ISSN 2042-2695

CENTRE for ECONOMIC PERFORMANCE

CEP Discussion Paper No 1567

August 2018

Foreign Expansion, Competition and Bank Risk

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Abstract
Using a novel dataset on the 15 European banks classified as G-SIBs from 2005 to 2014, we find that the impact of foreign expansion on risk is always negative and significant for most individual and systemic risk metrics. In the case of individual metrics, we also find that foreign expansion affects risk through a competition channel as the estimated impact of openings differs between host countries that are more or less competitive than the source country. The systemic risk metrics also decline with respect to expansion, though results for the competition channel are more mixed, suggesting that systemic risk is more likely to be affected by country or business models characteristics that go beyond and above the differential intensity of competition between source and host markets. Empirical results can be rationalized through a simple model with oligopolistic/oligopsonistic banks and endogenous assets/liabilities risk.

Key words: banks' risk-taking, systemic risk, geographical expansion, gravity, diversification, competition, regulatory arbitrage
JEL: G21; G32; L13

This paper was produced as part of the Centre's Trade Programme. The Centre for Economic Performance is financed by the Economic and Social Research Council.

We are grateful to José-Luis Peydró and Neeltje van Horen for their insightful discussions and other participants for their useful comments at the NBER International Seminar on Macroeconomics hosted by the Central Bank of Ireland in Dublin on June 29-30, 2018. We are indebted with Despoina Balouktsi, Eugenia Menaguale, Giulia Lo Forte, Maximilian Mayer and Soren Karau for outstanding research assistance.
Ester Faia, Goethe University, Frankfurt and CEPR. Sebastien Laffitte, ENS Paris-Saclay and CREST. Gianmarco Ottaviano, Bocconi, CEPR, and Department of Economics and Centre for Economic Performance, London School of EconomicsKing's Business School and Centre for Economic Performance, London School of Economics.

Published by
Centre for Economic Performance
London School of Economics and Political Science
Houghton Street
London WC2A 2AE

1 Introduction

How bank globalization affects risk is an open question. Already prior to the 2007-2008 crisis, Rajan [53] highlighted the consequences of financial and banking globalization for risk and contagion. As the full insurance paradigm is difficult to achieve, stronger financial linkages among countries and global banks' entries in foreign markets were expected to increase the correlation of shocks and the probability of contagion. In the aftermath of the 2007-2008 financial crisis this premonition seemed to materialize as a financial and banking crisis originated in the US spread worldwide. It also became apparent that around the world, banks had been loading too much risk on their balance sheets (Adrian and Shin [4]). Banks' risk-taking was then attributed to two main causes: lax monetary policy and banking globalization.

An extensive literature has studied the role of expansionary monetary policy.[1] Low interest rates indeed induce banks to excessive leverage since short-term liabilities become cheaper than equity capital.[2] They also make banks invest in riskier assets due to a search-for-yield attitude.[3] Several empirical studies have investigated the impact of monetary policy on bank risk. Many of these studies use novel datasets to measure individual bank risk. For instance, Paligorova and Santos [51] use information on changes in lending standards from lending surveys; Altunbas, Gambacorta, and Marquez-Ibanez [7] use rating agency estimates; Dell'Arriccia, Laeven and Suarez [32] use banks' internal ratings on loans. Other papers use credit registry information on default history (e.g. Jimenez et al. [42], Ioannidou, Ongena and Peydro [41]). All these papers focus on the role of monetary policy for banks' risk-taking, use data from single countries and measure risk at individual bank level mostly relying on book-based indexes.

While there has been large consensus that low interest rates can trigger banks' risk-taking, studies on banking globalization are more divided. Goetz, Laeven and Levine [38] and Levine, Lin and Xie [45] find that geographic expansion across US states reduces banks' riskiness thanks to better asset diversification. Faia, Ottaviano and Sanchez-Arjona [35] reach a similar conclusion in the case of the geographic expansion of European banks across European countries. A number of other papers focus on whether foreign banks stabilize or destabilize local credit in response to shocks. De Haas and Van Lelyveld [31] find that in emerging European countries lending by

[1] See Borio and Zhu [18] and Adrian and Shin [4].

[2] See Angeloni and Faia [10].

[3] See Dell'Ariccia, Laeven and Marquez [32] and Martinez-Miera and Repullo [46] among others.

foreign banks has been more stable than lending by domestic banks during crises and Claessens and van Horen [30] find that even after the crisis foreign bank presence declined by less than other cross-border activities. Cetorelli and Goldberg [25] show that, following liquidity shocks, multinational banks can be a stabilizing force as they can transfer liquidity across borders. Other papers note that multinational banks have less experience and monitoring abilities vis-a-vis local lending and asset management and this can tighten credit, in particular for small and medium enterprises. Mian [48] finds that in Pakistan foreign banks avoid lending to opaque firms since the cultural distance between the firms' CEO and the loan officer is large. Giannetti and Ongena [37], using evidence for Eastern Europe, find that informationally opaque firms are penalized by multinational banks. While none of those papers directly examines the role of multinational banks for risk-taking, Faia, Ottaviano and Sanchez Arjona [35] look at the impact of foreign expansion on bank risk operating through asset diversification.

The aim of the present paper is to contribute to this body of knowledge in several ways. First, we provide a deeper investigation of the impact of banks' foreign expansion on risk-taking from both individual and systemic viewpoints, and relying on both book-based and market-based risk measures.[4] Second, we study a someway neglected channel through which banks' foreign expansion may affect risk-taking when national banking markets differ in terms of the intensity of competition. Third, to do so, we build a rich cross-country dataset on European global banks' foreign expansion including their main characteristics as well as key features of their countries of operation. Fourth, to inform the empirical analysis, we develop a simple model of the banking sector that highlights the effects of competition on risk working through both the assets and the liabilities sides of banks' balance sheets. Finally, we adopt a novel instrumentation strategy to deal with possible reverse causation from banks' risk-taking to their foreign expansion in markets with different intensity of competition.

In our model, imperfectly competitive banks raise deposits from households to finance firms' projects through loans. On the assets side, loans are risky due to firms' moral hazard arising from limited liability (Boyd and De Nicolo [19]; Faia and Ottaviano [34]). On the liabilities side, as deposits are short-term liabilities whereas loans are partially illiquid long-term assets, liquidity mismatch exposes banks to bank run-vulnerability (Morris and Shin [49]; Rochet and

[4]This is important as book-based measure may respond more slowly than market-based measure to changes in competition or regulation. We will discuss the pros and cons of different risk measures in Section 3.1.

Vives [54]). In this setup, the impact of more competition on overall bank risk in ambiguous for two reasons. First, more competition may increase or decrease the amounts of deposits raised and loans extended by the bank ('scale effect of competition'). Second, the change in firm risk-taking on the assets side may dominate or be dominated by the opposite change in bank run-vulnerability on the liabilities side ('risk effect of scale'). Accordingly, whether overall risk increases when a bank expands its operations to a foreign market depends on whether the probability of no bankruptcy in that market is higher or lower than in the home market. This in turn depends on whether the number of competing banks is different between the two markets. However, the ambiguous signs of the scale effect of competition and of the risk effect of scale imply that whether a larger number of banks are associated with larger or smaller probability of no bankruptcy is undecided from a theoretical viewpoint. Whether foreign expansion increases or decreases overall risk is ultimately an empirical issue that depends on which effects dominates in reality.

To address this empirical issue we have assembled a novel dataset on the activities of the 15 European banks classified as G-SIBs by the Basel Committee on Banking Supervision [12] (BCBS) at the end of 2015 over a 10-year time period from 2005 to 2014. The focus on G-SIBs is explained by their centrality as risk spreaders. These banks are located in 8 home countries: BNP Paribas, Crédit Agricole Group and Société Générale in France; Banco Santander in Spain; Unicredit in Italy; HSBC, Standard Chartered, RBS (Royal Bank of Scotland) and Barclays in the United Kingdom; Deutsche Bank in Germany; ING Bank in the Netherlands; UBS and Credit Suisse in Switzerland and Nordea in Sweden. We also consider BPCE, a banking group consisting of independent, but complementary commercial banking networks that provide also wholesale banking, asset management and financial services. The dataset includes 38 potential destination countries, 5 individual bank risk measures and 4 systemic risk metrics together with additional balance sheet information. Given the large interest in global banking other researchers have also assembled data on foreign expansion. Claessens and van Horen [29] and [30] were the first to build a dataset listing branches and subsidiaries located in 137 countries to answer questions related to the impact of global banking on credit conditions. Their dataset, however, does not report the name of the parent holding and information needed to compute risk metrics. Both are crucial for our analysis. Moreover, their dataset mostly focuses on retail-banking activities, while we also look at other activities (such as investment banking) that may contribuite to bank risk. Faia, Ottaviano and Sanchez Arjona [35] also use data on entries, but their dataset is different and less extensive than the one used in the present paper. In particular, the dataset we use here contains an expanded set of banks' foreign activities that better accounts for risk determinants and entries as well as additional variables that allow us to test how competition affects the relation between foreign expansion and bank risk, which is our specific focus.

We deal with the potential endogeneity bias due to reverse causation from banks' risk-taking to their foreign expansion by using a 2SLS strategy similar to the one adopted by Goetz, Laeven and Levine [38] and Levine Lin and Xi [45] in studies linking the volatility of equity prices for US banks with their cross-state expansion. The strategy consists in instrumenting the observed geographic expansion of a bank with the one predicted by a 'gravity equation'. This method is akin to the one used by Frankel and Romer [36], who study the impact of international trade on countries' economic performance by instrumenting the observed bilateral trade flows (which arguably depend on countries' economic performance) with the ones predicted by geographic variables and fixed country characteristics. Using this strategy and our own dataset we find that the impact of foreign expansion on risk is negative and significant for most individual and systemic risk metrics. In the case of individual metrics we also find that the competition channel is indeed at work, and this happens through a dominant 'margin effect' as the estimated coefficients on openings in lower concentration host countries (as measured by the Herfindahl index, or HHI on total assets) are not statistically different from zero whereas those in higher concentration host countries tend to be negative. As for systemic risk, our findings on the competition channel are mixed and this can be explained by the fact that systemic risk is more likely to be affected by a number of country and business models characteristics that go beyond and above the differential intensity of competition between source and host markets.

The interplay between competition and fragility is an important issue in the banking literature in general. Many theoretical contributions and empirical analyses have been conducted to examine whether more competition reduces or increases fragility in banking (Vives [60]). With respect to the existing literature, we innovate on both theory and empirics. Existing theoretical contributions largely use static models of banks operating in closed economy. These models tend to focus on Cournot-Nash competition. Allen and Gale [5] and [6] analyse competition among banks that can choose the level of assets' risk and show that more competition leads to more risk-taking. Their model hinges on competition in the deposit market. Banks seeking to attract deposits in a tougher competitive setting are forced to offer higher deposit rates. This forces banks to search for yield in assets, thus encouraging risk-taking. Boyd and De Nicolo [19] highlight a different channel through which more competition in the loan market reduces loan rates, thus inducing firms to select projects with lower returns but also lower risk. Through this channel, competition may improve the average quality of the loans' applicants and reduce adverse selection (see also Stiglitz and Weiss [58]).

Besides the closed economy case, a few papers analyse the theoretical underpinnings of global banking. Bruno and Shin [21] build a model of the international banking system where global banks raise short term funds at worldwide level, but interact with local banks for the provision of loans. They emphasize banks' leverage cycles. Niepman [50] proposes a model in which the pattern of foreign bank asset and liability holdings emerges endogenously because of international differences in relative factor endowments and banking efficiency. Competition and risk-shifting are not part of the analysis. More recently, building on Boyd and De Nicolo [19], Faia and Ottaviano [34] show that foreign expansion can induce for global banks a selection effect akin to the one highlighted by Melitz [47] for exporting firms. In a model of banking industry dynamics with domestic and foreign destination markets they find that expansion abroad has two main effects. First, by increasing competitive pressures it improves loans' selection, thereby raising the option value of entry. This in turn implies that only banks with better long run growth prospects enter the market. Second, the entry of foreign banks, by increasing total loans supply, generates strategic complementarities. The combination of these two forces implies that foreign expansion tends to reduce bank risk whenever loan rates fall reducing firms' risk-shifting incentives and promoting a better selection of projects with lower probability of default. Differently from all these contributions, our model allows for risk to arise not only on the assets side but also the liabilities side of banks' balance sheets.

The fundamental ambiguity highlighted by our model may explain why the existing evidence on the relation between competition and risk is largely inconclusive due to contradicting empirical findings. In principle, inconclusiveness could arise from the fact that several papers use traditional competition indicators, such as the Herfindahl-Hirschman index (HHI), the Lerner index or the Panzer-Rosse H-statistic, which are all plagued by various problems. The HHI suffers from endogeneity and ignores contestability; the Lerner index does not take risk or the macroeconomy into account; the Panzer-Rosse H-statistic delivers results that depend on the assumptions made about the production function. However, even in studies using regulatory reforms to overcome those limitations evidence remains inconclusive. Keeley [43] relates deregulation in the US to bank fragility by testing the charter value theory. The underlying idea is that competition erodes banks' profits and franchise values, thus inducing banks to invest in riskier activities.[5] For Spanish banks Jimenez et al. [42] show that non-performing loans fall as the Lerner index rises, but also find evidence of a U-shaped relation between risk and concentration.[6] Salas and Saurina [55] show that liberalization in Spain erodes banks' charter values and increases their likelihood of insolvency. For the US Hanson, Kashyap and Stein [39] point out that liberalization induces banks to leverage more, hence increasing risk-taking on the liability side. Using cross-country data Shehzad and De Haan [57] reach the conclusion that liberalization reduces the likelihood of systemic crises. Anginer et al. [9] find that competition, again measured by the Lerner index, induces banks to diversify more and reduces systemic risk.[7] Similar trade-offs have been investigated with respect to the specific question of the role of banks' internationalization for banking stability: foreign entry may improve services and reduce margins, but it can also erode charter values. Barth et al. [11], Claessens [26] and Yeyati and Micco [61] find that cross-border banking increases growth and reduces fragility. Buch, Koch and Koetter [23] empirically show that for German banks higher domestic market power is associated with lower risk, while bank internationalization is only weakly related to bank risk. Differently from all these contributions, we use a richer cross-country dataset, a novel instrumentation strategy and a more comprehensive set of risk measures for individual as well as systemic risk.

The rest of the paper is organized in six sections. Section 2 presents the theoretical model.

[5] Another reason why more competition may increase risk is by reducing incentives to relationship lending (see, e.g., Boot and Greenbaum [17] and Berger and Udell [15] among others). With tougher competition it is easier for firms to change bank, hence there is less expected time to recoup investments in relationship building. This discourages investment in monitoring and may increase the risk of non-performing loans.

[6] This is reminiscent of a theoretical result in Martinez-Miera and Repullo [46], who revisit the insights of Boyd and De Nicolo [19] when the correlation of projects' failures is imperfect as in Vasicek [59] rather than perfect as in the original paper. They note that lower loan rates reduce banks' profit margins from non-defaulting loans, which generates a U-shaped relation between competition and banks' aggregate failure rate ('systemic risk').

[7] A number of studies find that more risk is associated with larger banks and more concentrated markets. Laeven et al [44] show that, in terms of individual bank risk, larger banks are riskier than smaller ones. They also highlight that systemic risk, as measured by SRISK, increases with bank size and complexity.

Section 3 introduces the dataset and the variables we use. Section 4 explains our empirical strategy. Section 5 reports the results on foreign expansion and risk taking. Section 6 looks into the competition channel. Section 7 concludes.

2 The Model

Consider a bank headquartered in its home country that has expanded its operations also to a foreign one. National markets are segmented so that the bank maximizes profits separately at home and abroad. The two markets are identical in all respects except for the intensity of competition as captured by the number of competing banks. This symmetry allows to focus on the home market and extend the corresponding results to the foreign market by analogy.

In the home market the bank raises funds through short-term liabilities d ('deposits') and uses them to finance firms' projects through partially illiquid long-term assets l ('loans'). The structure of the banking market is imperfectly competitive. This implies that the bank maximizes profits based on deposits' residual supply ('oligopsony') and loan's residual demand ('oligopoly') as given by $d = (r_D)^{\varepsilon_D n}$ and $l = (r_L)^{-\varepsilon_L n}$ respectively, where $n > 1$ is the number of banks competing in the home market, r_D is the rate of return on deposits and r_L is the rate of return on loans. The exponents $\varepsilon_D n$ and $\varepsilon_L n$, with $\varepsilon_D > 1$ and $\varepsilon_L > 1$, are the deposit supply elasticity and the (absolute value of) the loan demand elasticity as perceived by the bank. They inversely capture its oligopsonistic market power in the deposit market and its oligopolistic market power in loan market, with both falling as the number of competitors increases. For any initial number of bank, $\varepsilon_D > \varepsilon_L$ ($\varepsilon_D < \varepsilon_L$) implies that a given change in n has stronger (weaker) impact on deposit supply elasticity than on loan demand elasticity, thus making deposits supplied relatively more (less) responsive to r_D than loans demanded to r_L.

As in Boyd and De Nicolo [19] and Faia and Ottaviano [34], home firms acquire bank loans to invest in risky investment projects, with higher investment returns being associated with lower success probability p ('probability of no default'). Given the return on loans r_L, firms choose both the amount of loans they demand and the projects' risk-return profiles. Due to moral hazard originating from limited liability, when confronted with higher loan rates, firms' incentives toward risk-shifting are higher so that risk-taking endogenously increases as firms invest more in tail risk. As loan demand is downward sloping, the negative relation between the loan rate r_L and the success probability p implies a positive relation between the amount of loans l and p itself, which we capture as $l = p^{\varepsilon_p}$ for $p \in [0,1]$ with $\varepsilon_p > 0$ where $1/\varepsilon_p$ is the elasticity of firms' risk-taking to bank loans. This implies:

$$p = \begin{cases} \left(\frac{l}{\alpha_p}\right)^{\frac{1}{\varepsilon_p}} & \text{for } l \leq \alpha_p \\ 1 & \text{for } l > \alpha_p \end{cases} . \tag{1}$$

To finance firms' projects, banks raise deposits. However, as loans are partially illiquid long-term assets whereas deposits are short-term liabilities, banks are exposed to liquidity mismatch opening up the possibility of bank runs. As in Morris and Shin [49] and Rochet and Vives [54], a bank run happens when depositors think that their bank does not have enough liquid assets to cover short-term liabilities.[8] This is the case for $r_D d > r_L \nu l$ where $r_D d$ is payments due by the bank to depositors, $r_L l$ is loan repayments due by firms to the bank and ν is a 'signal' on assets liquidity that depositors get. The signal is a random variable with support ranging from 0 (when loans are perfectly illiquid) to 1 (when loans are perfectly liquid) with c.d.f. $F(v)$. The 'probability of no bank run' is then given by $q = \Pr[r_D d \leq r_L \nu l] = 1 - F(r_D d / r_L l)$.

The bank maximizes expected profit $\pi = pq(r_L l - r_D d)$, given by the gap between firms' loan repayments $r_L l$ and the bank's payments to depositors $r_D d$, multiplied by the probability p that firms do not default on their loans and the probability q that there is no bank run. If loans are not repaid or a bank run occurs, the bank becomes insolvent and goes bankrupt. We further assume that: firms do not have internal funds and banks are their only source of funds; banks can only finance firms using own liabilities. This implies that the bank's amounts of loans and deposits have to match so that $d = l$ holds and the probability of no bank run can be restated as $q = 1 - F(r_D / r_L)$. Given $d = (r_D)^{\varepsilon_D n}$ and $l = (r_L)^{-\varepsilon_L n}$, the ratio r_D / r_L can be expressed as an increasing function of $d = l$ (i.e. $r_D / r_L = l^{(\varepsilon_L + \varepsilon_D)/\varepsilon_L \varepsilon_D n}$), so that q is itself a decreasing function of $d = l$: the larger the bank's operations, $d = l$, the lower is the probability of no bank run due to more likely liquidity mismatch. Without making specific assumptions about the signal distribution $F(v)$, we capture the negative relation between bank scale and the probability of no bank run by the reduced form $d = q^{-\varepsilon_q}$ with $\varepsilon_q > 0$ for $q \in [0,1]$, where $1/\varepsilon_q$ is the (absolute

[8] Runs are mainly modelled in the literature in two ways. 'Panic-based' runs arise from liquidity shocks to depositors. 'Information-based' runs arise from depositors' coordination on signals about fundamentals or bank balance sheet variables as in our case.

value of the) elasticity of the bank's run-vulnerability to mismatch. This implies:

$$q = \begin{cases} 1 & \text{for } d < \alpha_q \\ \left(\frac{d}{\alpha_q}\right)^{-\frac{1}{\varepsilon_q}} & \text{for } d \geq \alpha_q \end{cases} . \tag{2}$$

Recalling $d = l$ together with risk-taking (1) and run-vulnerability (2) allows us to express the overall probability of no bankruptcy as:

$$pq = \begin{cases} \left(\frac{l}{\alpha_p}\right)^{\frac{1}{\varepsilon_p}} & \text{for } l < \alpha_q \\ \left(\frac{l}{\alpha_p}\right)^{\frac{1}{\varepsilon_p}} \left(\frac{l}{\alpha_q}\right)^{-\frac{1}{\varepsilon_q}} & \text{for } \alpha_q \leq l \leq \alpha_p \\ \left(\frac{l}{\alpha_q}\right)^{-\frac{1}{\varepsilon_q}} & \text{for } l > \alpha_p \end{cases} , \tag{3}$$

which shows that: for low enough l the only source of uncertainty is firm risk-taking ('project insolvency'); for high enough l the only source of uncertainty is run-vulnerability ('bank illiquidity'); for intermediate l both firm risk-taking and run-vulnerability generate uncertainty as long as $\alpha_q < \alpha_p$ holds. In this case, pq is a piece-wise continuous function of l, increasing in l for $l < \alpha_q$ and decreasing in l for $l > \alpha_p$. For $\alpha_q \leq l \leq \alpha_p$ it is increasing (decreasing) in l when $\varepsilon_q > \varepsilon_p$ ($\varepsilon_q < \varepsilon_p$) holds, that is, when more loans and deposits reduce risk-taking more (less) than they raise run-vulnerability.

To better highlight the ambiguous effects of competition on bank risk, in what follows we focus on the case in which both firm risk-taking and run-vulnerability matter ($\alpha_q \leq l \leq \alpha_p$). In this case, after imposing $d = l$, (3) together with the expressions of deposit supply $d = (r_D)^{\varepsilon_D n}$ and loan demand $l = (r_L)^{-\varepsilon_L n}$, we can write banks' maximization with respect to l as:

$$\pi = \left[\left(\frac{l}{\alpha_p}\right)^{\frac{1}{\varepsilon_p}} \left(\frac{l}{\alpha_q}\right)^{-\frac{1}{\varepsilon_q}}\right] \left(l^{-\frac{1}{\varepsilon_L n}} - l^{\frac{1}{\varepsilon_D n}}\right) l. \tag{4}$$

where the first, second and third factors on the right hand side capture the three channels through which the amount of loans (and deposits) l affects profit: overall risk, loan-deposit margin and scale respectively. Larger l increases scale and decreases the loan-deposit margin. Differently, the impact of l on overall risk is ambiguous as more loans reduce firm risk-taking, but more loans and deposits raise bank run-vulnerability. Accordingly, larger l decreases overall risk, when it has a stronger impact on firm risk-taking than on bank run-vulnerability, which happens for $\varepsilon_p > \varepsilon_q$. Vice versa, larger l increases overall risk for $\varepsilon_p < \varepsilon_q$[9].

[9]In the knife-edge case with $\varepsilon_p = \varepsilon_q$, overall risk does not depend on l as assets risk and liabilities risk extactly offset each other.

Profit 4 is maximized for the amount of loans (and deposits):

$$l^* = \left(\frac{r_L^*}{r_D^*}\right)^{-\frac{\varepsilon_D \varepsilon_L}{\varepsilon_D+\varepsilon_L} n}, \tag{5}$$

where the optimal loan-deposit margin is given by:

$$\frac{r_L^*}{r_D^*} = \frac{1+\frac{1}{\varepsilon_p}-\frac{1}{\varepsilon_q}+\frac{1}{\varepsilon_D n}}{1+\frac{1}{\varepsilon_p}-\frac{1}{\varepsilon_q}-\frac{1}{\varepsilon_L n}} > 1. \tag{6}$$

This margin also determines the probabilities of no firm default and no bank run:

$$p^* = \left(\frac{1}{\alpha_p}\right)^{\frac{1}{\varepsilon_p}} \left(\frac{r_L^*}{r_D^*}\right)^{-\frac{\varepsilon_D \varepsilon_L}{\varepsilon_D+\varepsilon_L} \frac{n}{\varepsilon_p}} \quad \text{and } q^* = \left(\frac{1}{\alpha_q}\right)^{-\frac{1}{\varepsilon_q}} \left(\frac{r_L^*}{r_D^*}\right)^{\frac{\varepsilon_D \varepsilon_L}{\varepsilon_D+\varepsilon_L} \frac{n}{\varepsilon_q}} \tag{7}$$

with overall probability of no bankruptcy:

$$p^* q^* = \left(\frac{1}{\alpha_p}\right)^{\frac{1}{\varepsilon_p}} \left(\frac{1}{\alpha_q}\right)^{-\frac{1}{\varepsilon_q}} \left(\frac{r_L^*}{r_D^*}\right)^{\frac{\varepsilon_D \varepsilon_L}{\varepsilon_D+\varepsilon_L} \frac{\varepsilon_p-\varepsilon_q}{\varepsilon_p \varepsilon_q} n}.$$

The above expressions shed light on how more competition (larger n) affects bank risk. There are two opposite effects at work. On the one hand, holding r_L^*/r_D^* constant, (5) shows that larger n leads to smaller l^*. On the other hand, (6) shows that larger n also leads to smaller r_L^*/r_D^*, as r_L^* falls and r_D^* rises. Which effect dominates depends on the relative elasticities of loan demand and deposit supply. In particular, (6) implies that, when n increases, the fall in r_L^*/r_D^* is more pronounced for larger $\varepsilon_L/\varepsilon_D$. Hence, when ε_L is large (small) relative to ε_D, more competition increases (decreases) l^*. In turn, as l^* increases (decreases), firm risk-taking decreases (increases), but bank run vulnerability increases (decreases). Whether this leads to higher or lower overall bank risk depends on whether less (more) firm risk-taking dominates more (less) bank run-vulnerability, that is, on whether $\varepsilon_p > \varepsilon_q$ ($\varepsilon_p < \varepsilon_q$) holds.

To summarize, the impact of more competition on overall bank risk is ambiguous for two reasons. First, more competition may increase or decrease the amounts of deposits raised and loans extended by the bank ('scale effect of competition'). Second, the change in firm risk-taking on the assets side may dominate or be dominated by the opposite change in bank run-vulnerability on the liabilities side ('risk effect of scale'). Accordingly, whether overall risk increased when our bank expanded its operations to the foreign market, depends on whether the probability of no bankruptcy in that market was higher or lower than in the home market. This in turn depends on whether the number of competing banks is different between the two markets. However, the ambiguous signs of the scale effect of competition and of the risk effect of scale imply that whether a larger number of banks is associated with larger or smaller probability of no bankruptcy is ambiguous from a theoretical viewpoint, and thus whether foreign expansion increases or decreases overall risk is ultimately an empirical issue. In the next sections we will tackle this issue in two steps. First, we will check how foreign expansion affects bank risk. Second, we will check whether the sign of the effect of foreign expansion on bank risk is associated with more or less competition in the foreign market relative to the home one.

3 Data

As anticipated in the introduction, to analyse the impact of foreign expansion on risk-taking, we have built a novel dataset documenting the activities of the 15 European banks classified as G-SIBs by the BCBS [12] at the end of 2015 over a 10-year time period from 2005 to 2014. We focus on the G-SIBs as they are the main risk spreaders. These banks are located in 8 home countries: BNP Paribas, Crédit Agricole Group and Société Générale in France; Banco Santander in Spain; Unicredit in Italy; HSBC, Standard Chartered, RBS (Royal Bank of Scotland) and Barclays in the United Kingdom; Deutsche Bank in Germany; ING Bank in the Netherlands; UBS and Credit Suisse in Switzerland and Nordea in Sweden. We also consider BPCE, a banking group created in 2009 consisting of independent, but complementary commercial banking networks that provide also wholesale banking, asset management and financial services. The panel includes 38 potential destination countries in Europe (see Appendix 3 for the complete list) and is balanced as for each bank we consider all potential host countries and years, even if the bank did not establish presence in a foreign country in a specific year.[10]

Our analysis needs measures of bank risk and exogenous variation in bank expansion. We discuss risk metrics first and then how we construct exogenous variation in expansion through an instrumental variable approach.

3.1 Measuring Risk

Our dataset includes parent holdings' balance sheets and other information needed to measure bank risk. We use several standard risk metrics taken from the literature. Most importantly, we

[10] If the bank did not establish presence in a foreign country in a specific year, the count of its openings is set equal to zero.

consider both individual and systemic risk metrics.[11] Overall, we extend the number of metrics generally used in the literature and cover a large number of different risk.

3.1.1 Individual Risk

For individual risk we use market-based metrics as well book-based indicators founded on banks' internal risk models. This will allow us to make sure that our results are not driven by either exuberant market conditions or biased internal risk assessment. In particular, the metrics we consider are CDS price, loan-loss provision ratio (LLP), the standard deviation of returns, the Z-score and the leverage ratio.

The CDS price and the standard deviation of weekly returns (taken from Bloomberg) are market-based metrics. As such they have both advantages and disadvantages. On the one hand, they are not subject to potential bias associated with risk metrics computed from banks' internal risk models. On the other, they may be subject to fluctuations in market exuberance. To mitigate this exuberance bias, we take the average CDS price and control for year fixed effects. In detail, the CDS price corresponds to the price of insurance against the default of the bank. This is an overall market assessment of bank risk on both the asset and the liability sides. The higher the CDS price, the higher the risk taken by its seller and the higher the defaulting probability priced by the market. Differently, the standard deviation of returns is based on a bank's future stream of profits. Higher equity price volatility indicates higher uncertainty about the bank's ability to generate profits, hence perception of higher bank risk. As in the case of the CDS price, we control for potential bias from market exuberance by taking the average standard deviation of returns and controlling for year fixed effects.

LLP is a book-based metric defined as the ratio of loan-loss provisions to total loans taken from Bureau Van Dijk's Bankscope and measures the liquidity buffer that a bank sets aside to cover losses in the event of defaulting borrowers. Hence, LLP captures the bank's own assessment of asset risk. For a given level of total assets, an increase in LLP indicates that the bank assigns higher probability of loan losses (less solvent borrowers). This measure is obviously immune from market exuberance, but it might be subject to internal biases. Moreover, it mainly captures asset risk abstracting from liability risk.

The Z-score refers to the number of standard deviations a bank's profits can fall before

[11] Where needed, such as in the case of ΔCoVaR, we run our own estimations using European data.

triggering bankruptcy:

$$\text{Z-score} = \frac{\text{ROA} + \text{Capital Asset Ratio}}{\sigma(\text{returns})}. \tag{8}$$

As the Z-score combines book-based and market-based variables, it is largely immune from the potential biases associated with the other individual risk measures. Note that a larger value of the Z-score indicates that the bank is *less* likely to go bankrupt. We will have to keep this in mind when interpreting our findings.

The leverage ratio (from the Centre for Risk Management of Lausanne and complemented with data from the V-Lab) corresponds to the total value of a bank divided by its equity. This basic book-based measure is used to specifically capture the probability of bank run or illiquidity as it is by now well understood that in the run up to many financial crises (including the 2007-2008 one), leverage has played a an important role as a key stress factor.[12]

3.1.2 Systemic Risk

Whether foreign expansion poses a threat for the economy as a whole depends very much on whether it can create contagion and propagation effects to the entire banking system and to the real economy. Interconnections in the banking system, arising for instance from cross-lending in the interbank market or from cross-holdings positions of CDS contracts, can indeed amplify the propagation of individual bank risk. Other pecuniary externalities, such as fire sales, also induce contagion and propagation of individual shocks. The role of those aggregate externalities is best captured by systemic risk metrics.

As systemic risk metrics we use the conditional capital short-fall (SRISK; Brownlees and Engle [20]), the long-run marginal expected shortfall (LRMES; Acharya et. al. [2]) and the ΔCoVaR computed using either CDS prices or equity prices (Adrian and Brunnermeier [3]). SRISK is the capital short-fall of a bank conditional on a severe market decline. LRMES is the propensity to be under-capitalized when the system as a whole is under-capitalized. Both metrics are computed similarly, but are complementary. A key difference, according to Bisias et al. [16] and Benoit et al. [13] is that LRMES represents the too-interconnected-to-fail paradigm, while the SRISK, by taking into account the size of the institution, is closer to the too-big-to-fail paradigm. Finally, ΔCoVaR measures the contribution to systemic risk when an institution goes

[12] See, e.g., Adrian and Shin [4], Borio and Zhu [18], Hanson, Kashyap and Stein [39]. Angeloni and Faia [10] among many others.

from normal to stressed situation (as defined by the VaR). ΔCoVaR is a mixture of both systemic risk paradigms.[13]

As an overview, Table 1 reports the average risk and ranking for all metrics considered. The table reveals that the ranks provided by the metrics are not perfectly correlated, which suggests their complementarity.[14] The table highlights that the individual risk may not be correlated with the systemic risk. For instance Credit Agricole (AGRI) and Barclays (BARC) are ranked similarly according to the individual risk measures. Looking at systemic risk offers a different image. Despite having similar risk in terms of CDS price, Barclays is much more risky according to LRMES, SRISK and Δ CoVaR. The table also highlights that within a single group of metrics (individual or systemic), the ranking may be different. The comparison between the LRMES column and the SRISK column highlights that bigger banks tend to have a greater SRISK. This is for instance the case for Deutsche Bank (DEUT), the second biggest G-SIB in our sample. On the contrary, ING Bank (INGB), one of the smallest bank in our sample is ranked 6^{th} in terms of SRISK, while it is ranked first in terms of LRMES. Comparing the leverage ranking with SRISK reveals the correlation between these two metrics as explained in Appendix B.

3.2 Measuring Foreign Expansion

The main sources for the data on foreign expansion consist of the banks' annual reports, ORBIS vintages and SEC reports. Specifically, we collect all entries and exits from the ORBIS vintages. When information is missing in the ORBIS vintages, we resort to the banks' annual reports. If these present only synthetic information or missing information, we examine the SEC reports. When merging the various sources, we make sure that the type of activities recorded are consistent. In some cases new affiliates appear in the various reports simply as the result of a change in the name of the local bank. For these cases we consult Bloomberg or Bankers' Almanac to track the exact bank number and to avoid double counting. For cases in which the holding group has consolidated, merged with another group or changed name (this is for instance the case for Natixis, a French bank now named BPCE), we consult other complementary sources, such as consolidated statements, websites, archives, press releases and reports from national central

[13]Additional details on the computation or estimation of these systemic risk metrics can be found in Appendix B.

[14]Looking at correlations between each risk measure provides similar findings, see appendix C.

Table 1 – Descriptive statistics – Average risk

Bank	ln(CDS)	LLP	ln(σ returns)	ln(Z-score)	Leverage	LRMES	SRISK	Δ CoVaR	Δ CoVaR Equ
AGRI	4.18	3.05	-3.16	5.68	39.73	29.88	52.67	0.47	0.12
	(9)	(5)	(5)	(13)	(5)	(15)	(5)	(9)	(4)
BARC	4.2	1.73	-3.15	5.86	45.89	43.58	63.03	0.58	0.11
	(6)	(9)	(4)	(10)	(3)	(3)	(3)	(2)	(12)
BNPA	3.96	3.57	-3.31	5.86	33.39	45.93	63.49	0.5	0.13
	(13)	(2)	(9)	(11)	(8)	(2)	(2)	(7)	(3)
BPCE	5.05	3.46	-3.17	5.88	49.30	31.55	39.80	0.19	0.11
	(1)	(3)	(6)	(9)	(2)	(14)	(7)	(15)	(13)
BSCH	4.4	2.55	-3.46	6.11	16.11	37.8	15.38	0.46	0.12
	(3)	(7)	(13)	(6)	(13)	(9)	(12)	(11)	(5)
CRES	4.17	0.53	-3.39	6.34	23.07	35.63	18.62	0.57	0.1
	(10)	(14)	(11)	(2)	(11)	(10)	(11)	(3)	(14)
DEUT	4.19	1.07	-3.27	5.89	53.37	42.01	72.19	0.48	0.12
	(7)	(11)	(8)	(8)	(1)	(5)	(1)	(8)	(10)
HSBC	3.92	1.87	-3.75	6.46	13.21	35.25	13.37	0.44	0.09
	(15)	(8)	(15)	(1)	(15)	(11)	(13)	(12)	(15)
INGB	4.06	0.78	-3.19	6.27	39.475	51.21	44.12	0.56	0.12
	(12)	(12)	(7)	(3)	(6)	(1)	(6)	(4)	(6)
NDEA	3.92	0.71	-3.48	5.98	18.47	33.69	8.97	0.27	0.12
	(14)	(13)	(14)	(7)	(12)	(13)	(14)	(14)	(9)
RBOS	4.36	2.91	-3.06	5.69	42.05	38.37	55.55	0.34	0.12
	(4)	(6)	(1)	(12)	(4)	(8)	(4)	(13)	(11)
SCBL	4.19	1.24	-3.4	6.24	15.92	39.76	1.34	0.55	0.12
	(8)	(10)	(12)	(5)	(14)	(7)	(15)	(5)	(7)
SOGE	4.22	3.46	-3.12	5.62	38.39	42.74	37.43	0.66	0.16
	(5)	(4)	(2)	(15)	(7)	(4)	(8)	(1)	(1)
UBSW	4.08	0.43	-3.36	6.27	23.84	41.09	30.65	0.51	0.12
	(11)	(15)	(10)	(4)	(10)	(6)	(9)	(6)	(8)
UNCR	4.53	6.04	-3.13	5.62	27.75	34.75	21.47	0.47	0.13
	(2)	(1)	(3)	(14)	(9)	(12)	(10)	(10)	(2)

For each bank, the number gives the average risk during the period for the risk metric considered. The rank is given below into parentheses. More risky banks have a rank closer to 1. The correspondence between the full name of the bank and the code given here is provided in appendix A.

banks, regulatory agencies, international organizations and financial institutions.

For each bank we measure foreign expansion in a year looking at the number of foreign unit openings in that year. Foreign units refer to incorporated foreign banks or financial companies with more than 50 percent ownership. We define an opening in a host country as a parent bank applying one of the following growth strategies: 'Organic growth' by opening directly a new foreign branch or subsidiary or increasing the activity of already-existing units; 'Merger and Acquisition' through purchases of interest in local banks (ownership $\geq$ 50%) or takeovers; and 'Joint ventures'. Therefore, we consider that a bank enters a foreign market whenever it opens directly a branch or a subsidiary, or acquires, either directly or indirectly, a foreign entity, with at least 50% ownership (see also Claessens, Demirguc-Kunt, and Huizinga [27]). The opening would take place in this case either by increasing own ownership in an already-controlled institution or by acquiring a majority interest in a new one. We do not consider as an opening any new institution resulting from the merger among previously-owned entities. The establishment of representative offices, customer desks and the change of legal entity type (branch/subsidiary) are disregarded as well. The parent bank is listed even if the opening was actually implemented by a foreign unit owned by the bank.

Regarding the type of activities considered, our sample includes traditional retail and commercial banking services, private and investment banking, asset and wealth management, financial joint ventures, factoring companies performing pure commercial credit-related activities. The type of activities that we consider is broader than the one normally collected for US bank, the reason being that European banks follow a universal model and many of those non-retail activities can have an impact on risk.[15]

Table 2 presents some summary statistics.[16] We observe 852 openings in the period 2005-2014. The countries with parent holdings expanding the most are Germany, France and the UK. Comparing our banks with the Top 65 European banks in terms of assets reveals that our G-SIB sample represents almost 40% of the assets of the Top 65 banks, with the average G-SIB bank

[15] We have also checked the robustness of our findings in two ways, by using a dummy for expansion instead of a count variable (to control for possible miscounting of entries) and the full set of G-SIBs' activities without dropping any (such as real estate and holding companies). Results are qualitatively the same as reported in the Online Appendix.

[16] Additional details on the construction of the dataset on foreign expansion can be found in Appendix A.

being larger than the average Top 65 bank.[17] In turn, the Top 65 banks account for roughly 60% of the total assets of all active banks in Europe. Moreover, the G-SIB banks generate on average two times more income than the average Top 65 bank. The quality of loans and the Capital ratio are, instead, comparable.

Table 2 – DESCRIPTIVE STATISTICS: BANKS INCLUDED IN THE SAMPLE IN 2014

Bank	Country	Total Assets	Net income	LLP	K Ratio	# Openings
HSBC	UK	2634139	14135	1.25	15.6	2
Groupe BPCE	France	1223298	1926	2.87	13.8	4
Standard Chartered	UK	725914	3618	1.38	16.71	7
ING Bank	Netherlands	992856	3778	1.14	14.58	10
Royal Bank of Scotland	UK	1051019	-1316	4.97	17.1	13
Nordea	Sweden	669342	2843	0.91	20.7	17
Credit Suisse	Switzerland	921462	4070	0.28	20.8	18
UBS	Switzerland	1062478	2723	0.22	25.6	19
Barclays	UK	1357906	3811	1.26	16.5	31
Banco Santander	Spain	1266296	7355	3.65	13.3	49
Societe Generale	France	1308138	2896	4.31	14.3	77
Unicredit	Italy	844217	2171	9.63	13.41	125
Deutschebank	Germany	1708703	3761	1.27	17.2	139
Credit Agricole	France	1589044	2751	3.04	18.4	143
BNP Paribas	France	2077758	6030	3.85	12.6	198
Sum Top 65		48894842	130021	–	–	–
Average Top 65		752228	2000	2.76	16.99	–
Sum		19432570	60553	–	–	852
Share of top 65		39.7 %	46.6 %	–	–	–
Average		1295505	4037	2.67	16.71	57
St. dev.		530271.7	3380.9	2.446	3.530	63.7

Banks are ranked by total entries. Total assets and Net Income are expressed in millions of dollars. LLP corresponds to the Loan-Loss provisions to total loans ratio, K ratio to the Capital ratio, and # Openings to the total number of openings over the period. The top 65 includes the 15 banks in our sample and the top 50 largest European banks in terms of total assets (once the banks in our sample are excluded).

3.3 Competition and Other Variables

As an inverse measure of competition we use the total assets Herfindahl Index for Credit Institutions (HHI) collected from the ECB Statistical Data Warehouse and complemented by

[17] The Top 65 European banks consist of our 15 G-SIB banks plus the top 50 European banks in terms of total assets once the G-SIB banks are excluded.

the corresponding index calculated from Bureau Van Dijk's Bankscope data.

Our dataset also includes additional variables to be used as controls, all taken from Bureau Van Dijk's Bankscope: banks' size as proxied by total assets; overall financial health and strength as proxied alternatively by the Capital ratio and by the Tier1-to-assets ratio; banks' profitability as proxied by the Return on assets; diversification as proxied by income diversity

$$Income\ Diversity = 1 - \frac{|Interest\ inc. - noninterest\ inc.|}{Total\ income}$$

and asset diversity

$$Asset\ Diversity = 1 - \frac{|Loans - Other\ assets|}{Total\ assets}.$$

Key descriptive statistics are summarized in Table 3.[18]

Table 3 – Descriptive statistics of the main independent variables

Variable	Obs.	Mean	Std. Dev.	Min	Max
Expansion	145	5.88	11.38	0	74
ln(Tot. Assets)	145	13.97	0.48	12.28	14.81
ROA	144	0.35	0.44	-1.61	1.14
Income diversity	144	0.71	0.49	-4.42	0.99
Asset diversity	144	0.71	0.19	0.23	1
Tier1/Assets	136	45.84	15.53	12.81	81.11
Deposits/Assets	144	652.33	162.19	251.37	1257.70

Finally, the dataset covers a number of geographical variables needed to instrument foreign expansion as detailed below. These are lifted from the CEPII databases.[19]

3.4 Descriptive Statistics

Figure 1 displays a map of the actual expansion of G-SIBs in the potential destination countries. Looking at source countries, French banks are the ones expanding the most. This is due to their sheer number. Out of 15 G-SIBs, 4 banks are French and 4 are from the United Kingdom. It is also due to their acquisition of large banking groups. BNP Paribas acquired Banca Nazionale del Lavoro in 2006 and Fortis in 2009. These two acquisitions resulted in large entries in foreign markets by BNP Paribas. Despite the same number of G-SIB as France, the UK exhibits a

[18] Income diversity can be negative because of negative values for non-interest income.

[19] See http://www.cepii.fr/cepii/fr/bdd_modele/presentation.asp?id=6.

lower number of foreign openings. Turning to host countries, we observe a large concentration of openings in Western Europe. The host countries with the most openings are the UK, the Netherlands and Luxembourg, reflecting their attractiveness for banking activities. Compared with its neighbors, France is not a large entry destination for foreign banks. This may be due to the large local activity of French banks. Overall, there are more openings in Western than Eastern Europe.

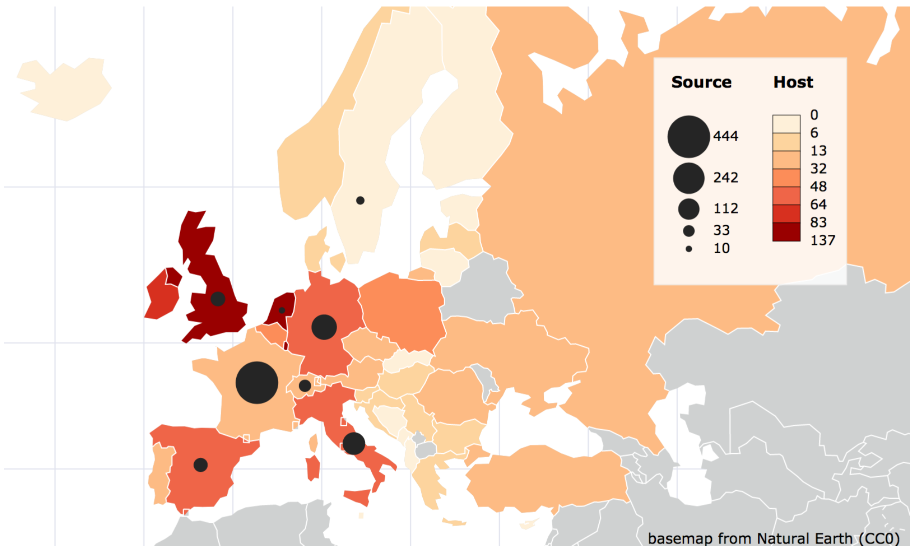

Figure 1 – Expansion of banks in Europe (2005-2014)

Figure 2 presents the distribution of the 852 recorded openings in the period 2005-2014. The top bank in terms of foreign openings is BNP Paribas, mainly due to its two large acquisitions (Banca Nazionale del Lavoro and Fortis). Deutsche bank comes second also due to large acquisitions such as Tilney in 2006 and Sal. Oppenheim in 2010. The third bank in terms of openings is Credit Agricole with large acquisitions such as Fidis or Emporiki. Then comes Unicredit, with a lot of openings in Eastern Europe following the acquisition of Bank Austria in 2007. The remaining banks were less active in terms of acquisitions in Europe. Overall, Figure 2 reveals large variation in the foreign expansion strategies of different banking groups.

Figure 3 and 4 present the average evolution of our individual and systemic risk metrics. For ease of comparison, in Figure 3, the Z-score has been inverted so as to be increasing with risk and the leverage ratio has been divided by ten for presentation purposes. In both figures, the global trend of risk exhibits two peaks around 2008-2009 and 2011-2012. There are, however, discrepancies among the different metrics. Looking at individual risk, the CDS spread and loan-

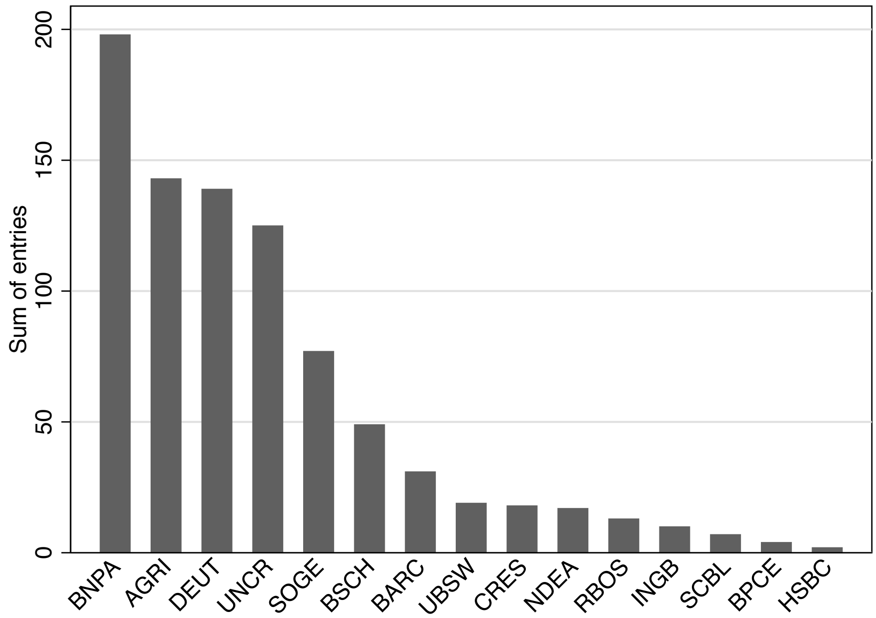

Figure 2 – Number of openings by banks.

loss provisions ratios show a permanent tendency to increase following the financial crisis after the steeper rise of the former until 2008 and of the latter until 2009 for loan-loss provisions. On the contrary, the standard deviation of returns, the Z-score and the leverage feature a fall after the crisis peak, with only another peak in 2011 coinciding with the sovereign debt crisis.

In the case of systemic risk metrics, Figure 4 reveals close trends for long-run marginal expected shortfall, SRISK and Δ CoVaR computed using equity prices. The three measures feature a dominant peak at the 2007-2008 financial crisis appears before, some exhibit a second pick, albeit more muted, at the sovereign debt crisis. All in all, while risk measures share some common features within categories (individual vs. systemic), there are fewer common points between categories apart from the big peak around the financial crisis.

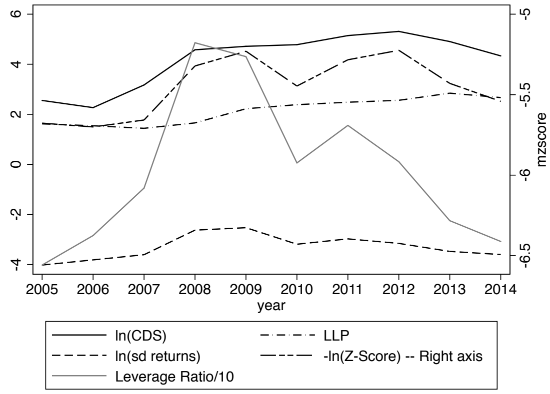

Figure 3 – Individual risk metrics

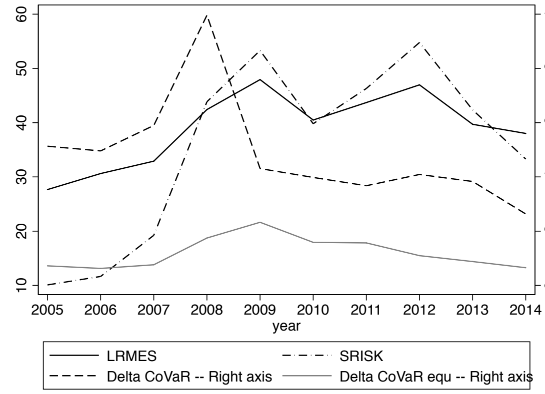

Figure 4 – Systemic risk metrics

To illustrate the relationship between risk and openings between 2005 and 2014, Figure 5 depicts the trajectories of average CDS prices and of the sum of total openings from 2005 to 2014. The figure also shows the trajectories of the maximum and minimum CDS prices, revealing that the evolution of risk follows qualitatively similar rising patterns for all banks. The number of foreign entries globally decreases between 2005 and 2014, with a rebound in 2009 due to the acquisition of Fortis by BNP Paribas. Figure 5 reveals a clear negative correlation between risk and openings. However, it also hints at possible endogeneity: foreign expansion could explain risk variation, but risk variation is also arguably a potential determinant of foreign expansion, especially in coincidence of an important crisis episode.

4 Empirical Strategy

For the empirical analysis we proceed as follows. In this section we describe our methodology and, in particular, our IV strategy. In Section 5 we present and comment the results on the relation between foreign expansion and risk-taking, using both individual risk metrics and systemic ones. In Section 6 we check whether differences in the intensity of competition between host and source markets play a role in explaining relation between foreign expansion and risk-taking as predicted by the model in Section 2.

4.1 Specification

The basic empirical specification estimates by OLS an equation linking bank risk (either individual or systemic), foreign expansion and a set of controls. Specifically, we consider bank k headquartered in country i expanding to countries $j \neq i$ in year t, and we start by estimating

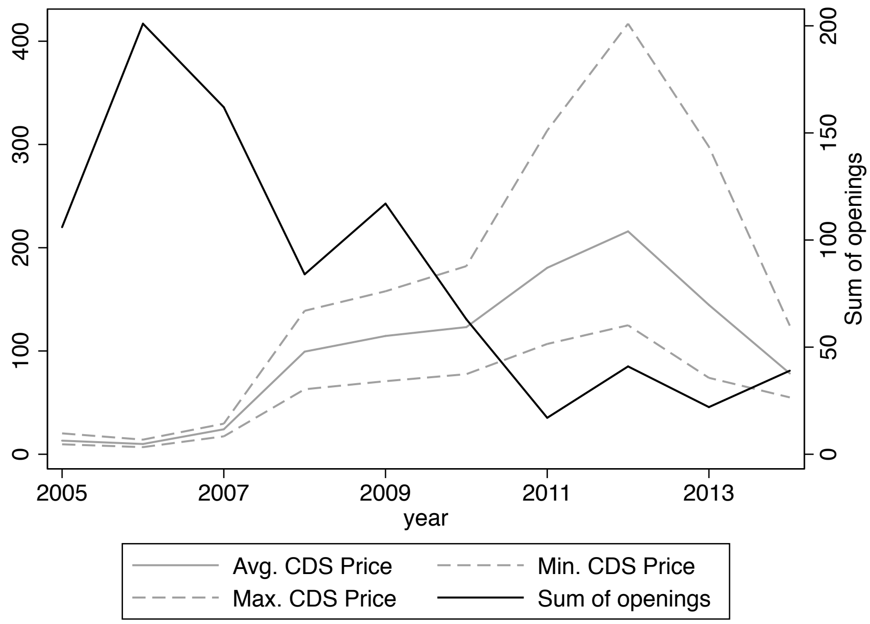

Figure 5 – A first look at entries and risk.

the following regression by OLS:

$$Riskiness_{kt} = \alpha + \beta_1 \cdot Expansion_{kt} + Z_{kt} \cdot \Gamma + \mu_k + \mu_t + \epsilon_{kt}, \tag{9}$$

where $Riskiness_{kt}$ refers to the (Naperian) logarithm of the bank's average (individual or systemic) risk metric over year t, $Expansion_{kt} = \sum_{j \neq i} Openings_{kjt}$ corresponds to its total number of foreign openings, and Z_{kt} is a set of control variables. In addition, we include time fixed effects (μ_t) to control for specific trends in the data (including the crisis of 2007-2008). We also include bank fixed effects (μ_k) to account for bank-specific factors that may influence risk. Because of the inclusion of bank fixed effects, estimated coefficients capture *within* bank effects. Standard errors are robust to heteroskedasticity.[20]

4.2 Instrumental Variables

The OLS estimation described above could potentially be biased by a number of endogeneity problems. First, the expansion decision itself could be driven by the banks' risk profile. Banks with risky portfolios might expand abroad in an attempt to diversify. Besides reverse causality,

[20]Ideally standards errors are best clustered at bank level. This would, however, require a larger sample. When we ran regressions with that level of clustering, we obtained results that are overall in line with the ones we report here (see Online Appendix).

also the presence of confounding factors might induce endogeneity. For instance, the adoption of a business model geared toward search for yield might jointly be responsible for investment in risky asset portfolios and for the decision to expand. As a result, our OLS estimates of the impact of expansion on risk might be upward biased.

We deal with this potential endogeneity bias by using a 2SLS strategy similar to the one adopted by Goetz, Laeven and Levine [38] (hereafter GLL) and Levine Lin and Xi [45] (hereafter LLX) in studies linking the volatility of equity prices for US banks with their cross-state expansion. The strategy consists in instrumenting the observed geographic expansion of a bank with the one predicted by a 'gravity equation'. This method is akin to the one used by Frankel and Romer [36], who study the impact of international trade on countries' economic performance by instrumenting the observed bilateral trade flows (which arguably depend on countries' economic performance) with the ones predicted by geographic variables and fixed country characteristics.

Specifically, our IV method can be described as follows. First, we compute the predicted bilateral openings from a gravity regression of actual openings in country j by bank k headquartered in country i at date t by estimating the following regression:

$$Openings_{kjt} = X_{kjt} \cdot \beta + \nu_{jt} + \nu_k + \varepsilon_{kjt}, \tag{10}$$

where X_{kjt} are standard dyadic gravity variables (e.g. distance, common border, common language, etc.), ν_{jt} is a destination country-time fixed effect and ν_k is a bank fixed effect.

Second, we aggregate the bilateral predicted openings across destinations to obtain a prediction of the total number of openings of bank k at date t:

$$Expansion_{kt}^{pred} = \sum_{j \neq i} \left(X_{kjt} \cdot \widehat{\beta} + \widehat{\nu}_{jt} + \widehat{\nu}_k \right). \tag{11}$$

As an alternative, we will exclude all fixed effects as in GLL and LLX. We will use IV1 and IV2 to refer to the instruments obtained from this alternative specification and from (10) respectively. Moreover, we will also estimate a third specification including bank-time fixed effects ν_{kt} instead of bank fixed effects ν_k and destination-country-time fixed effects ν_{jt}. However, since the latter might be potentially correlated with bank risk, we will not use this third specification to construct any instrument, but only for comparison with the gravity literature. All three specifications include log(distance), contiguity, official common language, common membership of the European Union or the Eurozone, and difference in legal systems as regressors. Note that IV1 has a very limited time variation (only generated through the Eurozone and the EU membership variables), while IV2 is time-varying at the host-country level due to the fixed effects. In particular these fixed effects account for the variations in the host-market economic, legal and institutional conditions.

Given that our entry data are structured as count data, we are bound to estimate equation (10) using Poisson Pseudo Maximum Likelihood (PPML hereafter). With count data, normality assumptions on estimators do not hold. Accordingly, OLS estimators are not appropriate, whereas PPML are robust to distribution mis-specification (Santos-Silva and Tenreyro [56]). As it is standard in gravity models, we cluster standards errors at the country-pair level (Head and Mayer [40]).

5 Empirical Results

We are now ready to look at our results. We start from gravity and then we turn to the impacts of a bank's foreign expansion on its individual and systemic risk metrics.

5.1 Gravity Prediction

Table 4 reports results for the gravity regression (10). As discussed earlier we test different specifications with and without fixed effects. While more commonly used, the specification with bank-time fixed effects may lead to instruments that depend on bank risk variation and are thus not valid. The corresponding results are shown in column (1). The specification is analogous to standard trade gravity estimations that include multilateral resistance terms, with the latter proxyng the average barriers of a country with all its trade partners (Anderson and Van Wincoop [8]; Head and Mayer [40]). For given bilateral barriers between two countries, i and j, higher barriers between i and the rest of the world are likely to raise the number of new affiliates that a bank headquartered in j opens in i. This specification serves mainly for comparison with the literature on gravity equations. We do not use its predicted expansion as our instrument. Our instruments are, instead, based on the specifications corresponding to the second and third columns of Table 4. In particular, column (3) reports the results with bank and destination country-time fixed effects while column (2) reports those without fixed effects.

In all columns of Table 4 the coefficients on distance are negative and significant. The elasticity of openings to distance ranges from a minimum of -0.560 in column (3) to a maximum of -0.811 in column (2). These magnitudes are comparable with the ones found in other banking gravity studies.[21] Sharing a common language, being in the EU and the difference in the legal systems do not have any significant impact. This might be explained by the fact that those variables are collinear to distance. In column (2) being in the Eurozone fosters openings.

The predicted expansion based on the gravity estimates in columns (2) and (3) will be used as our instruments, which we will call IV1 and IV2 respectively. Our preferred instrument will be IV2.[22] Being generated using bank (k) and hosting country-year (jt) fixed effects, it is more accurate than IV1, making the predicted openings of the gravity equation more precise and time-varying. Moreover, the exclusion of bank-time fixed effects makes it likely independent from bank risk variation. We will, therefore, take IV2 as our baseline instrument, while using IV1 only to make sure that our baseline results are not driven by potential correlation of the fixed effects in IV2 with bank risk.

5.2 Expansion and Individual Risk

We now study the impact of foreign expansion on bank risk, comparing the OLS estimates with the 2SLS ones that use IV1 and IV2 as alternative instruments. We start by examining individual bank risk, using our market- and book-based metrics. Table 5 compares the corresponding results. The first three columns give results without controls while columns (4) to (6) include the following set of controls: ln(Total Assets), Income Diversity, Asset Diversity, Tier1 ratio and the Deposit-to-asset ratio. Note that the presentation of the table is not standard: the variable in the left-hand side corresponds to the dependant variable while the independent variable is always the bank expansion.[23] Each regression includes bank and year fixed effects. The inclusion of bank fixed effects in all specifications allows us to look at the relation within banks ('within

[21] An earlier paper measuring the impact of geographical variables on cross-banking is Portes and Rey [52]. Buch [22] conducts similar analysis using data of foreign asset holdings of banks located in France, Germany, the UK and the US. She finds an elasticity of 0.65 in 1999 that varies between 0.31 in France to 1.13 in Italy. Berger et al. [14] propose a gravity analysis of bank expansion through M&A. They find a distance elasticity of 0.88 when they include host country and source country fixed effects. Finally, Claessens and Van Horen [28] study the foreign location decisions of banks in a large number of countries in 2009.

[22] When the instrument is constructed as IV2, it is generated using out-of-sample prediction. Observations that are always 0 for an origin-destination pair are dropped from the PPML estimation.

[23] In our online appendix we display the full tables.

Table 4 – Banking gravity

	(1)	(2)	(3)
		PPML	
Dep. var.: # of openings		IV 1	IV 2
ln(Distance)	-0.560**	-0.811***	-0.569**
	(0.247)	(0.197)	(0.253)
Contiguity	0.0245	1.086***	0.114
	(0.245)	(0.300)	(0.254)
Off. Com. Langu.	0.558	-0.518	0.577
	(0.376)	(0.386)	(0.395)
Both in the EU	0.0410	0.0952	-0.0728
	(0.572)	(0.699)	(0.604)
Both using Euro	-0.667**	1.762***	-0.450
	(0.332)	(0.339)	(0.335)
Diff. legal syst.	0.104	0.303	0.311
	(0.310)	(0.314)	(0.283)
Observations	1,812	5,365	2,657
R-squared	0.569	0.036	0.351
Bank FE	No	No	Yes
Bank × year FE	Yes	No	No
Host country × year FE	Yes	No	Yes

Robust standard errors clustered at the Bank × Host country level in parentheses. *** p<0.01, ** p<0.05, * p<0.1

effect'). This nets out any composition effect through which the observed relation between the average riskiness of our banks and foreign expansion could be driven by the fact that banks with different *ex ante* riskiness expand at different rates ('between effect'). Time fixed effects account for common time trends in the risk metrics. IV1 refers to the instrument generated without fixed effects. IV2 refers to the instrument generated with bank and host-country-time fixed effects. Results are reported sequentially in each row for CDS price, loan-loss provisions, the standard deviation of returns, the Z-score and the leverage ratio.

The impact of expansion on risk is always negative and significant in most cases. The coefficient decreases and becomes more significant when we include the instrument and the controls. Note that both instruments generate good F-stats in the first stage regressions, confirming that they are not weak. In sum, for all individual risk metrics and for all set of controls and instrumental variables, we find a robust negative impact of foreign expansion on individual bank risk.

The regressions based on our baseline instrument IV2 – in columns (3) and (6) – generate estimates of intermediate magnitude between OLS and IV1-based 2SLS. In particular, column (6) tells us that on average each new foreign opening by a bank decreases its CDS price by 1.5%, its loan-loss provisions ratio by 0.027 percentage points, the standard deviation of the returns by 1%, increases the Z-score (which is inversely related to risk) by 0.89% and decreases the leverage ratio by0.65 points of percentage. These effects correspond to the impact of one foreign opening per year, the median number of openings per bank being two. For banks with number of openings corresponding to the fourth quartile (those that open six foreign units a year), the cumulated effect of their openings translates on average into a decrease of roughly 9% in the CDS spread, 0.162 percentage points in the loan-loss provisions ratio, roughly 6% in the standard deviation of market returns, 3.9% in the leverage ratio and an increase of 5.3% in the Z-score.

To summarize, after its foreign expansion the market considers a bank as less risky in terms of: asset and liability risk, as captured by smaller CDS spread, distance to default, as captured by higher Z-score, and its ability to generate a stable income stream, as captured by smaller standard deviation of returns. Moreover, foreign expansion induces the bank to set aside lower loan-loss provisions, which implies that its self-assessed asset risk is also smaller. Finally, lower leverage ratio suggests that foreign expansion also disciplines the liabilities side of the balance

Table 5 – Individual risk metrics

	(1)	(2)	(3)	(4)	(5)	(6)
		No controls			Controls	
	OLS	IV1	IV2	OLS	IV1	IV2
First Stage		22.5495***	1.6030***		28.5419***	1.7289***
		(5.8428)	(0.3526)		(6.6751)	(0.3806)
ln(CDS)	-0.00463**	-0.0258***	-0.0107***	-0.00473**	-0.0274***	-0.0146***
	(0.00189)	(0.00908)	(0.00366)	(0.00191)	(0.00789)	(0.00446)
Observations	145	145	145	136	136	136
R-squared	0.964	0.934	0.962	0.972	0.936	0.965
F-Test 1st		14.89	20.67		18.28	20.63
LLP	-0.00906	-0.0588**	-0.0175	-0.00691	-0.0727***	-0.0273**
	(0.0131)	(0.0270)	(0.0127)	(0.0112)	(0.0249)	(0.0123)
Observations	143	143	143	135	135	135
R-squared	0.286	0.032	0.279	0.461	0.031	0.420
F-Test 1st		12.43	20.21		16.50	20.28
ln(σ returns)	-0.00339**	-0.0186***	-0.00781***	-0.00381**	-0.0190***	-0.00991***
	(0.00143)	(0.00650)	(0.00291)	(0.00157)	(0.00547)	(0.00303)
Observations	145	145	145	136	136	136
R-squared	0.894	0.823	0.888	0.909	0.832	0.896
F-Test 1st		14.89	20.67		18.28	20.63
ln(Z-score)	0.00429**	0.0238***	0.00785**	0.00434**	0.0221***	0.00887***
	(0.00195)	(0.00765)	(0.00320)	(0.00153)	(0.00655)	(0.00269)
Observations	135	134	134	135	134	134
R-squared	0.842	0.718	0.838	0.885	0.784	0.879
F-Test 1st		17.93	19.58		20.99	20.63
Leverage	-0.244**	-0.982***	-0.519***	-0.289	-0.959***	-0.647***
	(0.108)	(0.323)	(0.161)	(0.169)	(0.256)	(0.205)
Observations	145	145	145	136	136	136
R-squared	0.583	0.400	0.558	0.651	0.484	0.604
F-Test 1st		14.89	20.67		18.28	20.63

Robust standard errors in parentheses. The first stage regressions are the ones with ln(CDS) as risk metric in the 2SLS estimation (for other metrics the first stage statistics could be slightly different as the number of observations could be different). Each regression includes bank and year fixed effects. IV1 refers to the instrument generated without fixed effects. IV2 refers to the instrument generated with bank and host-country-time fixed effects. Control Set: ln(Total Assets), Income Diversity, Asset Diversity, Tier1 ratio and the Deposit-to-asset ratio. *** p <0.01, ** p<0.05, * p<0.1

sheet risk.[24]

5.3 Expansion and Systemic Risk

There are several reasons why international expansion may cause an increase in systemic risk. First, new entrants in the market tend to increase the degree of interconnections in the system thereby fostering direct contagion channels. Second, by investing in local loans, they increase the degree of asset commonality. New entrants may also obtain short-term funds from the local deposit market and provide short-term funds to the local interbank market. All this implies that the new entrant may be exposed to the same funding risk as the local banks in each destination country, and may also potentially contribute to spread liquidity risk.

To see whether this is the case, Table 6 mirrors Table 5 for systemic rather than individual risk metrics: the long-run marginal expected shortfall (LRMES), the conditional capital shortfall (SRISK), and the ΔCoVaR computed using either CDS prices or equity prices. For three risk measures (LRMES, SRISK and ΔCoVaR computed with equity prices) there is a negative and significant causal effect of international expansion on systemic risk with remarkable consistency across the different measures. The impact of expansion on ΔCoVaR computed with CDS is generally negative, but not significant.

Our conclusion is that in our sample of European banks there is strong and robust evidence that banks' foreign expansion decreases risk, not only from an individual viewpoint but also from a systemic viewpoint.

6 Expansion and Competition

Having established the negative impact of foreign expansion on bank risk, we now examine whether this impact can be explained by different intensities of competition between source and host markets as predicted by the model presented in Section 2. To do so, for each parent holding we create two groups of openings depending on whether the intensity of competition (as measured by the total assets Herfindahl Index for Credit Institutions, or HHI) in the host country is higher or lower than in the source country. This procedure allows us to exploit the variation in the

[24] A channel through which global banks can reduce runnable liabilities is cross-border liquidity management. For instance, Cetorelli and Goldberg [25]) find that large global groups optimally manage internal liquidity by swiftly shifting it to where it is most needed. This reduces the need of raising runnable liabilities locally.

Table 6 – Systemic risk metrics

	(1)	(2)	(3)	(4)	(5)	(6)
		No controls			Control Set 1	
	OLS	IV1	IV2	OLS	IV1	IV2
LRMES	-0.136	-0.452*	-0.189*	-0.151	-0.499***	-0.193*
	(0.147)	(0.243)	(0.101)	(0.144)	(0.190)	(0.105)
Observations	145	145	145	136	136	136
R-squared	0.622	0.519	0.620	0.663	0.537	0.661
F-Test 1st		14.89	20.67		18.28	20.63
SRISK	-0.320	-1.622***	-0.904***	-0.350	-1.605***	-0.989***
	(0.266)	(0.481)	(0.256)	(0.281)	(0.374)	(0.318)
Observations	145	145	145	136	136	136
R-squared	0.664	0.326	0.596	0.726	0.401	0.641
F-Test 1st		14.89	20.67		18.28	20.63
Δ CoVaR CDS	-0.000736	-0.00289	-0.00139	-0.000369	-0.000601	-0.000939
	(0.00145)	(0.00417)	(0.00150)	(0.00135)	(0.00342)	(0.00139)
Observations	145	145	145	136	136	136
R-squared	0.687	0.680	0.686	0.745	0.745	0.745
F-Test 1st		14.89	20.67		18.28	20.63
Δ CoVaR Equ.	-0.000221	-0.00280***	-0.000860**	-0.000259	-0.00262***	-0.00104**
	(0.000248)	(0.000963)	(0.000329)	(0.000280)	(0.000810)	(0.000399)
Observations	145	145	145	136	136	136
R-squared	0.852	0.711	0.843	0.855	0.730	0.841
F-Test 1st		14.89	20.67		18.28	20.63

Robust standard errors in parentheses. Each regression includes bank fixed effects and year fixed effects. IV1 refers to the instrument generated without fixed effects. IV2 refers to the instrument generated with bank and host-country-time fixed effects. Control Set: ln(Total Assets), Income Diversity, Asset Diversity, Tier1 ratio and the Deposit-to-asset ratio. *** p<0.01, ** p<0.05, * p<0.1

degree of competition across HHI groups and countries. Using the gravity predictions we made before (only for IV2 with bank and host-year fixed effects, for ease of presentation), we obtain two corresponding groups of predicted openings based on IV2: predicted openings in host countries with HHI lower or higher than the source country.[25]

According to our model, the competition channel is at work whenever the impact of foreign expansion on bank risk differs between the two (instrumented) groups of openings. Moreover, the 'margin effect' of competition dominates (is dominated by) its 'scale effect' whenever risk falls more for expansion to host countries with lower (higher) intensity of competition, i.e. higher (lower) HHI than the source country.

Tables 7 and 8 present the results for individual and systemic risk measures respectively. In particular, Table 7 shows that the competition channel is indeed at work, and this is due to a dominant 'margin effect', in the case of loan-loss provisions, the standard deviation of returns and the Z-score: the estimated coefficients on openings in lower HHI host countries are not statistically different from zero, whereas those in higher HHI host countries are negative (although not statistically significant for LLP). Differently, in the case of CDS the opposite pattern holds: estimated coefficients on openings in higher HHI host countries are not statistically different from zero, while those in lower HHI host countries are negative and statistically significant. This discrepancy may be explained by the fact that the CDS tends to price the risk of the parent holding more than the risk of affiliated banks in specific markets. The regressions with leverage do not reveal a significant difference between expansion in competitive and not competitive markets.

As for systemic risk, the results reported in Table 8 are more mixed. They still generally indicate that risk falls with openings, particularly so for openings in countries with higher intensity

[25] In their study of the effects of competition on bank risk across US states, Jiang, Levine and Lin (2017) enrich the gravity instrument exploiting the fact that individual states began interstate deregulation in different years and followed different dynamic paths from 1982 until the Riegle-Neal Act eliminated restrictions on interstate banking in 1995. In particular, for each state and each year, they measure which other state's banks can establish subsidiaries in its borders obtaining state-year measures of the competitive pressures facing a state's banking system. They then integrate these state-year interstate bank deregulation measures with the gravity model to differentiate among banks within a state and construct time-varying, bank-specific competition indices. In the case of our sample their procedure is hard to implement as we cover the period 2005-2014 and changes in regulation for European countries took place only around 2014 after the creation of the banking union and the implementation of the banking directives (when changes started to happen almost contemporaneously in all countries).

Table 7 – Testing for the competition channel – Individual risk metrics.

		(1)	(2)	(3)	(4)
		No controls		**Controls**	
		OLS	2SLS	OLS	2SLS
ln(CDS)	Open. in countries with lower HHI	-0.0112*	-0.0193***	-0.0137**	-0.0291***
		(0.00554)	(0.00649)	(0.00468)	(0.00767)
	Open. in countries with higher HHI	-0.000200	-0.00381	0.000948	-0.00300
		(0.00483)	(0.00730)	(0.00360)	(0.00603)
	Observations	145	145	136	136
	R-squared	0.965	0.963	0.973	0.967
	F-Test 1st		11.15		13.25
LLP	Open. in countries with lower HHI	0.0357	0.0438*	0.0269	0.00689
		(0.0245)	(0.0259)	(0.0208)	(0.0261)
	Open. in countries with higher HHI	-0.0400	-0.0670**	-0.0342	-0.0529**
		(0.0239)	(0.0318)	(0.0243)	(0.0257)
	Observations	143	143	135	135
	R-squared	0.325	0.300	0.513	0.477
	F-Test 1st		10.16		12.49
ln(σ returns)	Open. in countries with lower HHI	0.00202	0.000594	0.00196	-0.00544
		(0.00302)	(0.00543)	(0.00256)	(0.00609)
	Open. in countries with higher HHI	-0.00707**	-0.0145***	-0.00797***	-0.0133***
		(0.00287)	(0.00465)	(0.00193)	(0.00435)
	Observations	145	145	136	136
	R-squared	0.896	0.887	0.911	0.899
	F-Test 1st		11.15		13.25
ln(Z-score)	Open. in countries with lower HHI	-0.00540	-0.00435	-0.00333	0.00290
		(0.00450)	(0.00607)	(0.00372)	(0.00583)
	Open. in countries with higher HHI	0.0108***	0.0175***	0.00972***	0.0134***
		(0.00345)	(0.00607)	(0.00146)	(0.00436)
	Observations	135	134	135	134
	R-squared	0.848	0.841	0.889	0.882
	F-Test 1st		10.75		13.20
Leverage	Open. in countries with lower HHI	-0.205	-0.300	-0.175	-0.654*
		(0.298)	(0.303)	(0.300)	(0.352)
	Open. in countries with higher HHI	-0.271	-0.694**	-0.339*	-0.640**
		(0.207)	(0.316)	(0.178)	(0.323)
	Observations	145	145	136	136
	R-squared	0.583	0.552	0.662	0.611
	F-Test 1st		11.15		13.25

Robust standard errors in parentheses. Each regression includes bank and year fixed effects. IV2 refers to the instrument generated with bank and host-country-time fixed effects. Control Set: ln(Total Assets), Income Diversity, Asset Diversity, Tier1 ratio and Deposit-to-asset ratio, Average MPI in entering countries and Average comovement in entering countries. The two last variables are introduced to control for diversification and regulation channels.

*** p<0.01, ** p<0.05, * p<0.1

Table 8 – Testing for the competition channel – Systemic risk metrics.

		(1)	(2)	(3)	(4)
		No controls		Controls	
		OLS	2SLS	OLS	2SLS
LRMES	Open. in countries with lower HHI	-0.246	-0.568**	-0.194	-0.552*
		(0.401)	(0.284)	(0.371)	(0.279)
	Open. in countries with higher HHI	-0.0618	0.115	-0.106	0.0890
		(0.101)	(0.105)	(0.111)	(0.129)
	Observations	145	145	136	136
	R-squared	0.625	0.607	0.675	0.653
	F-Test 1st		11.15		13.25
SRISK	Open. in countries with lower HHI	-0.412	-0.976**	-0.459	-1.397***
		(0.574)	(0.437)	(0.528)	(0.496)
	Open. in countries with higher HHI	-0.257	-0.847*	-0.278	-0.654
		(0.330)	(0.450)	(0.255)	(0.484)
	Observations	145	145	136	136
	R-squared	0.665	0.598	0.734	0.656
	F-Test 1st		11.15		13.25
ΔCoVaR CDS	Open. in countries with lower HHI	0.00852**	0.00423	0.00889**	0.00396
		(0.00288)	(0.00338)	(0.00403)	(0.00349)
	Open. in countries with higher HHI	-0.00702***	-0.00588***	-0.00694***	-0.00475***
		(0.00210)	(0.00213)	(0.00162)	(0.00164)
	Observations	145	145	136	136
	R-squared	0.711	0.706	0.773	0.767
	F-Test 1st		11.15		13.25
ΔCoVaR Equ.	Open. in countries with lower HHI	9.75e-05	0.000544	-7.27e-05	-6.45e-06
		(0.000620)	(0.000632)	(0.000680)	(0.000708)
	Open. in countries with higher HHI	-0.000438	-0.00198***	-0.000389	-0.00185***
		(0.000451)	(0.000583)	(0.000454)	(0.000573)
	Observations	145	145	136	136
	R-squared	0.852	0.835	0.856	0.837
	F-Test 1st		11.15		13.25

Robust standard errors in parentheses. Each regression includes bank and year fixed effects. IV2 refers to the instrument generated with bank and host-country-time fixed effects. Control Set: ln(Total Assets), Income Diversity, Asset Diversity, Tier1 ratio and Deposit-to-asset ratio, Average MPI in entering countries and Average comovement in entering countries. The two last variables are introduced to control for diversification and regulation channels.

*** p<0.01, ** p<0.05, * p<0.1

of competition, but a robust (opposite) pattern emerges only for the CoVaR measures. However, more nuanced results for systemic than individual measures are to be expected as systemic risk is more likely to be affected by a number of country characteristics that go beyond and above the differential intensity of competition between source and host markets.

7 Conclusion

How bank globalization affects risk is an open question. In the run-up to the 2007-2008 financial crisis banks around the world had been loading too much risk on their balance sheets. Banks' risk-taking has been attributed to two main causes: lax monetary policy and banking globalization.

An extensive literature has studied the role of expansionary monetary policy for banks' risk-taking. Based on data from single countries and risk measures at the individual bank level, a consensus has emerged that low interest rates can trigger banks' risk-taking. Differently, studies on banking globalization are more divided as they do not examine the role of global banks for risk-taking directly.

We have contributed to this body of knowledge in three ways. First, we have provided a deeper investigation of the impact of banks' foreign expansion on risk-taking both from individual and systemic viewpoints. Second, we have studied a someway neglected channel through which banks' foreign expansion may affect risk-taking when national banking markets differ in terms of the intensity of competition. Third, in doing so, we have assembled a rich cross-country dataset on global banks' foreign expansion including their main characteristics as well as key features of their countries of operation.

To organize the different moving parts of our empirical analysis, we have proposed a simple static model showing that whether risk-taking increases when a bank expands its operations in a foreign market depends on whether the probability of no default in that market is higher or lower than in its home market. This in turn depends on whether the number of competing banks is different between the two markets. However, two opposite effects of competition on risk-taking imply that whether a larger number of banks is associated with more or less risk-taking is ambiguous from a theoretical viewpoint. On the one hand, for a given loan-deposit margin, a larger number of banks leads to more loans and deposits, which in itself would raise the probability of no default ('scale effect'). On the other hand, a larger number of banks decreases the loan-deposit margin, which in itself would reduce the probability of no default ('margin effect').

Using data on the 15 European banks classified as G-SIBs covering a 10-year time period from 2005 to 2014, we have found that the impact of foreign expansion on risk is always negative and significant for most individual and systemic risk metrics. In the case of individual metrics, we have also found that the competition channel is indeed at work. This happens through a dominant 'margin effect' as the estimated coefficients on openings in lower HHI host countries are not statistically different from zero whereas those in higher HHI host countries tend to be negative. As for systemic risk, our findings are mixed and this can be explained by the fact that systemic risk is more likely to be affected by a number of country or business model characteristics that go beyond and above the differential intensity of competition between source and host markets.

As our period of observation includes the 2007-2008 financial crisis, it is useful to further discuss how we have taken the crisis's impact and the related policy responses into account. Moreover, as our evidence is based on European banking groups, some discussion is warranted on how the European banking system evolved during this period, also in relation to the developments observed in the US. First and foremost, to make sure that the financial crisis and its policy responses do not drive our results, all our regressions control for a common time trend ('time fixed effect'). Second, one may argue that our emphasis on banks' openings neglects the possible impact of banks' exits, which could be sizeable following a financial crisis. We have checked this issue by collecting data on exits. We have found that they are in much fewer than openings and controlling for them does not make any difference as the corresponding coefficients turn out to be statistically insignificant. The reason is that data on exits are very noisy and possibly distorted by the fact that in most cases we do not observe a true exit but just a change of bank name or a restructuring. Yet, the relatively small number of exits we observe is in line with the fact that in the aftermath of the crisis de-banking has been mild in Europe and much more contained than in the US.[26] In some regressions we also control for indicators of macro-prudential policy. Our

[26]Exits in Europe have been less than a third of those in the US (ESRB [33]). Sales of affiliates by European GSIBs happened mainly in countries outside Europe as this is their core market. Sales of affiliates were instead much more common among smaller banks. A well known case is the sale of Austria's Volksbank operations in eight Eastern European countries to Sberbank. No significant case can be detected for GSIBs.

results are robust to those controls.[27]

A final comment concerns the relation between banking concentration and the likelihood or the severity of the financial crisis. After the crisis governments pushed for consolidation with no clear evidence on whether consolidation is good or bad for risk. First, as noted in Vives [60], some countries with concentrated banking system such as Belgium, the Netherlands and the UK (but also Germany and Italy) have suffered severely from the crisis. This is indicative of the fact that concentration might not be good for stability. Second, a recent report by the ESRB [33] using data for 195 banks for the period 1994-2012 finds that a system characterized by large and universal banks (hence likely concentrated) is correlated with higher systemic risk. To properly account for the universal nature of the European banks, our data on foreign entries include activities such as insurance and factoring that go beyond strict retail banking, but still contribute to riskiness. This has allowed us to avoid underestimating bank risk while casting a shadow on consolidation as necessarily risk-reducing.

[27] Policy responses might have opposite effects on risk and as such they might offset each other. Consider first prudential policy. On the one hand, stricter regulatory requirements or bail-in policies might increase barrier to entry, reduce profitability and increase insolvency. On the other hand, imposing higher loss absorption capacity drives down the market pricing of risk and banks' risk-taking incentives. In the aftermath of the crisis there have been also some bail-outs. Those can also have opposite effects. Ex ante the presence of an implicit government guarantee might drive the market pricing of risk, however ex post bail-outs foster moral hazard, hence banks' risk-taking.

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A Data Description

Our analysis exploits a novel dataset providing the number of foreign affiliates opening for the 15 biggest G-SIBs banks in Europe between 2005 and 2014. We consider the following banks: Banco Santander (BSCH), Barclays (BARC), BNP Paribas (BNPA), BPCE Groupe (BPCE), Credit Suisse (CRES), Credit Agricole (AGRI), Deutschebank (DEUT), HSBC , ING Direct (INGB), Nordea (NDEA), Royal Bank of Scotland (RBOS), Société Générale (SOGE), Standard Chartered (SCBL), UBS (UBSW) and UniCredit (UNCR). We identify 38 destination countries: Albania, Austria, Belgium, Bulgaria, Bosnia-Herzegovina, Croatia, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Lithuania, Luxembourg, Latvia, Malta, Montenegro, Netherlands, Norway, Poland, Portugal, Romania, Russia, Serbia, Slovenia, Slovakia, Spain, Sweden, Switzerland, Turkey, Ukraine and the United Kingdom. The panel is balanced, as we consider for each bank all potential host countries and years; if a bank did not establish an affiliate in a foreign country in a given year, the count of its openings is assumed to be equal to zero.

We combined many data sources, the two main sources being the banks' annual reports and ORBIS vintages. Orbis provides the vintages of the fiscal years 2008 to 2014 (the access to these vintages is restricted to a 10-years time window). The data provided by Orbis includes a wide range of subsidiaries, such as banks, financial companies, insurance companies, corporate companies, mutual and pension funds, private equity firms and others. In order to keep track of only the most relevant affiliates, we filtered the data keeping only the subsidiaries for which the bank had a level of ownership greater than or equal to 50%. We also adjusted the names of the entities observed when it was necessary to ensure consistency of the dataset over time, since banks' names may change, especially following an acquisition episode.

In order to complement Orbis data with older entities from 2004 (in order to register entries in 2005), we manually collected majority-owned foreign affiliates lists from annual reports of the banks. To deal with incomplete reports, we use several other sources such as SEC fillings, the Claessens and Van Horen database of Bank Ownership (hereafter CvH),[28] internet websites of the banks, press reports, etc. The CvH database provides ownership information for 5,498 banks active in 139 countries over the period 1995-2013. We manually assigned these banks to their

[28] Available at: https://www.dnb.nl/en/onderzoek-2/databases/bank.jsp

global ultimate owner to track the information about foreign entry of the 15 GSIB considered in this paper. We extended the coverage using annual reports.

In order to harmonize the sources and limit possible inaccuracies in reporting, we dropped the affiliates specialized in real estate activities as well as those specialized in leasing activities. We also reviewed manually the database containing affiliates names to avoid any double counting. Double counting may occur if an entity changes name during the period studied and between the different sources. We also had to control for the entry of holding companies. For example: if Bank A enters a market (say country C) with retail banking and insurance activities, it may open three entities named: "Bank A Holdings in C", "Bank A Retail Banking" and "Bank A Insurance". In this case we only kept the two last entities in our database. We also dropped identified trust and shelf companies. Finally, we dropped all entities located in UK's oversea territories such as Jersey, Guernsey, British Virgin Islands, Gibraltar, etc. BPCE bank is only considered from its date of creation in 2009.

This gives us a dataset where an observation corresponds to an affiliate of a G-SIB European bank k (headquartered in country i), registered in country j (with $j \neq i$). We have access to the presence of this affiliate between 2004 and 2015. We register an entry whenever we record the first entry in the period. Considering that entry, followed by an exit and a new entry of the same entity is very rare, we do not consider 'new entries' since they may be due to our data sources rather than a true activity of the bank. We then sum for each bank k in destination country j the number of openings in a given year. With 8 home countries, 38 destinations and 10 years, we end up with a balanced dataset of 5550 observed (foreign) $Openings_{kjt}$ for $j \neq i$ and 145 observed $Expansion_{kt} = \sum_{j \neq i} Openings_{kjt}$.

B Systemic Risk Metrics

In this paper, we use four different metrics for systemic risk: the long-run marginal expected shortfall, the SRISK metric and the Δ CoVaR computed using two different methods. We will first briefly describe the construction of each metric and then highlight common points and differences.

B.1 Long-Run Marginal Expected Shortfall

The Marginal Expected Shortfall (MES) and its long-run version (LRMES) has been introduced in the seminal papers of Acharya et al. [2] and Brownlees and Engle [20]. The MES corresponds to the firm's expected equity loss following the fall of the market under a given threshold. It is defined as a 2% market drop in one day for the MES and as a 40% market drop over six months for the LRMES. The LRMES will give the marginal contribution of a bank to the systemic risk following the market decline. Formally, the LRMES for bank i, in a market M and cumulative returns between t and t+6 $R_{i,t:t+6}$ is:

$$LRMES_{i,t:t+6} = -\mathbb{E}\left[R_{i,t:t+6} | R_{M,t:t+6} \leq -40\%\right] \tag{12}$$

Higher LRMES corresponds to a higher contribution of the bank to the systemic risk. Our measure of LRMES comes from the Center for Risk Management of Lausanne and has been computed following methods adapted for European banks (see Engle, Jondeau and Rockinger, 2012). The construction of LRMES combines DCC, GARCH and copula models.

B.2 SRISK

This measure has been proposed by Acharya, Engle and Richardson [1] and Brownless and Engle [20]. The SRISK is based on MES but takes into account the liabilities and the size of the bank. Following Acharya, Engle and Richardson [1] and Benoit et al. [13], SRISK is defined as:

$$LRMES_{it} = max\left[0; \left[kL_{it} - 1 + (1-k)LRMES_{it}\right] W_{it}\right] \tag{13}$$

with k being the prudential capital ratio, L_{it}, the leverage of the bank and W_{it} the market capitalization.

This definition highlights that SRISK increases with the market capitalization and the leverage.

B.3 Δ CoVaR

The ΔCoVaR measure has been proposed by Adrian and Brunnermeier [3]. The CoVaR corresponds to "the value at risk (VaR) of the financial system conditional on institutions being under financial distress". The ΔCoVaR is then defined as the difference between the CoVaR when bank i is under distress and the CoVaR when bank i is in its median state.

The $VaR(p)$, the VaR at the confidence level p is defined as the loss in market value that is exceeded with a probability $1-p$ in a given period. For instance the $VaR(5\%) = x$ corresponds to an expected loss lower than x in 95% of the cases. Formally $VaR(p)$ of the market return r_i is defined as:

$$\mathbb{P}(r_i \leq VaR_i(p)) = p \tag{14}$$

The CoVaR is defined as the VaR of a bank conditional on some event $\mathbb{C}(r_i)$ affecting bank i returns:

$$\mathbb{P}(r_i \leq CoVaR^{i|\mathbb{C}(r_i)}(p)|\mathbb{C}(r_i)) = p \tag{15}$$

The ΔCoVaR is then computed as the difference between the CoVaR when the loss is equal to the VaR (distress event) and the CoVaR in a normal situation (defined as the median return):

$$CoVaR^{i|r_{it}=VaR_{it}(p)} - CoVaR^{i|r_{it}=Median(r_{it})} \tag{16}$$

This definition of the ΔCoVaR allows its estimation using simple quantile regressions techniques.

We estimate the ΔCoVaR for our 15 banks following the methodology and the codes of Adrian and Brunnermeier [3]. As ΔCoVaR can be estimated using returns on equity or on CDS, we choose to compute both.

The ΔCoVaR extends the VaR measure to take into account the contribution of each institution to the overall risk in the market. The metric is especially designed to compare the contribution of different banks to the systemic risk. As stated by Adrian and Brunnermeier [3] the ΔCoVaR is not equivalent to the VaR.

B.4 Comparison

As stated by Benoit et al. [13] no systemic risk metric covers all the dimensions of systemic risk. Each different metric takes into account different features of the systemic risk than other might not consider. Based on this remark we can state that the three different systemic risk metrics used in this paper are complementary.

A key difference between the LRMES and the SRISK metrics is the implicit paradigm of systemic risk. The LRMES naturally increases for interconnected institutions. This corresponds to the too-interconnected-to-fail paradigm. On the contrary, the SRISK weights the systemic risk by the size and the leverage of the bank. It is then closer to the too-big-to-fail paradigm (see Benoit et al. [13]). Despite having similar trends, these two measures are weighted differently and reveal different aspects of systemic risk.

According to Benoit et al. [13], the conditions under which ΔCoVaR and LRMES and ΔCoVaR and SRISK provide similar rankings of systemic risk are restrictive. They confirm this in their empirical analysis where they observe that rankings of riskiness based on ΔCoVaR seems un-correlated with other rankings. This is confirmed in our sample as well.

B.5 Data Sources

As for data sources, CDS prices come from Bloomberg and equity prices from Datastream. Both are averaged to obtain monthly (for computing ΔCovar) and yearly (as left-hand side variables) measures. The LRMES and the SRISK metrics are taken from the Centre for Risk Analysis of Lausanne and correspond to a yearly average using four values by year.[29] Concerning the variables used as states in the ΔCoVaR estimation: the VIX is taken from the Chicago Boards Option Exchange; the S&P composite index from Datastream; the Moody's Seasoned Baa Corporate Bond Yield Relative to Yield on 10-Year Treasury Constant Maturity, the three-months yield, the ten-years yield and the LIBOR rate come from the Federal Reserve Bank of Saint Louis. All these variables are averaged to obtain monthly values.

[29] The results are robust to redefining the annual LRMES/SRISK as the one at the end of December.

C Descriptive statistics

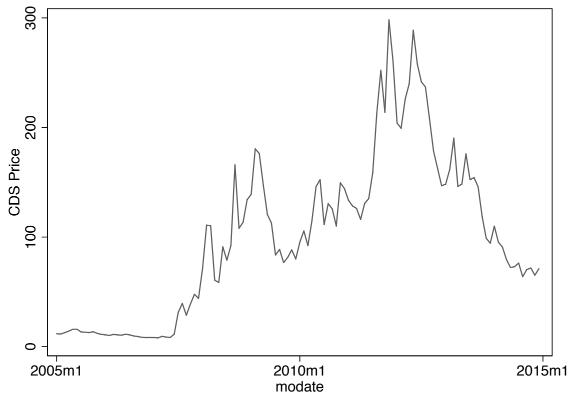

Figure 6 – Trend for CDS prices

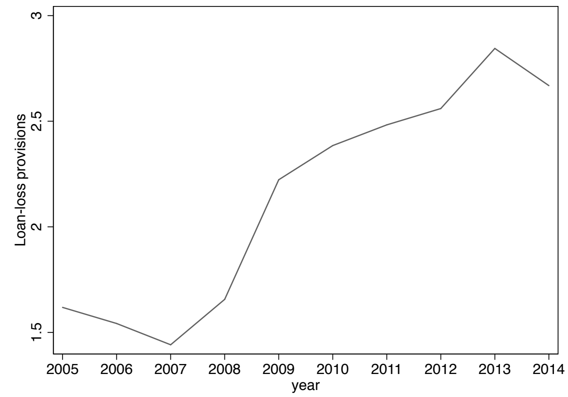

Figure 7 – Trend for loan-loss provisions to total loans

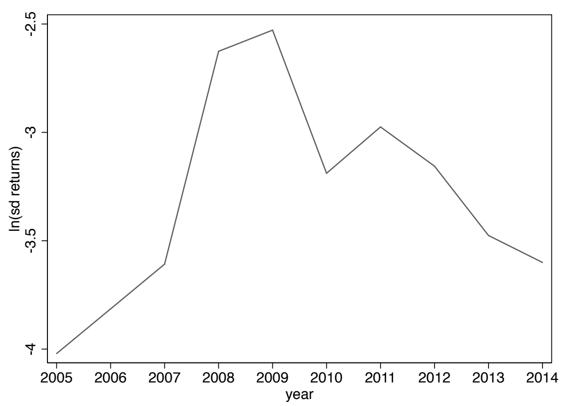

Figure 8 – Trend for the ln(σ weekly returns)

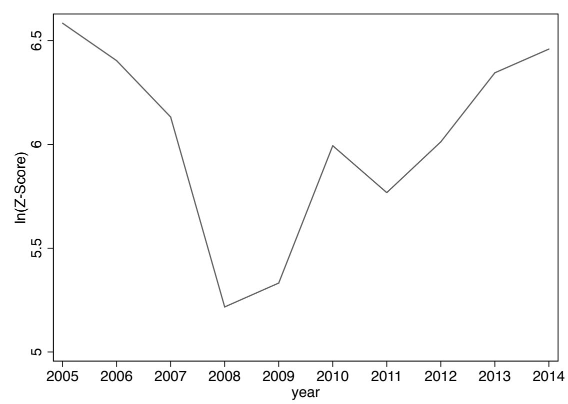

Figure 9 – Trend for ln(Z-score)

Figure 10 – Trend for LRMES

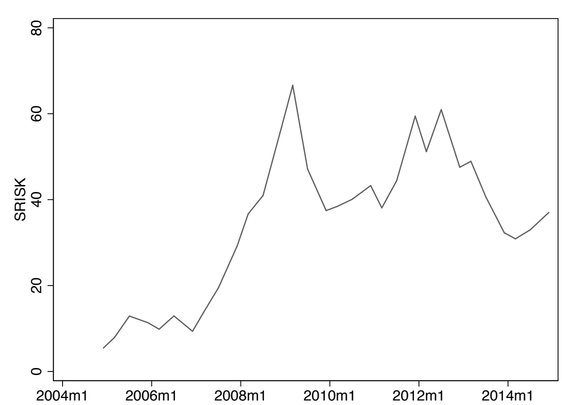

Figure 11 – Trend for SRISK

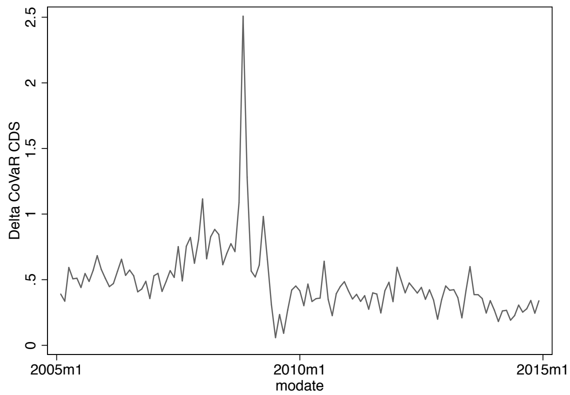

Figure 12 – Trend for Δ CoVaR CDS

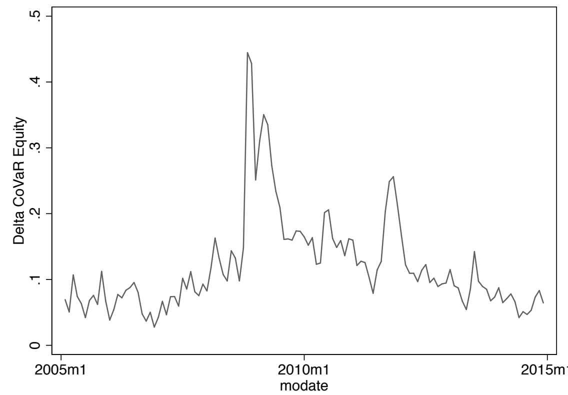

Figure 13 – Trend for Δ CoVaR EQU

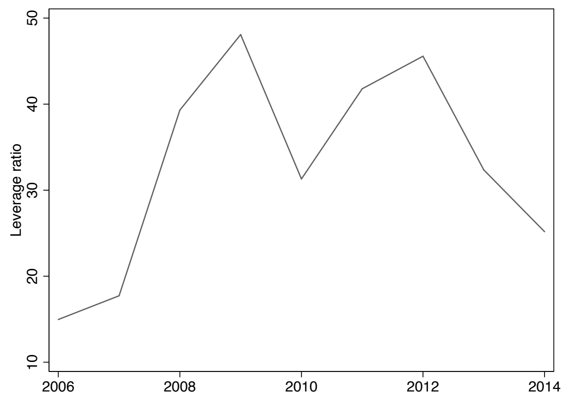

Figure 14 – Trend for Leverage ratio

Figures 6 to 14 correspond to the eight risk metrics. CDS prices, loan-loss provisions, volatility of returns, Z-score, SRISK, LRMES and ΔCoVaR EQU have similar trends with peaks in 2009 and 2013. The trend of the ΔCoVaR CDS is a bit different with a peak only in 2009. The loan-loss provisions to total loans, for which we only have annual measures, has an increasing trend from 2007 to 2014.

Table 9 presents the correlation between each risk metrics.

Table 9 – Correlation between risk metrics

	ln(CDS)	LLP	ln(σ returns)	ln(Z-score)	LRMES	SRISK	Δ CoVaR	Δ CoVaR Equ	Leverage
ln(CDS)	1	–	–	–	–	–	–	–	–
LLP	0.3506	1	–	–	–	–	–	–	–
ln(σ returns)	0.675	0.27	1	–	–	–	–	–	–
ln(Z-score)	-0.4904	-0.3586	-0.925	1	–	–	–	–	–
LRMES	0.6026	0.1021	0.5941	-0.4446	1	–	–	–	–
SRISK	0.5156	0.2373	0.6135	-0.5423	0.5946	1	–	–	–
Δ CoVaR	-0.1561	-0.1317	0.2287	-0.311	0.0816	-0.0108	1	–	–
Δ CoVaR Equ	0.5081	0.1908	0.8149	-0.7658	0.4614	0.3978	0.1417	1	–
Leverage	0.5491	0.2236	0.6935	-0.6219	0.5192	0.8818	0.0365	0.505	1

Online Appendix: Foreign Expansion, Competition and Bank Risk

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July 2018.

Contents

A Full Tables

Table 1 – Dependant variable: ln(CDS)

	(1) OLS	(2) IV1	(3) IV2	(4) OLS	(5) IV1	(6) IV2
Expansion	-0.00463**	-0.0258***	-0.0107***	-0.00473**	-0.0274***	-0.0146***
	(0.00189)	(0.00908)	(0.00366)	(0.00191)	(0.00789)	(0.00446)
ln(Tot Assets)				-0.0222	0.102	0.0318
				(0.180)	(0.169)	(0.135)
ROA				-0.209***	-0.216**	-0.212***
				(0.0648)	(0.0885)	(0.0679)
Income diversity				-0.0388	-0.00905	-0.0259
				(0.0378)	(0.0640)	(0.0465)
Asset diversity				-0.294	-0.0707	-0.197
				(0.471)	(0.403)	(0.328)
Tier1/Asset				-0.00214	-0.000368	-0.00137
				(0.00825)	(0.00597)	(0.00517)
Deposits/Asset				-0.000505*	-0.000630	-0.000560**
				(0.000265)	(0.000459)	(0.000275)
Observations	145	145	145	136	136	136
R-squared	0.964	0.934	0.962	0.972	0.936	0.965
F-Test 1st		14.89	20.67		18.28	20.63

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 2 – Dependant variable: Loan-Loss Provisions

	(1) OLS	(2) IV1	(3) IV2	(4) OLS	(5) IV1	(6) IV2
Expansion	-0.00906	-0.0588**	-0.0175	-0.00691	-0.0727***	-0.0273**
	(0.0131)	(0.0270)	(0.0127)	(0.0112)	(0.0249)	(0.0123)
ln(Tot Assets)				-0.490	-0.129	-0.378
				(0.880)	(0.499)	(0.473)
ROA				-0.835**	-0.854*	-0.841*
				(0.283)	(0.453)	(0.459)
Income diversity				0.0680	0.155	0.0949
				(0.117)	(0.230)	(0.191)
Asset diversity				-1.336	-0.823	-1.177
				(1.052)	(1.039)	(0.885)
Tier1/Asset				0.00832	0.0145	0.0102
				(0.0158)	(0.0168)	(0.0141)
Deposits/Asset				-0.00241***	-0.00271*	-0.00250***
				(0.000786)	(0.00156)	(0.000945)
Observations	143	143	143	135	135	135
R-squared	0.286	0.032	0.279	0.461	0.031	0.420
F-Test 1st		12.43	20.21		16.50	20.28

Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 3 – Dependant variable: ln(σ returns)

	(1) OLS	(2) IV1	(3) IV2	(4) OLS	(5) IV1	(6) IV2
Expansion	-0.00339**	-0.0186***	-0.00781***	-0.00381**	-0.0190***	-0.00991***
	(0.00143)	(0.00650)	(0.00291)	(0.00157)	(0.00547)	(0.00303)
ln(Tot Assets)				0.114	0.197	0.147
				(0.245)	(0.128)	(0.127)
ROA				-0.164***	-0.169**	-0.166***
				(0.0387)	(0.0659)	(0.0499)
Income diversity				-0.0255	-0.00553	-0.0175
				(0.0254)	(0.0296)	(0.0218)
Asset diversity				0.0918	0.242	0.152
				(0.237)	(0.244)	(0.199)
Tier1/Asset				0.00135	0.00254	0.00183
				(0.00697)	(0.00478)	(0.00469)
Deposits/Asset				-0.000396**	-0.000480	-0.000430
				(0.000184)	(0.000368)	(0.000266)
Observations	145	145	145	136	136	136
R-squared	0.894	0.823	0.888	0.909	0.832	0.896
F-Test 1st		14.89	20.67		18.28	20.63

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 4 – Dependant variable: ln(Z-score)

	(1) OLS	(2) IV1	(3) IV2	(4) OLS	(5) IV1	(6) IV2
Expansion	0.00429**	0.0238***	0.00785**	0.00434**	0.0221***	0.00887***
	(0.00195)	(0.00765)	(0.00320)	(0.00153)	(0.00655)	(0.00269)
ln(Tot Assets)				-0.212	-0.320**	-0.240*
				(0.247)	(0.136)	(0.132)
ROA				0.287***	0.292***	0.288***
				(0.0479)	(0.0805)	(0.0610)
Income diversity				0.00804	-0.0169	0.00169
				(0.0307)	(0.0444)	(0.0303)
Asset diversity				0.227	0.0189	0.174
				(0.247)	(0.307)	(0.236)
Tier1/Asset				-0.00112	-0.00240	-0.00145
				(0.00770)	(0.00532)	(0.00500)
Deposits/Asset				0.000116	0.000224	0.000144
				(0.000191)	(0.000386)	(0.000243)
Observations	135	134	134	135	134	134
R-squared	0.842	0.718	0.838	0.885	0.784	0.879
F-Test 1st		17.93	19.58		20.99	20.63

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 5 – Dependant variable: Leverage ratio

	(1) OLS	(2) IV1	(3) IV2	(4) OLS	(5) IV1	(6) IV2
Expansion	-0.244**	-0.982***	-0.519***	-0.289	-0.959***	-0.647***
	(0.108)	(0.323)	(0.161)	(0.169)	(0.256)	(0.205)
ln(Tot Assets)				16.07	19.72**	18.02**
				(11.71)	(8.129)	(8.118)
ROA				-7.174**	-7.370**	-7.279***
				(2.676)	(3.262)	(2.735)
Income diversity				1.252	2.131	1.721
				(1.480)	(1.871)	(1.465)
Asset diversity				16.42	23.01*	19.93
				(15.82)	(13.51)	(12.50)
Tier1/Asset				0.372	0.424	0.399
				(0.377)	(0.297)	(0.302)
Deposits/Asset				-0.0377**	-0.0414**	-0.0397**
				(0.0141)	(0.0201)	(0.0167)
Observations	145	145	145	136	136	136
R-squared	0.583	0.400	0.558	0.651	0.484	0.604
F-Test 1st		14.89	20.67		18.28	20.63

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 6 – Dependant variable: LRMES

	(1) OLS	(2) IV1	(3) IV2	(4) OLS	(5) IV1	(6) IV2
Expansion	-0.136	-0.452*	-0.189*	-0.151	-0.499***	-0.193*
	(0.147)	(0.243)	(0.101)	(0.144)	(0.190)	(0.105)
ln(Tot Assets)				-1.405	0.490	-1.177
				(6.709)	(5.613)	(5.069)
ROA				-0.979	-1.081	-0.991
				(1.535)	(1.957)	(1.504)
Income diversity				-1.588	-1.133	-1.533
				(1.243)	(1.115)	(1.046)
Asset diversity				14.13	17.55	14.54
				(11.75)	(11.14)	(10.51)
Tier1/Asset				-0.256	-0.229	-0.253*
				(0.183)	(0.148)	(0.136)
Deposits/Asset				0.000504	-0.00141	0.000274
				(0.00704)	(0.0105)	(0.00653)
Observations	145	145	145	136	136	136
R-squared	0.622	0.519	0.620	0.663	0.537	0.661
F-Test 1st		14.89	20.67		18.28	20.63

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 7 – Dependant variable: SRISK

	(1) OLS	(2) IV1	(3) IV2	(4) OLS	(5) IV1	(6) IV2
Expansion	-0.320	-1.622***	-0.904***	-0.350	-1.605***	-0.989***
	(0.266)	(0.481)	(0.256)	(0.281)	(0.374)	(0.318)
ln(Tot Assets)				14.17	21.02**	17.66*
				(18.12)	(9.926)	(9.347)
ROA				-10.49*	-10.86*	-10.68**
				(5.938)	(6.494)	(5.182)
Income diversity				-1.653	-0.00774	-0.815
				(2.433)	(2.580)	(1.801)
Asset diversity				21.24	33.58*	27.53*
				(20.60)	(19.70)	(16.11)
Tier1/Asset				-0.0760	0.0219	-0.0261
				(0.533)	(0.333)	(0.313)
Deposits/Asset				-0.0259	-0.0328	-0.0294
				(0.0253)	(0.0341)	(0.0253)
Observations	145	145	145	136	136	136
R-squared	0.664	0.326	0.596	0.726	0.401	0.641
F-Test 1st		14.89	20.67		18.28	20.63

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 8 – Dependant variable: Δ CoVaR CDS

	(1) OLS	(2) IV1	(3) IV2	(4) OLS	(5) IV1	(6) IV2
Expansion	-0.000736	-0.00289	-0.00139	-0.000369	-0.000601	-0.000939
	(0.00145)	(0.00417)	(0.00150)	(0.00135)	(0.00342)	(0.00139)
ln(Tot Assets)				0.0186	0.0198	0.0217
				(0.0807)	(0.0586)	(0.0602)
ROA				-0.0487	-0.0487	-0.0488
				(0.0441)	(0.0418)	(0.0417)
Income diversity				-0.0965***	-0.0962***	-0.0958***
				(0.0285)	(0.0282)	(0.0279)
Asset diversity				-0.0956	-0.0934	-0.0900
				(0.245)	(0.164)	(0.167)
Tier1/Asset				-0.00525	-0.00523*	-0.00520*
				(0.00401)	(0.00272)	(0.00275)
Deposits/Asset				0.000306**	0.000305**	0.000303**
				(0.000108)	(0.000134)	(0.000135)
Observations	145	145	145	136	136	136
R-squared	0.687	0.680	0.686	0.745	0.745	0.745
F-Test 1st		14.89	20.67		18.28	20.63

Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 9 – Dependant variable: Δ CoVaR Equ

	(1) OLS	(2) IV1	(3) IV2	(4) OLS	(5) IV1	(6) IV2
Expansion	-0.000221	-0.00280***	-0.000860**	-0.000259	-0.00262***	-0.00104**
	(0.000248)	(0.000963)	(0.000329)	(0.000280)	(0.000810)	(0.000399)
ln(Tot Assets)				0.00599	0.0189	0.0103
				(0.0315)	(0.0203)	(0.0186)
ROA				-0.0135**	-0.0142	-0.0138**
				(0.00526)	(0.00920)	(0.00662)
Income diversity				0.0173***	0.0204***	0.0183***
				(0.00411)	(0.00731)	(0.00529)
Asset diversity				-0.0288	-0.00560	-0.0211
				(0.0431)	(0.0373)	(0.0318)
Tier1/Asset				0.000346	0.000530	0.000407
				(0.000798)	(0.000745)	(0.000695)
Deposits/Asset				-2.92e-05	-4.22e-05	-3.35e-05
				(2.36e-05)	(5.04e-05)	(3.06e-05)
Observations	145	145	145	136	136	136
R-squared	0.852	0.711	0.843	0.855	0.730	0.841
F-Test 1st		14.89	20.67		18.28	20.63

Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

B Robustness tests

B.1 Clustering strategy

In the baseline tables, the standard errors are only robust to heteroskedasticity. We also apply a small sample correction. One could argue that the standards errors need to be clustered at the bank level. Such clustering strategy would give us 15 cluster groups which could be considered as too small to provide consistent estimates. Nevertheless, we provide here a replication of tables 5 and 6 where we cluster the standards errors at the bank level.

Table 10 – INDIVIDUAL RISK METRICS

	(1)	(2)	(3)	(4)	(5)	(6)
		No controls			Controls	
	OLS	IV1	IV2	OLS	IV1	IV2
First Stage		22.5495**	1.6030***		28.5419***	1.7289***
		(9.7088)	(0.3658)		(9.9771)	(0.2859)
ln(CDS)	-0.00463**	-0.0258*	-0.0107*	-0.00473**	-0.0274**	-0.0146***
	(0.00189)	(0.0144)	(0.00530)	(0.00191)	(0.0106)	(0.00432)
Observations	145	145	145	136	136	136
F-Test 1st		5.394	19.20		8.184	36.56
LLP	-0.00906	-0.0588	-0.0175	-0.00691	-0.0727*	-0.0273
	(0.0131)	(0.0536)	(0.0245)	(0.0112)	(0.0381)	(0.0157)
Observations	143	143	143	135	135	135
F-Test 1st		4.934	19.35		7.767	36.29
ln(σ returns)	-0.00339**	-0.0186*	-0.00781**	-0.00381**	-0.0190**	-0.00991***
	(0.00143)	(0.00914)	(0.00319)	(0.00157)	(0.00726)	(0.00301)
Observations	145	145	145	136	136	136
F-Test 1st		5.394	19.20		8.184	36.56
ln(Z-score)	0.00429**	0.0238*	0.00785*	0.00434**	0.0221**	0.00887**
	(0.00195)	(0.0122)	(0.00421)	(0.00153)	(0.0101)	(0.00321)
Observations	135	134	134	135	134	134
F-Test 1st		6.919	18.85		9.138	37.08
Leverage	-0.244**	-0.982**	-0.519**	-0.289	-0.959**	-0.647**
	(0.108)	(0.416)	(0.223)	(0.169)	(0.357)	(0.276)
Observations	145	145	145	136	136	136
F-Test 1st		5.394	19.20		8.184	36.56

Robust standard errors clustered at the bank level in parentheses. The first stage regressions are the ones with ln(CDS) as risk metric in the 2SLS estimation (for other metrics the first stage statistics could be slightly different as the number of observations could be different). Each regression includes bank and year fixed effects. IV1 refers to the instrument generated without fixed effects. IV2 refers to the instrument generated with bank and host-country-time fixed effects. Control Set: ln(Total Assets), Income Diversity, Asset Diversity, Tier1 ratio and the Deposit-to-asset ratio. *** p <0.01, ** p<0.05, * p<0.1

Table 11 – Systemic risk metrics

	(1)	(2)	(3)	(4)	(5)	(6)
		No controls			Control Set 1	
	OLS	IV1	IV2	OLS	IV1	IV2
LRMES	-0.136	-0.452	-0.189	-0.151	-0.499*	-0.193
	(0.147)	(0.328)	(0.187)	(0.144)	(0.263)	(0.184)
Observations	145	145	145	136	136	136
F-Test 1st		5.394	19.20		8.184	36.56
SRISK	-0.320	-1.622**	-0.904***	-0.350	-1.605***	-0.989**
	(0.266)	(0.671)	(0.293)	(0.281)	(0.488)	(0.348)
Observations	145	145	145	136	136	136
F-Test 1st		5.394	19.20		8.184	36.56
Δ CoVaR CDS	-0.000736	-0.00289	-0.00139	-0.000369	-0.000601	-0.000939
	(0.00145)	(0.00726)	(0.00194)	(0.00135)	(0.00464)	(0.00146)
Observations	145	145	145	136	136	136
F-Test 1st		5.394	19.20		8.184	36.56
Δ CoVaR Equ.	-0.000221	-0.00280*	-0.000860	-0.000259	-0.00262*	-0.00104*
	(0.000248)	(0.00157)	(0.000551)	(0.000280)	(0.00136)	(0.000564)
Observations	145	145	145	136	136	136
F-Test 1st		5.394	19.20		8.184	36.56

Robust standard errors clustered at the bank level in parentheses. Each regression includes bank fixed effects and year fixed effects. IV1 refers to the instrument generated without fixed effects. IV2 refers to the instrument generated with bank and host-country-time fixed effects. Control Set: ln(Total Assets), Income Diversity, Asset Diversity, Tier1 ratio and the Deposit-to-asset ratio. *** p<0.01, ** p<0.05, * p<0.1

B.2 Alternative Datasets

In this section, we replicate tables 5 and 6 of the paper with alternative datasets. Firstly, we use the Claessens and Van Horen [1] (CvH hereafter) dataset that is mainly focused on retail banking. We restrict the dataset available online[1] to the years and the host and origin countries covered in the paper. CvH dataset stops in 2013 so our analysis is restricted to the 2005-2013 period. Then, for each entity, we recover the parent holding through manual searches on the Internet. Finally, we only keep the parent holdings corresponding to the 15 G-SIBs covered in the paper. The CvH dataset is much more restricted than ours since it is mainly concentrated in retail banking. Over the period, we observe 50 openings.

We also use the dataset of the paper before the manual treatment of all observations. In this manual treatment, we corrected for the limitations of our sources and we excluded some activities (for instance real estate activities). In this robustness test, we only apply two treatments: first, we delete all affiliates located in U.K. overseas territories or in Gibraltar and then we adjust the openings at the dates that correspond to the merge between two different sources in 2011. We also observe unusual entries in 2014 in Orbis, probably due to changes from the data provider. Only for these two years (2011 and 2014) we use the openings recorded in the treated datasets.

[1] `https://www.dnb.nl/en/onderzoek-2/databases/bank.jsp`

Table 12 – Individual risk metrics – CvH Dataset

	(1)	(2)	(3)	(4)	(5)	(6)
		No controls			Controls	
	OLS	IV1	IV2	OLS	IV1	IV2
First Stage		146.7381**	-0.0004**		178.8492***	-.0007**
		(60.5311)	(0.0002)		(63.2478)	(0.0004)
ln(CDS)	-0.0358*	-0.406**	-0.504**	-0.0464**	-0.387***	-0.424**
	(0.0187)	(0.178)	(0.223)	(0.0177)	(0.143)	(0.212)
Observations	144	144	144	135	135	135
R-squared	0.964	0.876	0.823	0.972	0.895	0.877
F-Test 1st		5.877	5.632		7.996	3.954
LLP	-0.130	-1.500**	-2.246**	-0.211	-1.493**	-2.525**
	(0.0935)	(0.693)	(0.962)	(0.147)	(0.576)	(1.144)
Observations	142	142	142	134	134	134
R-squared	0.288	-0.640	-1.928	0.479	-0.297	-2.052
F-Test 1st		8.517	4.809		11.14	3.827
ln(σ returns)	-0.0132	-0.272**	-0.353*	-0.0231*	-0.257**	-0.197
	(0.0167)	(0.126)	(0.190)	(0.0124)	(0.101)	(0.120)
Observations	144	144	144	135	135	135
R-squared	0.891	0.696	0.553	0.906	0.735	0.812
F-Test 1st		5.877	5.632		7.996	3.954
ln(Z-score)	0.0161	0.338**	0.244	0.0326*	0.283**	0.172
	(0.0188)	(0.163)	(0.194)	(0.0162)	(0.117)	(0.119)
Observations	134	133	133	134	133	133
R-squared	0.838	0.512	0.674	0.883	0.693	0.825
F-Test 1st		5.522	4.815		7.793	3.951
Leverage	-0.0334	-13.51**	-28.32**	-0.894	-12.40**	-11.01*
	(1.030)	(6.173)	(13.95)	(0.994)	(4.973)	(6.419)
Observations	144	144	144	135	135	135
R-squared	0.564	-0.014	-1.986	0.623	0.157	0.262
F-Test 1st		5.877	5.632		7.996	3.954

Robust standard errors in parentheses. The first stage regressions are the ones with ln(CDS) as risk metric in the 2SLS estimation (for other metrics the first stage statistics could be slightly different as the number of observations could be different). Each regression includes bank and year fixed effects. IV1 refers to the instrument generated without fixed effects. IV2 refers to the instrument generated with bank and host-country-time fixed effects. Control Set: ln(Total Assets), Income Diversity, Asset Diversity, Tier1 ratio and the Deposit-to-asset ratio. *** p <0.01, ** p<0.05, * p<0.1

Table 13 – Systemic risk metrics – CvH Dataset

	(1)	(2)	(3)	(4)	(5)	(6)
	No controls			Control Set 1		
	OLS	IV1	IV2	OLS	IV1	IV2
LRMES	-0.786	-6.686*	-12.93*	-0.900	-7.371**	-8.177
	(0.668)	(3.772)	(6.801)	(0.583)	(3.055)	(5.473)
Observations	144	144	144	135	135	135
R-squared	0.625	0.270	-0.876	0.664	0.236	0.123
F-Test 1st		5.877	5.632		7.996	3.954
SRISK	0.284	-23.73**	-31.72**	-0.879	-22.06**	-16.66*
	(1.725)	(10.80)	(14.57)	(0.992)	(8.739)	(9.263)
Observations	144	144	144	135	135	135
R-squared	0.644	-0.448	-1.295	0.702	-0.176	0.215
F-Test 1st		5.877	5.632		7.996	3.954
Δ CoVaR CDS	-0.00806	-0.0618	0.143	-0.0114	-0.0127	0.0483
	(0.0131)	(0.0587)	(0.121)	(0.0106)	(0.0440)	(0.0787)
Observations	144	144	144	135	135	135
R-squared	0.688	0.646	0.361	0.747	0.747	0.693
F-Test 1st		5.877	5.632		7.996	3.954
Δ CoVaR Equ.	-0.00401	-0.0342**	-0.0288	-0.00461*	-0.0326**	-0.0176
	(0.00242)	(0.0155)	(0.0202)	(0.00249)	(0.0130)	(0.0125)
Observations	144	144	144	135	135	135
R-squared	0.853	0.669	0.728	0.857	0.689	0.821
F-Test 1st		5.877	5.632		7.996	3.954

Robust standard errors in parentheses. Each regression includes bank fixed effects and year fixed effects. IV1 refers to the instrument generated without fixed effects. IV2 refers to the instrument generated with bank and host-country-time fixed effects. Control Set: ln(Total Assets), Income Diversity, Asset Diversity, Tier1 ratio and the Deposit-to-asset ratio. *** p<0.01, ** p<0.05, * p<0.1

Table 14 – Individual risk metrics – Extended Dataset

	(1)	(2)	(3)	(4)	(5)	(6)
		No controls			Controls	
	OLS	IV1	IV2	OLS	IV1	IV2
First Stage		28.4202***	1.6641***		31.5984***	1.7255***
		(10.3122)	(0.2632)		(10.3859)	(0.2368)
ln(CDS)	-0.000547	-0.0115**	-0.00103	-0.000574	-0.0142**	-0.00160
	(0.000816)	(0.00542)	(0.00119)	(0.000934)	(0.00569)	(0.00148)
Observations	144	144	144	135	135	135
R-squared	0.963	0.919	0.963	0.971	0.901	0.970
F-Test 1st		6.998	40.59		9.162	53.95
LLP	-0.00893**	-0.0245**	-0.0101**	-0.00827**	-0.0347***	-0.0116***
	(0.00399)	(0.0109)	(0.00386)	(0.00299)	(0.0123)	(0.00346)
Observations	142	142	142	134	134	134
R-squared	0.326	0.186	0.325	0.495	0.124	0.489
F-Test 1st		6.303	43.04		8.751	55.05
ln(σ returns)	-0.00149**	-0.00819**	-0.00186***	-0.00177***	-0.00979***	-0.00239***
	(0.000530)	(0.00339)	(0.000700)	(0.000340)	(0.00350)	(0.000727)
Observations	144	144	144	135	135	135
R-squared	0.895	0.818	0.894	0.910	0.796	0.909
F-Test 1st		6.998	40.59		9.162	53.95
ln(Z-score)	0.00189***	0.0106**	0.00210***	0.00165***	0.0114***	0.00210***
	(0.000599)	(0.00423)	(0.000781)	(0.000405)	(0.00431)	(0.000730)
Observations	134	133	133	134	133	133
R-squared	0.844	0.706	0.844	0.885	0.721	0.885
F-Test 1st		7.440	41.77		9.419	54.44
Leverage	-0.0723	-0.442**	-0.0866	-0.0944	-0.495***	-0.135*
	(0.0597)	(0.193)	(0.0603)	(0.0648)	(0.180)	(0.0752)
Observations	144	144	144	135	135	135
R-squared	0.574	0.319	0.574	0.638	0.317	0.635
F-Test 1st		6.998	40.59		9.162	53.95

Robust standard errors in parentheses. The first stage regressions are the ones with ln(CDS) as risk metric in the 2SLS estimation (for other metrics the first stage statistics could be slightly different as the number of observations could be different). Each regression includes bank and year fixed effects. IV1 refers to the instrument generated without fixed effects. IV2 refers to the instrument generated with bank and host-country-time fixed effects. Control Set: ln(Total Assets), Income Diversity, Asset Diversity, Tier1 ratio and the Deposit-to-asset ratio. *** p <0.01, ** p<0.05, * p<0.1

Table 15 – Systemic risk metrics – Extended Dataset

	(1)	(2)	(3)	(4)	(5)	(6)
	No controls			Control Set 1		
	OLS	IV1	IV2	OLS	IV1	IV2
LRMES	-0.0180	-0.192	-0.0180	-0.0293	-0.256**	-0.0202
	(0.0312)	(0.127)	(0.0218)	(0.0316)	(0.127)	(0.0211)
Observations	144	144	144	135	135	135
R-squared	0.620	0.440	0.620	0.661	0.364	0.660
F-Test 1st		6.998	40.59		9.162	53.95
SRISK	-0.0976	-0.721**	-0.159	-0.106	-0.830***	-0.194
	(0.0923)	(0.306)	(0.109)	(0.0887)	(0.287)	(0.121)
Observations	144	144	144	135	135	135
R-squared	0.654	0.223	0.650	0.713	0.133	0.704
F-Test 1st		6.998	40.59		9.162	53.95
Δ CoVaR CDS	-0.000648	-0.00115	-0.000941***	-0.000498	-0.000257	-0.000890***
	(0.000437)	(0.00179)	(0.000328)	(0.000411)	(0.00176)	(0.000326)
Observations	144	144	144	135	135	135
R-squared	0.690	0.688	0.689	0.747	0.747	0.746
F-Test 1st		6.998	40.59		9.162	53.95
Δ CoVaR Equ.	-0.000172***	-0.00125**	-0.000252***	-0.000175***	-0.00135***	-0.000296**
	(4.96e-05)	(0.000526)	(8.59e-05)	(5.42e-05)	(0.000500)	(0.000113)
Observations	144	144	144	135	135	135
R-squared	0.853	0.717	0.853	0.856	0.688	0.855
F-Test 1st		6.998	40.59		9.162	53.95

Robust standard errors in parentheses. Each regression includes bank fixed effects and year fixed effects. IV1 refers to the instrument generated without fixed effects. IV2 refers to the instrument generated with bank and host-country-time fixed effects. Control Set: ln(Total Assets), Income Diversity, Asset Diversity, Tier1 ratio and the Deposit-to-asset ratio. *** p<0.01, ** p<0.05, * p<0.1

B.3 Alternative independent variable

One may argue that within a bank k expanding in a foreign country j at date t, the intensive margin of expansion (the number of openings) may be observed with some error. There could be many reasons for which we record more entries than what actually happened. We tried to manually treat this problem by systematically dropping duplicate observations. However some very small entities could be still recorded.

Here, to control for this possibility we use an alternative independent variable. Instead of counting the number of openings, we count the number of countries in which a G-SIB entered a given year. By doing this we eliminate the intensive margin of openings in a country. With j being a host country:

$$Openings_{kt} = \sum_{j} \mathbb{1}_{Opening_{jkt}}$$

For this exercise, we use two instrumental variables. First, we use our preferred instrument that is IV2 in the main text (in column 3 and 6 of baseline tables). We also consider an instrumental variable constructed in the same way as the independent variable. We consider that there is at least one foreign opening in a country as long as the number of predicted openings in country j is larger than 0.8. We refer to this instrument as IV2_{Dummy}.

Table 16 – Individual risk metrics

	(1)	(2)	(3)	(4)	(5)	(6)
		No controls			Controls	
	OLS	IV2	$IV2_{Dummy}$	OLS	IV1	$IV2_{Dummy}$
First Stage		0.4385***	0.7752***		0.4487***	0.7780***
		(0.0910)	(0.1466)		(0.0885)	(0.1450)
ln(CDS)	-0.0156**	-0.0390***	-0.0426**	-0.0177**	-0.0563***	-0.0652***
	(0.00687)	(0.0131)	(0.0193)	(0.00691)	(0.0156)	(0.0220)
Observations	145	145	145	136	136	136
R-squared	0.965	0.961	0.960	0.972	0.963	0.958
F-Test 1st		23.22	17.16		25.72	16.48
LLP	-0.0429	-0.0641	-0.0720	-0.0420	-0.105**	-0.112**
	(0.0477)	(0.0457)	(0.0620)	(0.0371)	(0.0434)	(0.0548)
Observations	143	143	143	135	135	135
R-squared	0.295	0.291	0.287	0.472	0.437	0.428
F-Test 1st		22.33	18.05		24.87	15.81
ln(σ returns)	-0.0105	-0.0285**	-0.0329**	-0.0134**	-0.0382***	-0.0461***
	(0.00602)	(0.0113)	(0.0157)	(0.00543)	(0.0113)	(0.0166)
Observations	145	145	145	136	136	136
R-squared	0.894	0.885	0.880	0.909	0.891	0.878
F-Test 1st		23.22	17.16		25.72	16.48
ln(Z-score)	0.0137	0.0294**	0.0385*	0.0146**	0.0344***	0.0396**
	(0.00851)	(0.0126)	(0.0200)	(0.00681)	(0.0108)	(0.0174)
Observations	135	134	134	135	134	134
R-squared	0.842	0.835	0.824	0.885	0.874	0.868
F-Test 1st		21.46	16.81		25.78	15.88
Leverage	-0.914**	-1.898***	-2.613***	-1.243***	-2.492***	-3.261***
	(0.335)	(0.586)	(0.894)	(0.411)	(0.685)	(0.898)
Observations	145	145	145	136	136	136
R-squared	0.589	0.559	0.499	0.672	0.620	0.536
F-Test 1st		23.22	17.16		25.72	16.48

Robust standard errors in parentheses. The first stage regressions are the ones with ln(CDS) as risk metric in the 2SLS estimation (for other metrics the first stage statistics could be slightly different as the number of observations could be different). Each regression includes bank and year fixed effects. IV1 refers to the instrument generated without fixed effects. IV2 refers to the instrument generated with bank and host-country-time fixed effects. Control Set: ln(Total Assets), Income Diversity, Asset Diversity, Tier1 ratio and the Deposit-to-asset ratio. *** p <0.01, ** p<0.05, * p<0.1

Table 17 – Systemic risk metrics

	(1)	(2)	(3)	(4)	(5)	(6)
		No controls			Control Set 1	
	OLS	IV2	$IV2_{Dummy}$	OLS	IV2	$IV2_{Dummy}$
LRMES	-0.478	-0.690*	-1.151**	-0.551	-0.744*	-1.502***
	(0.417)	(0.359)	(0.488)	(0.405)	(0.376)	(0.480)
Observations	145	145	145	136	136	136
R-squared	0.625	0.621	0.581	0.667	0.664	0.583
F-Test 1st		23.22	17.16		25.72	16.48
SRISK	-0.974	-3.306***	-4.661***	-1.256*	-3.812***	-5.052***
	(0.703)	(0.902)	(1.334)	(0.656)	(1.062)	(1.270)
Observations	145	145	145	136	136	136
R-squared	0.661	0.561	0.410	0.729	0.609	0.464
F-Test 1st		23.22	17.16		25.72	16.48
Δ CoVaR CDS	0.000537	-0.00508	0.000934	0.00222	-0.00362	0.00771
	(0.00606)	(0.00556)	(0.00743)	(0.00573)	(0.00545)	(0.00783)
Observations	145	145	145	136	136	136
R-squared	0.686	0.682	0.686	0.746	0.741	0.741
F-Test 1st		23.22	17.16		25.72	16.48
Δ CoVaR Equ.	-0.00136	-0.00314***	-0.00536**	-0.00158	-0.00402***	-0.00644***
	(0.000924)	(0.00120)	(0.00215)	(0.00103)	(0.00142)	(0.00236)
Observations	145	145	145	136	136	136
R-squared	0.854	0.848	0.823	0.859	0.847	0.811
F-Test 1st		23.22	17.16		25.72	16.48

Robust standard errors in parentheses. Each regression includes bank fixed effects and year fixed effects. IV1 refers to the instrument generated without fixed effects. IV2 refers to the instrument generated with bank and host-country-time fixed effects. Control Set: ln(Total Assets), Income Diversity, Asset Diversity, Tier1 ratio and the Deposit-to-asset ratio. *** p<0.01, ** p<0.05, * p<0.1

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