[0.342]
Log Assets($)	1.542	-18.45	-2.534	-1.700
	[1.075]	[13.11]	[22.37]	[2.997]
Tier 1 Ratio	0.124*	1.503**	-1.879	0.640
	[0.0625]	[0.678]	[1.877]	[0.414]
Tier 1 Ratio*Log Assets	-0.0460**	-0.576**	0.938	-0.164*
	[0.0201]	[0.228]	[0.602]	[0.0970]
Deposits/Assets	-0.528	3.366	58.92***	-5.742**
	[0.877]	[5.034]	[19.78]	[2.790]
Loans/Assets	0.637	-6.165*	-46.59***	6.467*
	[0.713]	[3.299]	[14.03]	[3.508]
Deposit Insurance*Log Assets	0.0941	4.213**	-5.769	0.252
	[0.162]	[1.801]	[3.978]	[0.292]
Log GDP per capita*Log Assets	-0.0711	2.552**	-0.308	0.315
	[0.110]	[1.224]	[2.229]	[0.246]
Country fixed effects	Y	Y	Y	Y
Observations	291	281	295	292
R-squared	0.809	0.861	0.454	0.543

Table 10. Risk regressions with longer sample period

This table reports regressions of systemic risk using alternative measure. All the dependent variables are computed over the period July 2007 – Dec 2009 rather than the period July 2007 – Dec 2008. 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.

VARIABLES	ΔCoVaR	SRISK	Return	Volatility
	July 2007 - Dec 2009	July 2007 - Dec 2009	July 2007 - Dec 2009	July 2007 - Dec 2009
	(1)	(2)	(3)	(4)
Dependent variable in 2006	1.140***	0.844***	-0.0467	0.811*
	[0.186]	[0.269]	[0.0970]	[0.416]
Log Assets($)	1.096***	14.38***	-6.721	2.186***
	[0.228]	[2.555]	[5.640]	[0.815]
Tier 1 Ratio	0.184**	1.609**	-0.622	0.732*
	[0.0720]	[0.773]	[2.065]	[0.368]
Tier 1 Ratio*Log Assets	-0.0614**	-0.707***	0.747	-0.189**
	[0.0235]	[0.236]	[0.583]	[0.0862]
Deposits/Assets	-0.658	4.264	68.01***	-6.139**
	[1.133]	[5.495]	[19.18]	[2.714]
Loans/Assets	0.952	-8.619**	-61.81***	9.843*
	[0.675]	[3.766]	[11.73]	[5.634]
Country fixed effects	Y	Y	Y	Y
Observations	298	278	302	304
R-squared	0.813	0.836	0.601	0.494