Global Banking: Endogenous Competition and Risk Taking*

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Abstract

When banks expand abroad, their riskiness decreases if foreign expansion happens in destination countries that are more competitive than their origin countries. We reach this conclusion in three steps. First, we develop a flexible dynamic model of global banking with endogenous competition and endogenous risk-taking. Second, we calibrate and simulate the model to generate empirically relevant predictions. Third, we validate these predictions by testing them on an original dataset covering the activities of the 15 European global systemically important banks (G-SIBs). Our results hold across alternative measures of individual and systemic bank risk.

JEL codes: *G21, G32, L13.*

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1 Introduction

Banking globalization has been blamed for generating and propagating risk in the run up to the financial crisis and through several channels.[1] More recently, however, evidence has suggested two new facts.[2] First, prior to 2007 most banking globalization had taken place through cross-border asset and liability holdings, while since the crisis cross-border activity declined sharply and the business model of global banks has changed to one of 'brick and mortar'(B&M).[3] Second, B&M seems to have reduced risk-taking as the direct involvement of global banks in local retail activities promotes local competition and improves projects selection.[4] If confirmed, this could represent a major development in terms of global financial stability, as many policymakers seem to think, instead, that some curbs on competition may be a price worth paying to improve stability (Economist, 2009).

The aim of the present paper is to contribute to the important debate on the role of global banks for financial stability by focusing on the competition channel. First, we develop a flexible dynamic model of global banking with endogenous competition and endogenous risk-taking with banks facing both individual and systemic risk. Second, we calibrate and simulate the model to generate empirically relevant predictions. Third, we validate these predictions by testing them on an original dataset covering the activities of the 15 European banks classified as G-SIBs by the Basel Committee on Banking Supervision (2014) at the end of 2015 over a 10-year time period from 2005 to 2014. We focus on the European banking system as global banks can effectively only emerge in countries with a universal banking model. Our conclusion is that, when banks expand abroad their riskiness decreases as long as foreign expansion happens in host markets that are more competitive than the markets banks are headquartered in. This result holds

[1]See Rajan (2005). More recently Ivashina, Scharfstein and Stein (2015) and Bruno and Shin (2015) found evidence and formalized a risk-taking channel of monetary policy through global banks. This interest in the interplay between globalization and risk-taking goes also beyond the financial industry. For instance recent papers examine the link between firm risk (measured as volatility) and firms' spatial diversification through their export portfolio (Kramarz, Martin and Méjean, 2020; Vannoorenberghe, Wang and Yu, 2016).

[2]See IMF (2015), McCauley et al. (2017).

[3]See Claessens and van Horen (2012, 2015) and van Horen and De Haas (2012, 2013).

[4]As claimed by IMF (2015).

across alternative measures of bank risk, being more robust for individual risk metrics than for systemic risk metrics. This validates the model mechanism qualitatively while quantitavely we also show that the reduced form evidence can be largely replicated using model-generated data.

In our model banks can decide to operate in different countries, and thus become 'multinational', through B&M by setting up local subsidiaries or branches.[5] In doing so, they face a fixed entry cost to create their headquarters and a fixed setup cost for each local subsidiary they open. Banks raise deposits from households and extend loans to firms. To account for the presence within banks of assets with loss absorption capacity such as equity buffers, deposits are fully insured. Banks pay the corresponding insurance fees and provide monitoring services on loans that firms use to finance risky projects under limited liability. There is moral hazard in that higher project returns are associated with higher probability of project failure, but limited liability implies that firms under-weigh the downside with respect to banks.[6] Despite the fact that deposits are fully insured, banks internalize the consequences of firms' risk-shifting when setting loan rates as their profits might turn negative after depositors are paid.

National markets are segmented and each market is imperfectly competitive with banks facing Cournot competition in both deposits (oligopsony) and loans (oligopoly), hence strategic externalities play a key role. On the other hand, households and firms have no market power, which allows banks to extract rents from the spread between the interest rate on loans and the interest rate on deposits, with the former above and the latter below their respective perfectly competitive levels. These rents generate the profits that may make it worthwhile for banks to enter and operate in the different national markets. Entry happens as long as banks' future discounted profits ('charter value') exceed entry and setup costs. Consistent with empirical evidence, monitoring loans in a country in which banks are not headquartered is more costly to them due to lower relationship lending ability. Due to strategic externalities the additional monitoring cost also implies that foreign loans leads to 'predatory banking', whereby banks penetrate the foreign market

[5]Entry and exit have been extensively studied for firms' industry dynamics (e.g. Hopenhayn, 1992).
[6]Stiglitz and Weiss (1981) and Jensen and Meckling (1976).

by accepting a lower loan-deposit spread than in their domestic market in exchange of a larger scale. Predatory banking incentives are stronger the smaller a bank's foreign market share is relative to its domestic one.[7] When firms' projects have imperfectly correlated outcomes, predatory banking is compounded by a 'selection effect', through which a bank survives only when the realized success rate of its loan portofolio does not fall short of an endogenous threshold ('survival cutoff') that rises with the intensity of competition.[8]

Several channels from foreign expansion to bank riskiness interact in our model. The interest rate on loans determines the risk appetite of firms, with higher loan rates inducing more risk-shifting under moral hazard so that banks' decisions on entry, deposits demanded and loans supplied drive the risk-return profile of firms' selected projects. In particular, by changing the number and the composition of incumbent banks, entry affects the intensity of competition in the banking sector and the loan rates on offer. The endogenous degree of banks' competition thus feeds back to firms' endogenous risk-taking through project selection.[9] This happens through different channels. For example, if additional banks enter, more competition in deposits reduces banks' oligopsonistic power, increasing the amount of deposits raised and the interest rate paid on them for given loan rate ('deposit rate channel'). More competition in loans reduces banks' oligopolistic power, increasing the amount of loans extended and decreasing the interest rate requested on them for given deposit rate ('loan rate channel'). These two effects combined reduce the loan-deposit spread, thereby decreasing banks' profits and charter value ('charter value channel'). As charter value falls, banks' entry eventually stops. When banks' entry is initially triggered by lower monitoring cost on foreign loans, more competition is accompanied by a re-balancing of market shares between domestic and foreign banks that reduces the scope for predatory banking ('predatory banking channel'). With imperfectly correlated project outcomes, tougher competition also raises the cutoff for banks' survival, allowing only the banks with the most successful portfolios to pull through ('selection channel').

[7] This is akin to 'dumping' in international trade (Brander and Krugman, 1983).

[8] This selection effect is akin to the one highlighted by Melitz (2003) in the case of international trade.

[9] The impact of competition on project selection parallels the idea advanced in the international trade literature that tougher competition associated with globalization leads to the survival of only the best performing firms (Melitz, 2003).

Whether firms' risk-taking eventually decreases or increases with entry depends on whether the interest rate on loans rises or falls, which itself depends on whether the compression of the loan-deposit spread dominates or is dominated by the rising interest rate on deposits. Higher rates on deposits would induce the bank to raise loan rates, thereby risk. But if the compression of the spread, due to stronger loan market competition, prevails, the loan rates falls and so does projects' risk. The end result hinges on the specific functional forms of the demand of loans, the supply of deposits, the relation between project return and risk, and parameter values. By calibrating and simulating the model in steady state, we show that, for empirically relevant and generally accepted functional forms, as competition increases the compression of the loan-deposit spread prevails leading to lower bank risk, both individually and systemically.[10] These predictions find empirical support in reduced-form estimates of the impact of banks' geographical expansion on individual and systemic risk metrics that pay due attention to issues related to identification and reverse causation in the wake of Goetz, Laeven and Levine (2013), Levine, Lin and Xie (2016) and Faia, Laffitte and Ottaviano (2019), and that can be replicated using data generated by our model. We then provide a model-based example of why these findings would matter in terms of policy prescriptions. Our modelling framework also delivers relevant insights regarding the current debate on the need for bank consolidation in Europe and other countries. In fact, in section 4.5 we show that keeping low barriers to the expansion of foreign banks is very important in order to preserve competition and limit risk-taking while promoting consolidation

Relation to the literature Our paper contributes to the recent but growing literature on global banks and financial stability. Some contributions focus on the link between global banks' risk-taking and monetary policy (Bräuning and Ivashina, 2019; Bruno and Shin, 2015), others on the role of dollar funding for global banks (Goldberg and Tille, 2008; Ivashina, Scharfstein and Stein, 2015; Gopinath and Stein, 2018), others on liquidity management and international shock transmission (Cetorelli and Goldberg, 2012*a*,*b*; Hale,

[10] While our model exhibits rich short-term patterns, in the present paper we exploit its short-term properties only for calibration purposes. Further details about the model's predictions on how the banking sector behaves along the business cycle can be found in Faia and Ottaviano (2017).

Kapan and Minoiu, 2019) or on the spillovers of capital regulations across countries (Forbes, 2020). None of the papers examine the impact of bank entry on risk-taking and stability through the competition channel, despite being and important dimension of banking.

From this point of view we also contribute, with a novel dataset on branching and subsidiaries, to an old and unsettled debate on the relation between bank competition and stability (Allen and Gale, 2000, 2004*b*; Hellmann, Murdock and Stiglitz, 2000; Vives, 2016; Berger et al., 2005 among others). Theoretically two general tendencies have been discussed. On the one side, higher competition fosters improved efficiency, also in monitoring, and thereby can decrease risk. On the other side, since banks are subject to liquidity risk, a larger market share might help to mitigate the risk of illiquidity.[11] Given this ambiguity numerous empirical studies have attempted to shed light on this relation, largely reaching contradicting results. In this respect our empirical analysis brings further insights also to this debate. The work by Keeley (1990) is one of the first studies in this area. It argues that competition, induced by deregulation, erodes banks' profits and franchise values, hence increases their risk. Salas and Saurina (2003) also show that deregulation in Spain eroded banks' charter values and increased their likelihood of insolvency. Several other studies relate bank risk to various competition indices. For instance Jimenez et al. (2014) relate loan risk to the Lerner competition index and finds evidence of a U-shaped relation between risk and market concentration. For the US Hanson and Stein (2011) show that liberalization induces banks to leverage more. Finally, other authors have studied the role of competition for incentives in relationship lending (see Berger and Udell, 2006 among others) and for banks' efficiency in general (see for instance Evanoff and Örs, 2008). It is argued that in a more competitive banking sector firms can more easily switch bank, hence banks loose incentives for relationship building and monitoring. We contribute to this literature by proposing a new selection channel, which we test in our data sample for European GSIBs.

The present paper goes beyond our previous work Faia, Laffitte and Ottaviano (2019).

[11]See Appendix B for an extension of the model including liquidity risk.

In particular, Faia, Laffitte and Ottaviano (2019) build their reduced-form empirical analysis on a static model with exogenous deposit-supply and loan-demand elasticities, and estimate the impact of banks' entry on risk conditioning on the absolute value of the Herfindahl index as a measure of competition in the destination country. This paper moves a step forward by investigating the exact mechanism and the channels driving the interaction of competition and risk-taking. To this end, it constructs a fully micro-founded, dynamic industry model with endogenous risk-taking, endogenous entry, individual as well as systemic risk, and banks' heterogeneity in terms of loan portfolios. Differently from Faia, Laffitte and Ottaviano (2019) and the other existing literature, the model in this paper features predatory banking and endogenous selection among heterogeneous banks. This implies that tougher competition can come along with an increase in the size of banks with better loan portfolios and, therefore, with an efficiency enhancing reallocation of market shares towards them and away from banks with worse portfolios. The latter indeed shrink or leave the market altogether. This allows us to revisit previous empirical results using a model-motivated competition index (Boone indicator).

The rest of the paper is organized as follows. Section 2 develops our dynamic model of global banking with endogenous market structure, focusing for ease of exposition on individual bank risk. Section 3 calibrates and simulates the steady state of the model to generate empirically relevant predictions, and also considers an extended version that allows for systemic bank risk. Section 4 validates the model's predictions by testing them in reduced form on our original dataset. It also shows that model-generated data can replicate the reduced form evidence. Section 5 concludes.

2 A Model of Global Banking

Consider an imperfectly competitive banking sector with endogenous entry that operates in two symmetric national markets, called h and f. Banks raise deposits from households under oligopsony and extend loans to firms under oligopoly for their investment projects. While banks and firms are risk neutral, households are risk averse. Firms' liability is limited and this generates risk-shifting incentives due to moral hazard.

Firms do not have internal funds and banks are their only source of funds, banks can only finance firms using own deposits, and depositors can only use their funds for deposits. The absence of bank equity is compensated by assuming that banks pay a fee $\xi > 0$ to a deposit insurance fund, which in the pecking order is the first loss absorber. Deposits are thus fully insured and this implies that also banks face risk-shifting incentives.

Banks are headquartered in only one of the two national markets, but can operate in both markets. However, when operating in the market they are not headquartered in, banks face an additional monitoring cost on loans $\mu > 0$. International expansion happens through a 'brick and mortar' (B&M) business model such that, in each national market, domestic and foreign banks can finance local loans only through local deposits and can use local deposits to fund only local loans. This is due to regulatory constraints that prevent banks from relocating liquidity across branches or subsidiaries in different countries and implies that banks optimize in the two markets separately ('market segmentation').

Despite market segmentation, the two markets are still linked through banks' entry decisions. These are forward-looking decisions that compare the total sum of future discounted profits from entry with a fixed entry cost $\kappa > 0$. This cost subsumes a headquarter setup cost $\kappa^b > 0$ and a subsidiary setup cost $\kappa^d > 0$ for each market banks' operates in ($\kappa = \kappa^b + 2\kappa^d$). A constant discount factor $\beta \in (0, 1)$ captures the exogenous per-period opportunity cost associated with financing κ in an un-modelled international capital market. The fact that the discount factor is constant means that the two national banking markets are 'small' with respect to the international capital market and thus financing conditions in the latter are not affected by banks' decisions in the former. While entry is endogenous, exit happens at exogenous death rate $\varrho \in (0, 1)$.[12] We use $N^a_{t,h}$ and $N^a_{t,f}$ to denote the numbers of active banks that, in any given period t, are headquartered in h and f respectively, and $N^a_t = N^a_{t,h} + N^a_{t,f}$ to denote the resulting total number of active banks.

Henceforth, as the two national markets are symmetric, we will focus for conciseness

[12]An extension of the model with endogenous exit is discussed in Appendix B.

on the description of market h, with analogous expressions holding for market f.

2.1 Entry and Exit

In any period active banks consist of incumbents that survived from the previous period and new entrants. Hence, using $N_{t-1,h}$ and $N^{e}_{t,h}$ to denote the numbers of incumbents and entrants headquartered in h in period t, we have that the corresponding number of active banks is:

$$N^{a}_{t,h} = N_{t-1,h} + N^{e}_{t,h} = \frac{N_{t,h}}{1-\varrho}, \tag{1}$$

where the second equality is due to the fact that the number of incumbents in any period is only a share $1-\varrho$ of the number of active banks in the previous period as the rest do not survive.

In deciding whether to enter or not, banks compare the fixed entry cost κ with the value of being active ('charter value'), that is, the present value of future profits. Entry takes place instantaneously as long as the charter value is larger than the entry cost so that free entry leads to the equalization of the two. Using the Bellman operator and denoting by $V_{t,h}$ the charter value in period t of a bank headquartered in h, the following recursive characterization holds:

$$V_{t,h} = \Pi_{t,hh} + \Pi_{t,hf} + \beta(1-\varrho)V_{t+1,h} = \kappa. \tag{2}$$

where $\Pi_{t,hh}$ and $\Pi_{t,hf}$ refer to the per-period profits the bank earns in markets h and f respectively and the last equality is granted by free entry. Note that the model is in perfect foresight, hence we do not need expectation operators for future variables.[13] Hence, in any given period t the charter value equals the entry cost: $V_{t,h} = \kappa$.[14]

[13] The model is flexible enough to also accommodate uncertainty. See Faia and Ottaviano (2017) for an application with productivity shocks.

[14] As entry happens instantaneously, the model does not feature any transitional dynamics.

2.2 Deposits and Loans

Banks have market power with respect to both depositors and borrowers. In particular, they exert oligopsonist power vis-à-vis the former and oligopolist power vis-à-vis the latter, behaving as Cournot-Nash competitors in both cases. Accordingly, in order to analyze their strategic decisions, we first need to characterize households' deposit supply as well as firms' loan demand and project selection. In doing so, to avoid cluttering the notation, as all agents' optimizations and banks' strategic interactions take place within period, we will leave the time index implicit whenever this does not generate confusion.

2.2.1 Deposit Supply

Depositors are risk averse households but deposits are fully insured by banks at a flat rate $\xi > 0$. This implies that in market h the total supply of deposits D_h^T as well as the return on deposits r_h^D do not depend on the riskiness of banks' portfolios. As thus households only care about the expected return on deposits, the (inverse) supply of deposits can be characterized as a return function of D_h^T only. For the market to be oligpsonistic this function $r_h^D = r^D\left(D_h^T\right)$ needs to satisfy $r^D(0) \geq 0$ and be twice differentiable with $r^{D\prime}\left(D_h^T\right) > 0$ and $r^{D\prime\prime}\left(D_h^T\right) \geq 0$.[15] Using D_{hh} and D_{fh} to denote the deposits raised by home and foreign banks respectively in market h, we then have $D_h^T = D_{hh} + D_{fh}$.[16]

2.2.2 Loan Demand

In each national market firms have access to a set of constant-return risky technologies ('projects') with fixed output normalized to 1. Projects are indexed by their returns r_h^I, which materializes with probability $p(r_h^I)$ for $r_h^I \in [0, \overline{r}^I]$ and 0 otherwise. The individual bank risk metrics is project default probability $1-p(r^I)$. However, as in this setup projects are perfectly correlated across firms and thus all fail with the same probability, $1 - p(r^I)$ is also the aggregate default probability, i.e. the systemic risk metrics.[17]

[15] See Allen and Gale (2000) and Allen and Gale (2004*a*).

[16] In principle, households could invest directly in firms' projects. They would, however, receive an uncertain return. By investing in insured bank deposits, they receive instead a certain return, which better suits their risk averse preferences.

[17] This would not be the case if projects were imperfectly correlated across firms. We will extend our model to allow for imperfectly correlated projects in Section 3.4.

Probability $p(r_h^I)$ satisfies $p(0) = 1$, $p(\overline{r}^I) = 0$, $p_1(r_h^I) < 0$ for all $r_h^I \in [0, \overline{r}^I]$ so that $p(r_h^I)r_h^I$ is strictly concave in r_h^I. The choice of projects by firms is unobservable to banks, which can only observe, at no cost, whether projects have been successful ($r_h^I > 0$) or not ($r_h^I = 0$).

As firms are risk neutral, the total demand of loans is $L_h^T = L_{hh} + L_{fh}$, where L_{hh} and L_{fh} denote the supply of loans from home and foreign banks respectively and do not depend on the riskiness of firms' projects. The inverse demand of loans can then be characterized as a return function of L_h^T only. This function $r_h^L = r^L\left(L_h^T\right)$ satisfies $r^L(0) > 0$ and is twice differentiable with $r^{L\prime}\left(L_h^T\right) < 0$, $r^{L\prime\prime}\left(L_h^T\right) \leq 0$ and $r^L(0) > r^D(0)$. Appendix A derives micro-foundations for this function showing that its properties satisfy a cut-off condition for funding profitable investment in a context with heterogenous firms. Finally, as banks can only finance loans through deposits and firms can only finance projects through bank loans, the total amounts of firms' investments I_h^T, banks' loans L_h^T and deposits D_h^T have to be the same: $I_h^T = L_h^T = D_h^T$, where the total amount of investments financed by home and foreign banks is $I_h^T = I_{hh} + I_{fh}$.

2.2.3 Investment and Risk

Due to limited liability firms repay their loans only if their projects succeed. Accordingly, firms have an incentive to risk-shifting, the more so the higher the cost of credit. This implies that, given risk neutrality, a firm chooses r_h^I in order to maximize expected per period profits:

$$p(r_h^I)(r_h^I - r_h^L), \tag{3}$$

as failure happens with probability $1 - p(r_h^I)$ but does not require any loan repayment.[18] Note that, given the monotonic relation between $p(r_h^I)$ and r_h^I, choosing r_h^I is equivalent to choosing $p(r_h^I)$. In this respect, firms choose the 'risk-return profile' of investments for given return on loans r_h^L.

[18]We could alternatively assume that firms earn a fixed amount $(1 - c)$ with probability $1 - p(r_h^I)$. This, however, would not change the main incentives faced by firms and banks. In case of failure, firms would be unable to repay the loans, banks would repossess the amount left $(1 - p(r_h^I))(1 - c)$ and firms would receive zero. The proceeds earned by banks would then enter banks' profits and their first order conditions would be simply scaled up by $(1 - p(r_h^I))(1 - c)$.

The first order condition for a firm maximizing (3) is:

$$p(r_h^I) + p_1(r_h^I)(r_h^I - r_h^L) = 0, \tag{4}$$

which shows that the firm trades off higher return $\left(p\left(r_h^I\right) > 0\right)$ against lower success probability $(p_1(r_h^I)(r_h^I - r_h^L) < 0)$. Making the dependence of r_h^L on L_h^T explicit allows us to rewrite (4) as:

$$\frac{p(r_h^I)}{p_1(r_h^I)} + r_h^I = r^L\left(L_h^T\right), \tag{5}$$

which expresses the return on investment r_h^I, and thus also risk $1 - p(r_h^I)$, as an implicit function of aggregate loans L_h^T. In particular, (5) shows that, by affecting L_h^T, banks indirectly command the return-risk profile chosen by firms. This is the channel through which, by affecting the total supply of credit, the intensity of competition in the banking sector will generate a strategic externality. Specifically, given the functional properties of $r^L\left(L_h^T\right)$ and $p(r_h^I)$, a contraction in bank credit (smaller L_h^T) induces firms to select a more 'aggressive' investment profile characterized by higher return (larger r_h^I) and higher risk (larger $p(r_h^I)$).

2.3 Banks' Competition

As banks can only finance local loans by local deposits, the loans $L_{r,hh}$ $(L_{r,fh})$ of any home (foreign) bank r have to exactly match its deposits $D_{r,hh}$ $(D_{r,fh})$. This implies $L_{r,hh} = D_{r,hh}$ $(L_{r,fh} = D_{r,fh})$ with $D_{hh} = \sum_{r=1}^{N_h} D_{r,hh}$ $(D_{fh} = \sum_{r=1}^{N_h} D_{fh})$ so that $L_{r,hh}$ or $D_{r,hh}$ $(L_{r,fh}$ or $D_{r,fh})$ can be equivalently chosen as a home (foreign) bank's choice variable. In what follows, we will choose $L_{r,hh}$ $(L_{r,fh})$. Then, Cournot-Nash behavior requires each home (foreign) bank r to take into account its individual impacts through L_h^T on both the return on deposits $r^D\left(L_h^T\right) = r^D\left(D_h^T\right)$ and the return on loans $r^L\left(L_h^T\right)$ when choosing its amount of loans $L_{r,hh}$ $(L_{r,fh})$.

Each period starts with a given number of incumbent banks in both markets that survived from the previous period. The timing of ensuing events for market h is the following. First, based on the number of incumbents, new banks may decide to enter, bringing the total number of active banks to $N^a = N_h^a + N_f^a$. Second, active banks simultaneously choose the amounts of loans $L_{r,hh}$ ($L_{r,fh}$) in market h separately from market f due to market segmentation. Aggregation of these simultaneous individual decisions up to L_h^T determines loans and deposits returns r_h^L and r_h^D. Third, based on r_h^L, firms design their risk-return profiles by choosing r_h^I or equivalently $p(r_h^I)$. Fourth, uncertainty over projects' outcomes is resolved. Successful firms repay their loans and, whatever happens, depositors receive return r_h^D thanks to full insurance. Finally, exogenous exit takes place at rate ϱ. Surviving banks become the new incumbents $N = N^a(1-\varrho)$, with $N_h = N_h^a(1-\varrho)$ and $N_f = N_f^a(1-\varrho)$, at the beginning of the next period.

Given this timing, the model's solution requires us first to characterize the Cournot-Nash equilibrium of the banking sector for given numbers of active banks, and then to endogenize those numbers using the free entry conditions $V_h = \kappa$ and $V_f = \kappa$.

2.3.1 Profit Maximization

Due to market segmentation, banks maximize profits independently in the two markets. In the case of market h, a bank r headquartered in h chooses $L_{r,hh}$ to maximize:

$$\Pi_{r,hh} = p(r_h^I)\left[r^L\left(L_h^T\right)L_{r,hh} - r^D(D_h^T)D_{r,hh} - \xi D_{r,hh}\right], \tag{6}$$

whereas a bank s headquartered in f chooses $L_{s,fh}$ to maximize:

$$\Pi_{s,fh} = p(r_h^I)\left[r^L\left(L_h^T\right)L_{s,fh} - r^D(D_h^T)D_{s,fh} - \xi D_{s,ff} - \mu L_{s,fh}\right], \tag{7}$$

subject to the constraint that local loans must match local deposits ($L_{r,hh} = D_{r,hh}$, $L_{s,fh} = D_{s,fh}$) as well as to the firms' first order condition (5), which implicitly defines firms' return on investment as a function of the loan rate $\left(r_h^I = r^I\left(r^L\left(D_h^T\right)\right)\right)$. In doing so, banks are aware that their individual decisions affect aggregate loans and hence deposits: $L_h^T = \sum_r L_{r,hh} + \sum_s L_{s,fh}$ and $D_h^T = \sum_r D_{r,hh} + \sum_s D_{s,fh}$ with $L_h^T = D_h^T$.

The first order condition for domestic bank r in market h is:

$$\begin{aligned} \frac{d\Pi_{r,hh}}{dL_{r,hh}} &= p(r_h^I)\left[r^L\left(L_h^T\right) - r^D(L_h^T) - \xi\right] + \\ &+p(r_h^I)\left[r^{L\prime}\left(L_h^T\right) - r^{D\prime}(L_h^T)\right]L_{r,hh} + \\ &+p_1(r_h^I)r^{I\prime}\left(r^L\left(L_h^T\right)\right)r^{L\prime}\left(L_h^T\right)\left[r^L\left(L_h^T\right) - r^D(L_h^T) - \xi\right]L_{r,hh} = 0. \end{aligned} \tag{8}$$

After the first equality, the first term is the 'scale effect'. It is positive and represents the marginal gain from increasing bank scale, as measured by the total amount of loans and deposits. The second term is the 'competition effect'. It is negative and captures the impacts of marginally larger bank scale on deposit return ($r^{D\prime}\left(L_h^T\right) > 0$) and loan return ($r^{L\prime}\left(L_h^T\right) < 0$). More deposits and loans lead to a rise in the rate on deposits and a fall in the rate on loans. The third and last term is the 'risk-taking effect'. It is positive and captures the effects of competition on firms' risk-return investment profile. More loans decrease the loan rate and this in turn induces firms to select profiles associated with lower return and higher probability of success.

The profit maximizing choice of loans by foreign bank s in market h satisfies an analogous first order condition:

$$\begin{aligned} \frac{d\Pi_{s,fh}}{dL_{s,fh}} &= p(r_h^I)\left[r^L\left(L_h^T\right) - r^D(L_h^T) - \xi - \mu\right] + \\ &\quad p(r_h^I)\left[r^{L\prime}\left(L_h^T\right) - r^{D\prime}(L_h^T)\right]L_{r,fh} + \\ &\quad p'(r_h^I)r^{I\prime}\left(r^L\left(L_h^T\right)\right)r^{L\prime}\left(L_h^T\right)\left[r^L\left(L_h^T\right) - r^D(L_h^T) - \xi - \mu\right]L_{s,fh} = 0, \end{aligned} \tag{9}$$

which differs from (8) only due to the presence of the additional monitoring cost μ.

2.3.2 Cournot-Nash Equilibrium

We focus on a symmetric outcome such that in both national markets all home banks achieve the same scale $L_{r,hh} = L_{s,ff} = \ell$ and all foreign banks achieve the same scale $L_{s,fh} = L_{r,hf} = \ell^*$. In this case, in each market total loans and thus also deposits are $L^T = (\ell + \ell^*)\,N/(1-\varrho)$. Then, for given N, in each market the Cournot-Nash equilibrium in any period is characterized by the solution of the following system of two equations in the two unknown scales ℓ and ℓ^*:

$$
\begin{aligned}
&p(r^I)\left[r^L\left(L^T\right) - r^D(L^T) - \xi\right] + \\
&p(r^I)\left[r^{L\prime}\left(L^T\right) - r^{D\prime}(L^T)\right]\ell + \\
&p^{'}(r^I)r^{I\prime}\left(r^L\left(L^T\right)\right)r^{L\prime}\left(L^T\right)\left[r^L\left(L^T\right) - r^D(L^T) - \xi\right]\ell = 0
\end{aligned}
\tag{10}
$$

and

$$
\begin{aligned}
&p(r^I, a)\left[r^L\left(L^T\right) - r^D(L^T) - \xi\right] + \\
&p(r^I)\left[r^{L\prime}\left(L^T\right) - r^{D\prime}(L^T)\right]\ell^* + \\
&p_1(r^I)r^{I\prime}\left(r^L\left(L^T\right)\right)r^{L\prime}\left(L^T\right)\left[r^L\left(L^T\right) - r^D(L^T) - \xi - \mu\right]\ell^* = 0,
\end{aligned}
\tag{11}
$$

where, exploiting symmetry between markets, we have dropped the market indexes from all variables.

With explicit time dependence reinstated for clarity, the values of ℓ_t and ℓ_t^* that solve system (10)-(11) determine the maximized values of domestic profits Π_t and foreign profits Π_t^*. These are the same for all banks ($\Pi_{t,hh} = \Pi_{t,ff} = \Pi_t$ and $\Pi_{t,hf} = \Pi_{t,fh} = \Pi_t^*$) and are functions of the number of active banks N_t^a. In turn, the equilibrium number of active banks N_t^a is pinned down by the free entry condition (2), which with symmetry becomes:

$$
V_t = \Pi_t + \Pi_t^* + \beta(1-\varrho)V_{t+1} = \kappa. \tag{12}
$$

Finally, the equilibrium values of ℓ_t, ℓ_t^* and N_t^a determine the equilibrium deposit return r_t^D, loan return r_t^L, and risk-return profile $(r_t^I, p(r_t^I))$. Given the number of incumbents, they also determine the equilibrium number of entrants by (1), which with symmetry can be written as:

$$
N_t^a = N_{t-1} + N_t^e = \frac{N_t}{1-\varrho}. \tag{13}
$$

The fact that the equilibrium of the two national markets can be characterized by such a parsimonious set of equations is obviously due to the assumption that the two markets are symmetric.

Note that we are focusing on Markov-stationary equilibria so that the oligopolistic game is repeated in every period, conditional on the predetermined state space.

3 Foreign Expansion, Competition and Risk

We now turn to a numerical analysis of the equilibrium behavior of the model in order to derive empirically relevant predictions.

3.1 Functional Forms

To investigate the equilibrium behavior of the model, we first have to select specific functional forms that comply with the properties detailed in Section 2.2. Based upon the micro-foundations in Appendix A and also compatibly with past literature, we assume that the demand of loans takes the following form: $r^L\left(L_t^T\right) = 1/\alpha - \nu L_t^T$ with $\nu > 0$.[19] The supply of deposits is assumed to follow $r^D\left(D_t^T\right) = \gamma D_t^T$ with $\gamma > 0$ so as to satisfy our assumption of an oligpsonistic market for deposits. We also assume that investment projects succeed with probability $p(r_t^I) = \left(1 - \alpha r_t^I\right)$ for $r^I \in [0, 1/\alpha]$ and zero otherwise. The implied profit-maximizing success probability chosen by firms and the associated project return evaluate to $p_t = \alpha\nu L_t^T/2$ and $r_t^I = 1/\alpha - \nu L_t^T$ respectively.

With these functional forms the equilibrium of the model is now fully characterized by a non-linear system of six equations, consisting of banks operating profits

$$\Pi_t + \Pi_t^* = \frac{\alpha\nu}{2} L_t^T \left[\frac{a_t}{\alpha} - (\nu+\gamma) L_t^T - \xi\right] \ell_t + \frac{\alpha\nu}{2} L_t^T \left[\frac{a_t}{\alpha} - (\nu+\gamma) L_t^T - \xi - \mu\right] \ell_t^*, \quad (14)$$

domestic banks' profit maximizing condition

$$L_t^T \left[\frac{1}{\alpha} - (\nu+\gamma) L_t^T - \xi\right] + \left[\frac{1}{\alpha} - 2(\nu+\gamma) L_t^T - \xi\right] \ell_t = 0, \quad (15)$$

[19]See also Martinez-Miera and Repullo (2010).

foreign banks' profit maximizing condition

$$L_t^T\left[\frac{1}{\alpha}-(\nu+\gamma)\,L_t^T-\xi-\mu\right]+\left[\frac{1}{\alpha}-2\,(\nu+\gamma)\,L_t^T-\xi-\mu\right]\ell_t^*=0, \tag{16}$$

total loans

$$L_t^T=\frac{N_t}{1-\varrho}(\ell_t+\ell_t^*), \tag{17}$$

banks' free entry condition (12) and the law of motion of the banks' number (13). This system of six equations can be solved in the six unknown variables: $\ell_t, \ell_t^*, L_t^T, N_t, N_t^a$ and $\Pi_t+\Pi_t^*$.

3.2 Calibration

Parameters in the calibration are set primarily such that the model matches the observed average long-run values of all variables in its deterministic steady state, in which case $V_t=V_{t+1}=\kappa$ holds and (2) implies $\Pi_t+\Pi_t^*=[1-\beta(1-\varrho)]\,\kappa$, where the last term is the annuity value of the overall fixed cost κ (which banks finance in the capital market upon entry): the larger are the fixed entry cost κ, the opportunity cost β of financing entry and the death rate ϱ, the larger profits have to be in order to justify entry. The numerical solution for the deterministic steady state is obtained solving the non-linear system of equations described in Section 3.1 through the Newton-Raphson iterative method.

The discount factor β is set so as to imply a 4% annual risk-free interest rate. The calibration of the intermediation spread, r^L-r^D, follows Repullo and Suarez (2013), who report an annual spread of roughly 4% based on FDIC statistics for US banks. This is achieved by setting α, γ and ν in the model so as to obtain a steady-state bank margin of 3.98%. Regarding the the calibration of the insurance cost ξ, those are paid by bank affiliates in destination markets. However, the design of deposit insurance is by now fairly common worldwide. We therefore base our calibration on the fees set by the FDIC or in Europe, for which there are reliable data. These range from 2.5 to 10 basis points for a typical bank in the US, but can go up to 45 basis points depending on banks' risk characteristics, in particular their equity ratios.[20] In Europe the average is around 8 basis points.[21] Since in our model banks do not have equity as an additional loss absorber, we set ξ to the FDIC's maximum fee of 45 basis points annually, so that it can include all other loss-absorbing liabilities. The value for μ is based on data from banks' loan-loss provisions (LLP). In the euro area, these amounted to 40 basis points of assets on average for the pre-crisis period (1991-2003), hence we set μ to 0.004.[22] In the model ϱ determines the ratio of exit of active banks ('entry rate'). Using the Claessens and van Horen (2015) dataset we compute exit rates for all foreign affiliates of European parent holdings for a pre-crisis sample. This gives a number above 3%. Exits have however increased in the more recent periods due to higher capital requirements. We therefore also refer to the realistic exit scenarios simulated in past literature under Basel II capital requirements (most specifically Corbae and D'Erasmo, 2019), who reports values above 4% or close to 5%. Based on this range we then simulate the model under a conservative value of 4.5%. Table 1 shows the calibrated parameter values. Table 2 reports the long-run values of variables.

3.3 Simulation

In our model the exogenous driver of foreign expansion is the additional monitoring cost on foreign loans $\mu > 0$. In particular, by making the monitoring ability of foreign banks converge towards that of domestic banks in each market, lower μ promotes the expansion of the former. We now show that, for the calibrated parameter values, our model predicts that lower μ leads to lower bank risk through tougher competition.

In measuring competition we follow the recent banking literature (van Leuvensteijn et al., 2011; Schaeck and Čihák, 2010; Cihak et al., 2012) that accounts for bank's endogenous entry and heterogeneity through the Boone indicator (BI). This is indeed more precisely tailored to measure the entry-selection channel compared to other standard com-

[20] See https://www.fdic.gov/bank/analytical/qbp/2015dec/dep4c.html.

[21] See https://eba.europa.eu/regulation-and-policy/recovery-and-resolution/deposit-guarantee-schemes-data.

[22] See https://www.ecb.europa.eu/pub/pdf/other/mb200403_focus02.en.pdf?e8111edca7e95d97246d6b10b516d560

petition measures such as the Herfindahl–Hirschman index (HHI) of market concentration (used by Faia, Laffitte and Ottaviano, 2019) or the Lerner index of price-cost margins. In industrial organization the BI is defined as the elasticity of profits to marginal cost in a given market, which is negative as long as lower cost firms are more profitable (Boone, 2008). By raising the profitability of lower cost firms relative to higher cost ones, tougher competition decreases the BI (i.e. increases its absolute value), leading to a more efficient allocation of resources between higher and lower cost firms. With heterogeneous firms the BI is preferred to the standard Herfindahl–Hirschman Index of market concentration because, when firms differ in terms of costs and cost differences are not fully passed through to consumers, tougher competition improves efficiency without reducing market concentration whenever lower cost firms grow to the detriment of higher cost ones. The standard HHI then rises and its usual interpretation mistakenly takes its higher value as a signal of weaker competition. With endogenous entry and heterogeneity the BI is also preferred to the Lerner index as the latter bears no connection to the number of entrants. Adapting the concepts underlying the BI to our banking setup in the wake of van Leuvensteijn et al. (2011), we compute the model's BI as the elasticity of banks' average profits, in proportion of total assets (ROA), to the insurance fee ξ (which is the marginal cost component common to both domestic and foreign banks).[23]

The long-run effect of lower μ are shown in Figure 1 by the dashed lines. In its panels the variables of interest are reported on the vertical axis, while μ increases rightward on the horizontal axis. The effects of lower μ can then be gauged by moving from right to left on the horizontal axis along the dashed curves. As μ falls, the evolution of the BI shows that competition intensifies. The number of banks rises and the market share of foreign banks increases. Deposits and loans per bank increase for foreign banks and fall for domestic banks. Intensified competition leads to an increase in the total amount of loans and deposits, a decrease in the return on loans and an increase in the return on deposits. As a consequence, the spread between loan and deposit rates shrinks. As for firms, lower loan rates make them more cautious, targeting projects with lower return

[23] See Appendix F.1 for details on how the Boone index is computed in the model and then in the data.

and higher probability of success so that bank risk falls. Despite more caution, the spread between the returns on investment and loans increases, whereas the spread between the returns on loans and deposits decreases.

Figure 1 also shows that, for all values of μ, the spread between loan and deposit rates is smaller for foreign than home banks once the monitoring cost is netted out. This reveals that banks practice 'dumping' in the sense of Brander and Krugman (1983): they are willing to accept a lower spread for their foreign operations than for their domestic ones and thus do not pass on the full additional costs of foreign operations to their foreign customers. This happens as banks perceive higher elasticities of loan demand and deposit supply in their foreign market given that, due to additional monitoring costs, their market share is smaller there, and explains why costly cross-hauling of identical banking services by banks headquartered in different national markets arises in equilibrium despite those additional costs. The partial absorption of μ by foreign banks becomes less pronounced as μ falls, driving the perceived elasticities of loans demand and deposits supply in their foreign market closer to the ones in their home market.

3.4 Systemic Risk

For banking stability the distinction between banks' individual risk and systemic risk is of paramount importance. So far, however, in our model the two types of risk coincide. As all projects fail with equal probability, the probability of banks' portfolio failure (i.e. the metric for banks' systemic risk) is equal to the simple average of the probability of project failure $1 - p(r^I)$. In reality such an extreme risk correlation across projects is hardly observed. In this case banks' portfolios may fail *ex post* despite the control banks have on $p(r^I)$ through the loan rate *ex ante*. It is thus of interest to check whether the implication of the model change when projects have less extreme, more realistic degrees of risk correlation.

In extending the model to imperfectly correlated projects' outcomes, we follow the established practice of conditioning those outcomes on common and idiosyncratic factors in the wake of Vasicek (2015).[24] This allows us to capture possible interconnections, asset commonality or other features that make the probability of banks' portfolio failure different from the simple average of the failure probability across projects. By checking the relation between entry and the resulting metric of systemic risk, we can also investigate how competition and risk taking interact in presence of contagion effects.

We focus again on the long-run deterministic steady state. However, we allow now projects to be subject to a risk of failure determined not only by firms' choices of the risk-return profile, but also by the realizations of common and idiosyncratic factors. In particular, we assume that there is a continuum of firms indexed i and the outcome of the project chosen by any given firm i is determined by the realizations of a random variable y^i defined as:

$$y^i = -\Phi^{-1}(1-p^i) + \sqrt{\rho}z + \sqrt{1-\rho}\varepsilon^i, \tag{18}$$

where Φ is the cumulative density function of a standard normal distribution, while z and ε^i are the common and idiosyncratic risk factors with distributions that are also independently standard normal. The project of firm i fails when the realization of y^i is negative. The parameter $\rho \in [0,1]$ measures the relative importance of the systematic risk factor with respect to the idiosyncratic one in determining the project's outcome, i.e. the degree of risk correlation among projects. For $\rho = 0$ failures are statistically independent across firms; for $\rho = 1$ they are perfectly correlated as before; for $\rho \in (0,1)$ they are imperfectly correlated. The projects' risk distributions are again assumed to be identical in the two national markets.

Given that both risk factors are generated by independent standard normal distributions, the probability of failure evaluates to $\Pr[y^i < 0] = 1 - p^i$. Hence, given (3), firm i chooses its risk-return profile $(p^i, r^{I,i})$ to maximize expected profit $p^i(r^{I,i} - r^L)$ subject to $r^{I,i} = (1-p^i)/\alpha$ as implied by the assumed functional form $p(r^I) = 1 - \alpha r^I$. Given that all firms face the same loan return $r^L = 1/\alpha - \nu L^T$, the first order condition implies that they all choose the same success probability, namely $p = (1-\alpha r^L)/2 = \alpha\nu L^T/2$, together with the same associated return $r^I = 1/\alpha - (\nu L^T)/2$. The fact that probability

[24] See, for example, Martinez-Miera and Repullo (2010) and Bruno and Shin (2015).

p is a decreasing function of r^L reveals again the presence of a risk-shifting effect: faced with higher loan return, firms select projects with higher failure rate $1-p$. However, as z follows a standard normal distribution, the cumulative density of the aggregate success rate $\varkappa$ is now given by:

$$G(\varkappa) = \Pr\left[\varsigma(z) \leq \varkappa\right] = \Phi\left(\frac{\Phi^{-1}(1-p) - \sqrt{1-\rho}\,\Phi^{-1}(1-\varkappa)}{\sqrt{\rho}}\right), \tag{19}$$

where $\varsigma(z)$ is the probability of success of the representative firm conditional on the realization z.[25] According to (19), the success rate has mean p, while ρ regulates the dispersion around this mean with larger ρ associated with more dispersion.[26]

Banks again maximize expected profits, now taking the distribution of the aggregate shock z and the idiosyncratic shock ϵ^i into account. Given (19), with explicit time dependence the profits that a bank expects to earn in its domestic market can be written as:

$$\Pi_t = \int_{\hat{\varkappa}_t}^{1} \varkappa_t \ell_t m(L_t^T) dG(\varkappa_t), \tag{20}$$

where $m(L_t^T) = 1/\alpha - (\nu+\gamma)L_t^T - \xi$ is the lending-to-deposit rate spread (net of the insurance premium) and $\hat{\varkappa}$ is the threshold aggregate success probability above which the bank will be active. Due to symmetry, the profits Π_t^* that a bank headquartered in f makes in its foreign market h can be expressed analogously, replacing $m(L_t^T)$ with $m^*(L_t^T) = 1/\alpha - (\nu+\gamma)L_t^T - \xi - \mu$. For the simulation of the long-run effects of lower μ it is, however, convenient to integrate (20) by parts in order to write the bank's total

[25] As the (ex ante) risk-return profile chosen by firms, before risk factors are realized, is the same across firms and we have a continuum of firms, the Law of Large Numbers implies that (ex post) the share of projects that succeed (i.e. the aggregate success rate) depends only on the realization of the common risk factor z and coincides with the probability of success of the representative firm conditional on the realization z:

$$\varsigma(z) = \Pr\left[-\Phi^{-1}(1-p) + \sqrt{\rho}z + \sqrt{1-\rho}\varepsilon^i \geq 0 \mid z\right] = 1 - \Phi\left(\frac{\Phi^{-1}(1-p) - \sqrt{\rho}z}{\sqrt{1-\rho}}\right),$$

where we have used the fact that ε^i follows a standard normal distribution.

[26] In the limit, for $\rho \to 0$, $G(\varkappa)$ becomes a Dirac delta function that is zero everywhere except at $\varkappa = p$: with independent failures a fraction p of projects succeed with probability 1. For $\rho \to 1$, $G(\varkappa)$ converges to p: with perfectly correlated failures all projects succeed with probability p and fail with probability $1-p$ as before.

operating profits as:

$$\Pi_t + \Pi_t^* = \pi(p, \hat{\varkappa}_t) m(L_t^T) \ell_t + \pi(p, \hat{\varkappa}_t) m^*(L_t^T) \ell_t^* \tag{21}$$

with $\pi(p, \hat{\varkappa}_t) \equiv 1 - \hat{\varkappa}_t G(\hat{\varkappa}_t) - \int_{\hat{\varkappa}_t}^1 G(\varkappa_t) d\varkappa_t$. A bank's profit maximization in its domestic market then requires:

$$h(L_t^T) + \ell_t h'(L_t^T) = 0 \tag{22}$$

with $h(L_t^T) = \pi(p, \hat{\varkappa}_t) m(L_t^T)$ and

$$h'(L_t^T) = m'(L_t^T) \pi(p, \hat{\varkappa}_t) - m(L_t^T) \left[\hat{\varkappa}_t \frac{\partial G(\hat{\varkappa}_t)}{\partial L_t^T} + \int_{\hat{\varkappa}_t}^1 \frac{\partial G(\varkappa_t)}{\partial L_t^T} d\varkappa \right].$$

The necessary condition for profit maximization in the foreign market can be derived analogously replacing $m^*(L_t^T)$ with $m^*(L_t^T)$ in the foregoing expressions.

Equations (21), (22) and the latter's foreign analogue replace (14), (15) and (16). Hence, the equilibrium of the model with imperfectly correlated shocks is characterized by those three new equations together with the free entry condition (12), the law of motion (13) and total loans (17). However, the full characterization of the equilibrium now requires also the determination of the value $\hat{\varkappa}_t$ of aggregate success probability above which banks will be active. After entry, a bank will be active as long as the realized success rate $\varkappa_t$ is large enough to generate non-negative net cash flow: $\varkappa_t \left(m(L_t^T) \ell_t + m^*(L_t^T) \ell_t^* \right) \geq [1 - \beta(1 - \varrho)] \kappa$. This non-negativity condition generates a cutoff rule of survival and thus a 'selection effect' through which a bank will be active as long as the realized success rate $\varkappa_t$ does not fall short of

$$\hat{\varkappa}_t = \frac{(1 - \beta(1 - \varrho)) \kappa}{m(L_t^T) \ell_t + m^*(L_t^T) \ell_t^*}. \tag{23}$$

This completes the characterization of the equilibrium in terms of a system of seven equations in seven unknowns: ℓ_t, ℓ_t^*, L_t^T, N_t, N_t^a, $\Pi_t + \Pi_t^*$ and $\hat{\varkappa}_t$. Note that, with perfectly correlated projects ($\rho = 1$), the cutoff would instead be immaterial ($\hat{\varkappa}_t = 1$) so that equations (21), (22) and the latter's foreign analogue would revert to (14), (15) and (16).

The long-run effects of lower μ are shown in Figure 1 by the solid lines for $\rho = 0.8$. These effects are qualitatively the same as those described in the Section 3.3 for $\rho = 1$ (dashed lines). Comparing the two cases for given μ, the larger value of the Boone Indicator reveals that competition is weaker with imperfectly correlated shocks. The total number of active banks is smaller and this is associated with a smaller amount of loans and deposits as well as lower return on deposits, higher return on loans, and thus larger spread between them, which maps into higher return on investment and lower project success rate. Specific to the case of imperfectly correlated shocks is obviously the existence of a cutoff success rate for banks' survival. Lower μ has the effect of increasing this cutoff, thus making it harder for banks to survive. This generates a selection effect through which the probability of banks' portfolio failure falls, thus reducing systemic risk.

In the simulations so far we examined the quantitative difference made by accounting for systemic risk compared to individual risk. This comparison allows us to dissect the channels behind the endogenous risk-taking component of the model. A second novelty of our model lies in endogenous entry. To appreciate its importance in Figure A2 we repeat the simulations but hold the number of banks fixed, something which amounts to shutting off the endogenous entry channel. The biggest impact of endogenous entry for the steady state simulations is on the competition index. In the model with no entry the effect of lowering monitoring costs μ on competition is subdued, that is, the Boone indicator responds by less. Further, in steady state the total number of loans and deposits is unchanged, while the market share tilts toward domestic banks.

An implication of the model mechanism is a negative correlation between competition and the net interest margin. We verify whether this is supported by the data. Using the Global Financial Development Databse, we obtain the Boone index and the average net interest margin for the 37 countries of our sample between 2005 and 2014. Although there is not much variation we observe a negative correlation between competition and the net interest margin, confirming the mechanism of our model. A regression of net interest margin on the Boone index reveals a positive and significant coefficient ($\hat{\beta} = 0.03^{***}$).

Beyond the extension to systemic risk, we consider two further extensions of the model, one including also banks' liability risk (see Appendix B) and another considering cross-border loans instead of 'brick and mortar' (see Appendix C). In the latter we show that the beneficial effect of expansion on risk is more muted.

4 Reduced-Form Evidence

In this section we want to check whether the predictions of our calibrated model find support in reduced-form evidence on how foreign expansion affects banks' individual risk and systemic risk. The model predicts that both types of bank risk decrease when they expand abroad as long as foreign expansion is associated with an increase in competitive pressure.

4.1 Data and Variables

The main challenge in testing these predictions is the availability of relevant quality data for expansion, competition and risk. In the next paragraphs we present and discuss our choices for each of these three variables.

Expansion. The only off-the-shelf option to measure bank expansion is to rely on Claessens and van Horen (2012, 2015), whose rich cross-country dataset lists branches and subsidiaries located in 137 countries. Their dataset is well-suited for answering questions related to the impact of global banking on credit conditions. However, it is not ideal for our purposes as it does not report the name of the parent holding and information needed to compute risk metrics.

We therefore rely on an original data collection. We use the dataset recently assembled by Faia, Laffitte and Ottaviano (2019) leveraging standard sources such as ORBIS as well as bank reports, SEC reports, Bankers' Almanac and Bloomberg.[27] This dataset covers the activities of the 15 European banks classified as G-SIBs by the Basel Committee on Banking Supervision (2014) at the end of 2015 over a 10-year time period from 2005 to 2014. These banks are located in 8 home countries: BNP Paribas, Crédit Agricole Group

[27]The construction of this dataset is presented in details in Faia, Laffitte and Ottaviano (2019).

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. The dataset also includes BPCE, a banking group consisting of independent, but complementary commercial banking networks. The dataset includes 37 potential destination countries within Europe. It allows us to measure the foreign expansion of the 15 European G-SIBs through their openings of foreign affiliates (owned with a share larger than 50%). More precisely, our expansion variable measures the number of affiliate openings by a bank k in destination country j at date t. We record 852 foreign openings over the period.

Competition. We want to measure the level of competition in each of the 37 countries where the banks of our dataset may expand. There exist many different measures of the the competition among banks.

The Boone indicator (BI) is the natural candidate as it is also used in our model, as discussed in Section 3.3. The BI is estimated by regressing banks' profits as a proportion of total income (used to proxy ROA) on average cost (as a proxy of marginal cost).[28] Consistent with our theoretical framework, the estimated value is typically negative as lower cost banks are more profitable and increases in absolute value with the intensity of competition.[29]

We extract data on the Boone index from the Global Financial Development Database (Cihak et al., 2012). Its computation follows the methodology of Schaeck and Čihák (2010) and regresses the log of profits on the log of marginal costs.

Figure 2, illustrates the foreign expansion pattern of the European G-SIBs across time. Using the Boone index, we distinguish between expansion in more competitive countries (*i.e* with lower Boone index) and expansion in less competitive countries (*i.e* with higher

[28]See Appendix F.1 for more details.

[29]In Appendix F.2 we present a brief discussion of the patterns of the BI in our dataset suggesting that the indicator exhibits enough variation to exclude systematic bias in expansion toward countries with either low or high intensity of competition. In our sample the correlation between the HHI and the BI is just 0.19 while the Spearman's rank correlation is just 0.15, confirming that, though positively correlated, the two measures do not provide the same type of information.

Boone index). The figure illustrates that openings follow similar patterns in more and in less competitive countries. Nevertheless, before 2010 more openings are directed towards higher competitive countries. The figure also illustrates the relative decrease in openings following the crisis of 2007.

Risk. To account for the different dimensions of risk we use both individual and systemic risk metrics. Individual metrics include market-based (volatility of equity returns and CDS prices), accounting-based (loan-loss provisions) and hybrid metrics (Z-score and leverage). Market-based metrics account for all information on bank risk priced by the market. They might be, however, partly biased in presence of market exuberance. Accounting-based metrics follow more accurately the component of risk included in the internal value-at-risk (VaR) models, but they tend to backtrack market developments as banks' impairment exercises are conducted less frequently. Some of these metrics price both bank asset and liability risk.[30] This is true for instance for the volatility of equity, CDS prices or the Z-score. Others measure instead liability risk (e.g. leverage) or asset risk (e.g. LLP).

Systemic risk metrics include ΔCoVaR, Long Run Marginal Expected Shortfall (LRMES hereafter) and SRISK. The first is computed following Adrian and Brunnermeier (2016). This metric accounts for the role of banks' interconnections in propagating shocks. Given the VaR of the financial system conditional on institutions being under financial distress (CoVaR hereafter), the Δ CoVaR is defined as the difference between the CoVaR when a bank is under distress and the CoVaR when the bank is in its median state. We use two versions of the ΔCoVaR: CDS- and equity-based. The LRMES is computed following Acharya et al. (2017) and Brownlees and Engle (2017) as a bank's expected equity loss following a 40% market drop over six months. It gives the marginal contribution of a bank to the systemic risk following the market decline. Higher LRMES corresponds to higher contribution of the bank to systemic risk. The SRISK measure is the one proposed by Acharya, Engle and Richardson (2012) and Brownlees and Engle (2017). It is also

[30]For simplicity the model in Section 2 has focused on the asset side of bank risk. In Appendix B we show that its predictions on the behavior of the key variables for our reduced-form analysis (i.e. the success probability and the Boone Index) are essentially unaffected when we allow for liability risk due random deposit withdrawals.

based on the concept of marginal expected shortfall, but takes into account the liabilities and the size of the bank. It increases with market capitalization and leverage. LRMES better captures the 'too-interconnected-to-fail' dimension of systemic risk while SRISK is more suited to capture the 'too-big-to-fail' dimension.

Data for the volatility of equity returns and CDS prices is taken from Bloomberg; LLP from Bankscope; leverage, LRMES and SRISK from the Centre of Risk Management at Lausanne (CRML); Z-Score and ΔCoVaR are based on authors' own calculations.[31]

4.2 Empirical Strategy

Our theoretical model predicts that banks' riskiness decreases when they expand abroad as long as the foreign expansion is associated with an increase in competitive pressure. In order to test this prediction, we aggregate expansions at the level of the bank holding and distinguish between expansions in more competitive countries and expansions in less competitive countries. We run the following regression at the bank level:

$$Riskiness_{kt} = \alpha + \nu \cdot Expansion_{kt}^{higher} + \beta_2 \cdot Expansion_{kt}^{lower} + Z_{kt} \cdot \Gamma + \vartheta_k + \vartheta_t + \epsilon_{kt}, \quad (24)$$

where $Riskiness_{kt}$ is a measure (individual or systemic) of bank k risk at time t, $Expansion_{kt}^{higher}$ (resp. $Expansion_{kt}^{lower}$) corresponds to the expansion of the bank in countries with more (resp. less) intense competition than the bank's origin country at time t, Z_{kt} is a vector of control variables to account for exogenous variation in risk. The set of control variables includes the logarithm of total assets, the return on assets (ROA), the net interest margin, income diversity, asset diversity, the ratios of Tier 1 capital and deposits to total assets and the average regulation in countries where a bank enters as measured by Cerruti, Claessens and Laeven (2017).[32]

It is important to stress that we control for regulation, as this might affect bank risk. Our analysis is on cross-border affiliates not on cross-border loans. Capital requirements

[31] See Appendix E based on Faia, Laffitte and Ottaviano (2019) for additional details.
[32] The diversity indexes are *Income Diversity* computed as $1-|Interest\ inc. - noninterest\ inc.|/Total\ income$ and *Asset Diversity* computed as $1 - |Loans - Other\ assets|/Total\ assets$.

on the parent holding do not feature specific risk-weights for foreign affiliates, which are instead subject to local regulation. While generally following the prescription of the Basel accord, the implementation can vary partly across countries and stricter regulations might affect bank risk. For this reason we control for Pillar 1 regulations, which we capture with Tier 1 capital requirements and leverage ratios (deposit to assets). Both are included as controls so as to ensure that our results on the link between competition and bank risk are not affected by differences in regulatory stringency. As for the other parameters, while ϑ_k is a bank fixed effect accounting for any bank-specific factors that may influence risk, ϑ_t is a time fixed effect accounting for any time-specific trend that may impact riskiness. It should absorb any impact of economic factors common to all banks. It can absorb the effect of financial crises, which tend to increase bank risk, as well as explicit (bail-outs) or implicit government guarantees that might on the contrary reduce bank risk. In order to take into account the specificity of some countries in terms of government bail-out, we have added a different time trend for Italy and Spain, the two countries in our setting that benefited most from government guarantees. Our fixed effects structure implies that, in line with the model's predictions, we will estimate the average impact of a bank's expansion on its own risk.

Endogeneity. As a bank's risk profile may itself determine its propensity to expand abroad, the estimation of Equation (24) by OLS may suffer from an endogeneity bias. To deal with this issue, we follow the 'gravity approach' of Goetz, Laeven and Levine (2013), Levine, Lin and Xie (2016) and Faia, Laffitte and Ottaviano (2019), which is based on the observation that the gravity specification widely used to explain the international flows of goods can be successfully applied to explain also cross-border financial flows.[33] The gravity approach allows us to predict the openings in host country j at date t by bank k headquartered in origin country i using only variables that can be considered independent from the bank's risk-taking behavior. Specifically, we proceed as follows.[34] First, we

[33]Examples of successful application of the gravity approach to financial flows are Portes and Rey (2005) for cross-border banking, Buch (2003) for banks' foreign asset holdings and Berger et al. (2004) for banks' expansion through M&A.

[34]See Frankel and Romer (1999) for the original methodology applied to goods trade.

regress foreign openings on the distance between the origin and the host countries plus controls:

$$Openings_{kjt} = X_{kjt} \cdot \beta + \nu_{jt} + \nu_k + \varepsilon_{kjt}, \tag{25}$$

where X_{kjt} are standard dyadic gravity variables (such as distance between host and origin country, host and origin countries' contiguity, a dummy for common language, the difference in legal systems, a dummy for being both in the EU or in the Eurozone), ν_{jt} is a destination country-time fixed effect, and ν_k is a bank fixed effect.[35] Given that $Openings_{kjt}$ is a count variable, the gravity equation (25) is estimated using Poisson Pseudo Maximum Likelihood (PPML).[36] Second, we aggregate bank k's bilateral openings at date t as predicted by (25) across host countries to obtain the bank's total predicted openings in destination markets that are more or less competitive than the market of its origin country:

$$\begin{aligned}
\widehat{Expansion}_{kt}^{higher} &= \sum_{j \neq i} \left(X_{kjt} \cdot \widehat{\beta} + \widehat{\nu}_{jt} + \widehat{\nu}_k \right) \text{ if } B_i > B_j. \\
\widehat{Expansion}_{kt}^{lower} &= \sum_{j \neq i} \left(X_{kjt} \cdot \widehat{\beta} + \widehat{\nu}_{jt} + \widehat{\nu}_k \right) \text{ if } B_i < B_j.
\end{aligned}$$

where B_i and B_j denote the Boone indicator (BI) in the origin and host countries respectively. Recall that the BI is an inverse index of competition: lower BI means tougher competition. Third, we use $\widehat{Expansion}_{kt}^{higher}$ and $\widehat{Expansion}_{kt}^{lower}$ as IVs for $Expansion_{kt}^{higher}$ and $Expansion_{kt}^{lower}$ respectively to estimate (24) by 2SLS.

The exclusion restriction requires our instrumental variable to be exogenous, that is, we want to rule out any direct effect of the predicted bank expansion on bank risk-taking at the headquarter level. Our regressions focus on the *within-bank* effect of expansion (see the bank-level fixed effects in our baseline regression). We do not rely on cross-bank variation. Therefore, for our strategy to be valid, the instruments need to be

[35]Note that mirroring gravity equations in the trade literature would impose us to use a bank × year (kt) fixed effect. However, by definition, such a fixed effect would be correlated with the evolution of the bank's risk over time. To avoid introducing endogeneity through this fixed effect, we only include bank non-time-varying fixed effects. See also Faia, Laffitte and Ottaviano (2019).

[36]We use the *ppml* Stat command written by Silva and Tenreyro (2006).

uncorrelated with the within-bank variation of risk. Our instrument is generated using a gravity equation that includes factors that can be reasonably considered independent from bank risk. Specifically, it incorporates bank constant characteristics (captured by bank fixed effects), shocks in destination countries (captured by destination country × year fixed effects) and bilateral characteristics including distance between the headquarter country and the destination country. Bank constant characteristics are by definition independent from time-varying bank characteristics. The identification relies on the jt fixed effects, that is, on shocks in destination countries. The validity of our IV therefore relies on the exogeneity of these shocks on bank risk and expansion. Another source of variation comes from our definition of the destination country being more or less competitive than the headquarter country. This classification relies on the comparison between the Boone index in the two countries. As the Boone index is time varying in both countries, the classification of countries between more and less competitive is not fixed in time. Therefore, even in the absence of time variation in our predicted expansion at the bank-destination country level, we would have some time variation driven by changes in the competitive environment. In this case, the identification relies on switchers, that is, countries that change group in the sample period. In both cases, the exogeneity of our sources of variation requires that shocks in destination countries do not impact bank risk and expansion simultaneously.

This strategy addresses the main concern of excluding reverse causality between risk and entry, namely the fact that banks with different degrees of risk may face different incentives to enter in more or less competitive markets. However, as noted before, this strategy relies on the fact that shocks in destination countries do not impact bank risk and expansion simultaneously. First, and most importantly, risk in our empirical strategy is measured at the level of the headquarters, while expansion and competition are measured at the level of the destination country. The strategy of global groups generally consists in diversifying and investing in different markets, with the intent to avoid exposing the entire group, and its risk, to shocks in one single destination market. It is therefore unlikely that shocks in destination countries where the bank is already operating will affect bank risk at the headquarter. Second, bank entry and exit are lengthy processes. Therefore, even if an adverse shock happening in a destination market affected risk at the headquarter level, entry might not be directly affected by the shock. We propose a robustness check related to this aspect in the next section.

4.3 Results

We first estimate Equation (25) using PPML. We obtain the following results:

$$\begin{aligned} Openings_{kjt} = & - 0.569^{**} \times ln(Distance) + 0.114 \times Contig. \\ & + 0.577 \times Common\ Lang. - 0.0728 \times EU - 0.450 \times Euro \\ & + 0.311 \times Diff.\ legal\ system + \nu_{jt} + \nu_k + \varepsilon_{kjt} \\ & R^2 = 0.351; Obs. = 2,657. \end{aligned}$$

As expected, it reveals that the GSIB of our sample are less likely to expand in countries farther from the headquarter countries of these banks. We exploit this relationship as well as our set of destination × year fixed effects to generate an instrument for expansion exogenous from bank risk.

The first-stage estimates are displayed in Table 3 and show that $\widehat{Expansion}_{kt}^{higher}$ and $\widehat{Expansion}_{kt}^{lower}$ have positive and significant impacts on the corresponding variables $Expansion_{kt}^{higher}$ and $Expansion_{kt}^{lower}$. To further assess the quality of the instrument, we display the F-test of the first stages as well as the Sanderson-Windmeijer test of excluded instruments. Both tests exhibit large enough values, confirming that our instruments are well-suited for the analysis.[37]

The estimation results of the main regression (24) are displayed in Table 4 for the individual risk metrics and in Table 5 for the systemic risk metrics. In both tables, columns 1 and 2 report the OLS and 2SLS results respectively without control variables. The

[37] Further, the first-stage F-test in Table 4 suggests that our instrument is not weak. Stock and Yogo (2005) propose critical values to evaluate instruments weakness when there are two endogenous regressors under the assumption of homoskedasticity. The critical value for a worst-case relative bias equal to 10% or less is 7.03 in our case.

comparison between the two allows us to show also the correlation between competition and risk and to highlight how that turns into causation through our IV identification strategy. Controls are introduced in columns 3 and 4.

Table 4 shows that, consistently across the various metrics, the estimated impact of foreign expansion on individual risk is significantly negative if openings take place in host countries with more intense competition than the country of origin.[38] The only exception is LLP for which the estimated effect is not significant.[39] Differently, openings in less competitive host countries have no significant impact whatever the risk metric considered. It is interesting to highlight the results on leverage. As this captures banks' liability risk, the falling leverage of banks that expand into more competitive foreign markets lends support to the additional predictions of our model's extension in Appendix B allowing for random deposit withdrawals. According to that extension, by improving the risk-return profile of the asset side, increased competition reduces the overall probability of exit for any given distribution of the liquidity shocks.

Our findings on systemic risk are more nuanced. Table 5 shows significant negative effect on system risk driven by openings in more competitive countries for SRISK and Δ CoVaR computed with equity prices. No significant results are found, instead, for LRMES and Δ CoVaR computed with CDS. As explained earlier, LRMES captures the too-interconnected-to-fail dimension of systemic risk, while SRISK captures its too-big-to-fail dimension. Accordingly, foreign expansion seems to reduce the component of system risk associated with bank size, but not the one associated with bank interconnection. The fact that the effects on systemic risk are less stark than those on individual risk is understandable as the patterns of the former are likely to be driven also by other macroeconomic factors and market structure characteristics that go above and beyond expansion or competition.

Overall, these results are consistent with the predictions of our model as long as the foreign expansion of banks in Europe during the period 2005-2014 led to a contemporane-

[38]A larger value of the Z-score indicates that the bank is *less* likely to go bankrupt.

[39]This result might be due to lack of variation at the intensive margin. Other economic interpretations of the finding are that banks tend to adjust buffer holdings more in response to regulatory changes than in response to changes in competition or that adjustment in loan-loss provisions occurs with some delay.

ous decrease in their individual and systemic riskiness when expansion happened in more competitive markets.

As mentioned earlier, in a previous paper Faia, Laffitte and Ottaviano (2019) find a role for competition in reducing risk, but using a different competition index, the Herfindahl index. Hence, it is worth stressing that our results are robust also when using different competition measures. Our previous analysis however was meant to capture the impact of market competition more generally. In the current paper we propose, informed by the channels operating in our model, a specific cost-selection channel. Hence our empirical analysis is tailored precisely towards identifying this model-based channel.

In Appendix G we provide two robustness checks. First, we bootstrap the standard errors of the first-stage estimates in order to account for the bias due to the use of generated regressors as instrumental variables. Second, we provide a robustness exercise that accounts for potential confounding factors in our identification strategy. In the previous section, we ruled out the fact that shocks in destination countries can affect simultaneously expansion in these countries and bank risk in the headquarter country. To further support this argument, we propose a robustness check in which we drop destination countries where a bank has a large cross-border exposure, i.e. where local shocks are (if at all) most likely to affect the overall risk of the banking group. Specifically, we extract data on each bank's cross-border exposures in 2012 from Duijm and Schoenmaker (2020) and drop from our sample destination countries that represent more than 5% of the bank's cross-border exposure.[40] Our results, presented in Appendix G, are robust to this check.

4.4 Model-Based Regressions

To further cross-validate the channels proposed by our model with our empirical results, we replicate the reduced form evidence using data generated by the model. This confirms that the channels operating in the model can rationalize the data.

To estimate the reduced form regression in the model, we generate a series of steady-state simulations of our baseline model given different values of the monitoring cost

[40] This leads us to drop 15 bank-destination country pairs.

parameter μ_i, where the subscript i denotes different steady-states.[41] To align the empirical and the model based regressions a few comments are necessary as the model environment and the empirical data differ along some dimensions. Firstly, in the model home and foreign countries are symmetric, hence also the degree of competition is the same. Secondly, the model generates observations for the loan default rate, which does not map exactly into any of the several risk metrics explored in the data. Hence, the matching is not tied to one particular risk measure. Third, in the data we have only access to the extensive margin of banks' foreign expansion. Since we do not have information on the balance sheet of affiliates, it is not possible in this context to weight each expansion according to its size. Differently, expansions in the model are captured by the intensive margin (amount of loans and deposits issued through foreign affiliates). With those observations in mind we then adopt the following general specification for the model-based regressions:

$$log\left(Default\ Prob._i\right) = \beta_0 + \beta_1 Expansion_i + \beta_2 Competition_i + \beta_3 Expansion_i \times Competition_i + \epsilon_i \tag{26}$$

where expansions are measured by the amount of loans issued by the foreign affiliate (L_t^*) and competition is measured by the absolute value of the Boone index (to ease interpretation) or a dummy that takes a value of one when the Boone index is above the median and zero if below.[42] Risk is measured as the log probability of default $(1 - p_i)$. The coefficient of interest is β_3 where a negative sign would rationalize our empirical result that risk decreases especially when expansions happen in more competitive markets. Results of estimating Equation (26) are presented in Table 6.

Column (1) and (2) of Table 6 first display the direct effects of expansion and competition on risk. Estimates are highly significant and both negative, indicating that more expansion or competition in response to changes in monitoring costs reduce risk. The same holds true when adding both variables jointly in column (3). Next, column (4) augments the regression with the interaction between the two variables to mimic the main

[41] Values are randomly drawn from a uniform distribution between 0.001 and 0.004. This support is chosen in line with the bounds used for Figure 1.

[42] All continuous variables are standardized to have zero mean and unit variance.

variable of interest in our empirical specification in Equation (24). The negative sign on the interaction term shows that, in line with the empirical results, risk decreases more if banks expand more in more competitive markets. The coefficient is highly significant. Column (5) highlights that results are robust to using the dummy that takes on the value one if the Boone index is above its median. In particular, the negative coefficient on the interaction term indicates again that, in line with the empirical finding, the model implies that risk falls if banks expand more in more competitive markets.

Finally, we repeat the exercise in column (6) and (7) using data simulated by the model allowing for systemic risk ($\rho = 0.8$ as in Figure 1). In this case, for some parameter combinations, the solution failed to converge, resulting in a smaller sample size. Coefficients on the interaction term are again negative with comparable magnitude and still highly significant.

Overall, these results show that the model can not only rationalize the qualitative transmission channel, but also quantify its importance.

4.5 A Policy Experiment

In this section we provide an example of why the mechanism we have highlighted would matter in terms of policy prescriptions. The specific policy issue we discuss is consolidation in the banking sector, which refers to any business combination of pre-existing independent banks, including mergers between institutions and acquisition by one institution of another institution, but excluding intra-group transactions (ECB, 2020). As a policy objective in our model the targeted degree of consolidation can be translated in terms of some target number of active banks deemed desirable by the regulator, for example due to scale-related efficiency reasons (Altunbas, Evans and Molyneux, 2001). Be that as it may, we assume here that such target exists without spelling out why it exists as this is not central to our argument, and we discuss the implications for bank risk and competition of the different combinations of policy tools that can be used to hit that target.[43]

[43]For a detailed discussion of the logic underlying the existence of a desirable number of banks, we refer the interested reader to the vast literature on consolidation in the financial sector. See, e.g., the comprehensive report on the issue by the Group of Ten (2001).

Our model suggests two key policy tools that could be used to obtain any given target number of banks: barriers to entry (κ) and barriers to foreign expansion (μ). We now show that the model implies that these tools are substitutes in terms of hitting any given target number of banks, but they have very different implications in terms of competition and bank risk.

The three panels of Figure 3 report the results of the following thought experiment. We take as target the model's steady-state number of banks for the calibrated parameter values in Table 1 and then we ask which alternative combinations of κ and μ would still deliver that number. The answer to this question is displayed in the central panel of Figure 3, which unveils a negative relation between the levels of the barriers to entry and to foreign expansion that can be implemented jointly in order to hit the given target. In other words, the same degree of consolidation can be obtained with high entry barriers and low foreign expansion barriers or equivalently with low entry barriers and high expansion barriers. The other two panels of Figure 3 reveal however that, while the combinations of κ and μ traced out in the central panel deliver the same target number of banks, different combinations have very different implications in terms of competition and bank risk, as inversely measured by the Boone Index in the right panel and the loan success probability in the left panel respectively. Accordingly, combinations of high entry barriers and low expansion barriers can deliver the same degree of consolidation as alternative combinations of low entry barriers and high expansion barriers, but the former combinations imply stronger competition and lower bank risk. If taming bank risk is of concern while pursuing a given degree of consolidation, then regulating entry while deregulating foreign expansion dominates the alternative policy option of deregulating entry while regulating foreign expansion.

5 Conclusion

Venturing into foreign markets can enrich banks' opportunities, but can also have unintended consequences for risk-taking. It has, however, been argued that direct involvement in local retail activities promotes competition and, through this channel, reduces risk-taking. We have investigated this argument in three steps. First, we have developed a dynamic model of global banking with endogenous market structure. Second, we have calibrated and simulated the long-run equilibrium of the model to generate empirically relevant predictions, introducing at this stage also systemic bank risk. Third, we have validated the model's predictions by testing them on an original dataset covering 15 European GSIBs.

We have found that, when banks expand abroad, their riskiness decreases as long as foreign expansion happens in host markets that are more competitive than the market banks are headquartered in. This result holds across alternative measures of bank risk, being more robust for individual risk metrics than for systemic risk metrics. If confirmed by future research, these findings could represent a major development in terms of understanding the governance of global financial stability.

Also in terms of future research, our model features global banks without smaller banks, which may nonetheless play a substantial role in the banking market. Smaller banks could be introduced by allowing for the presence of 'fringe' competitors. For example, Parenti (2018) shows that in an oligopolist product market the presence of fringe competitors can generate situations in which the entry of large firms is 'anti-competitive'. In our model, the interaction of oligopoly in the loan market with oligopsony in the deposit market can already generate situations in which entry has 'anti-competitive' effects on the loan-deposit spread (though this does not happen in our calibration). In this respect, including fringe competitors would add another channel for possible 'anti-competitive entry'. This potentially interesting inclusion would require a major original extension of our model as long as, differently from Parenti (2018), fringe competitors would operate in both the oligopolist downstream (loan) market and the oligopsonist upstream (deposit) market.

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Appendix

A Loan Demand: Micro-foundation

Firms get funds and can invest only in one national market. As markets are symmetric, we drop market indices. In each market there is continuum of firms with heterogenous outside options for investment. Firms' outside options k follow a continuous distribution with c.d.f. $G(k)$ for $k \geq 0$. Each firm can make only one unit investment yielding return:

$$p(r^I)(r^I - r^L). \tag{27}$$

The firm will make the investment as long as its expected profit does not fall short of its outside option. As a result investment is governed by a cutoff rule. Only firms with $p(r^I)(r^I - r^L) \geq \overline{k}$ invest, where $\overline{k}$ corresponds to the outside option of marginal firms that are indifferent between investing or not: $\overline{k} \equiv p(r^I)(r^I - r^L)$. In this setup, the demand for loans is equal to the total number of firms that invest:

$$L = G(\bar{h}) = G(p(r^I)(r^I - r^L)) \tag{28}$$

where r^I and r^L are linked by the firm's FOC:

$$\frac{d(p(r^I)(r^I - r^L))}{dr^I} = p_1(r^I)(r^I - r^L) + p(r^I) = 0 \tag{29}$$

In order to find under which conditions $r^L(L)$ satisfies $r^{L\prime}(L) < 0$ and $r^{L\prime\prime}(L) \leq 0$, we can totally differentiate (28) and use (29) to obtain

$$\frac{dL}{dr^L} = -g(p(r^I)(r^I - r^L))p(r^I) < 0 \tag{30}$$

and then

$$\frac{d^2L}{d\left(r^L\right)^2} = g'(p(r^I)(r^I - r^L))\left(p(r^I)\right)^2 \geq 0. \tag{31}$$

Hence, $r^{L\prime}(L) < 0$ always holds and $r^{L\prime\prime}(L) \leq 0$ also holds as long as

$$g'(.) \geq 0. \tag{32}$$

B Liability Risk: Random Deposit Withdrawals

While some of the market-based risk metrics considered in our empirical analysis capture both asset risk and liability risk, the model in the main text considers only the endogenous build-up of the former type of risk. To investigate how banks' foreign expansion may also affect liability risk, we consider the simpler case of $\rho = 1$ but now allow banks to be subject to random deposit withdrawals ('bank runs') that may impair their survival.

Specifically, we endogenize exit by introducing a fixed exit cost $\kappa^{exit} > 0$ and a log-normally distributed idiosyncratic liquidity shock λ_t with cumulative density function $\Phi(\lambda_t)$.[44] A bank hit by a large enough shock is forced to exit. If we use $\widetilde{\lambda}_t$ to denote the threshold value of λ_t above which exit happens, the endogenous aggregate exit rate is then given by $1 - \Phi(\widetilde{\lambda}_t)$. The threshold $\widetilde{\lambda}_t$ corresponds to the realization of the liquidity shock that makes a bank indifferent between staying in the market and exiting. This is the case when its charter value $\widetilde{V}_t$ equals the exit cost so that $\widetilde{\lambda}_t$ is defined by the 'free exit condition':

$$\widetilde{V}_t = \widetilde{\Pi}_t + \widetilde{\Pi}_t^* + (1 - \Phi(\widetilde{\lambda}_t))\mathbb{E}_t \left\{ \widetilde{V}_{t+1} \right\} = \kappa_t^{exit} \tag{33}$$

where $\widetilde{\Pi}_t = p(L_t^T) \left(r_t^L - r_t^D \widetilde{\lambda}_t - \xi \right) \ell_t$ and $\widetilde{\Pi}_t^* = p(L_t^T) \left(r_t^L - r_t^D \widetilde{\lambda}_t - \xi - \mu \right) \ell_t^*$.

The equilibrium of the model with endogenous exit is thus fully characterized by a non-linear system of seven equations. They include the six equilibrium equations in Section 3.1: banks operating profits (14), domestic banks' profit maximizing condition (15), foreign banks' profit maximizing condition (16), total loans (17), banks' free entry condition (12) and the law of motion of the banks' number (13). The additional equation is (33). This system of seven equations can be solved in seven unknown variables: $\ell_t, \ell_t^*, L_t^T, N_t,\ N_t^a,$

[44] We can think of idiosyncratic liquidity shocks as signals on deposits' withdrawals that might trigger a widespread run on deposits. See Angeloni and Faia (2013) and Rossi (2015) for further details on macroeconomic models with banks' default that are induced by bank runs triggered by coordination problems on signals.

$\Pi_t + \Pi_t^*$ and $\widetilde{\lambda}_t$.

As for calibration, based on pre-crisis estimates of entry costs and scrap values, Temesvary (2014) reports that banks could recover roughly 75% of their entry costs when closing their foreign offices. Accordingly, we set the exit cost κ_t^{exit} to 25% of the entry cost κ_t (i.e. $\kappa_t^{exit} = \kappa_t/4$).The calibrated values of all other parameters remain the same as in Section 3.2.

Figure A1 reports the simulation results of the model with endogenous exit. Comparison with the analogous Figure 1 with exogenous exit reveals that, as the monitoring cost μ decreases the behavior of the key variables of our reduced-form analysis, namely the success probability and the Boone indicator, is essentially unaffected. Moreover, also leverage decreases as consistent with the reduced-form results in Section 4.[45]

C Cross-Border Lending

The business model of multinational banks is one in which internationalization takes place through horizontal expansion, while the business model of cross-border lending is one in which internationalization takes place through vertical integration. We assume that, differently from multinational banks, cross-border lenders have a lighter foreign presence. This can be captured by a lower setup cost for foreign operations, which we normalize to zero. Accordingly, the overall fixed cost of a cross-border lender is $\kappa - \kappa^d$, where κ and κ^d are the overall fixed cost and the subsidiary setup cost of a multinational bank respectively.

A cross-border lender r headquartered in market H raises deposits $D_{r,H}$ in its domestic market and allocates them to domestic loans $L_{r,HH}$ and foreign loans $L_{r,HF}$. We use $D_{r,HH}$ and $D_{r,FH}$ to denote the complementary amounts of deposits allocated to loans in H and F respectively, so that we have $D_{r,HH} = L_{r,HH}$, $D_{r,FH} = L_{r,FH}$ and $D_{r,H} = D_{r,HH} + D_{r,HF} = L_{r,HH} + L_{r,HF}$. The lender then chooses $L_{r,HH}$ and $L_{r,HF}$ so as to maximize expected profit:

[45] In Figure A1 leverage is defined as $\Phi(\widetilde{\lambda}_t)/p(r^I)$, which is the mean ratio of deposits to loans.

$$\begin{aligned}\Pi_H &= p(r_H^I)\left(r_H^L\left(L_H^T\right)L_{r,HH} - r_H^D(D_H^T)L_{r,HH} - \xi L_{r,HH}\right)\\ &+ p(r_F^I, a_F)\left(r_F^L\left(L_F^T\right)L_{r,HF} - r_H^D(D_H^T)L_{r,HF} - \xi L_{r,HF} - \mu L_{r,HF}\right)\\ &- \left(\kappa - \kappa^d\right).\end{aligned}$$

The first order condition for profit maximization is:

$$\begin{aligned}\frac{\partial \Pi_H}{\partial L_{r,HH}} &= p_1(r_H^I)r_H^{I\prime}\left(r_H^L\right)r_H^{L\prime}\left(L_H^T\right)\left(r_H^L\left(L_H^T\right)L_{r,HH} - r_H^D(D_H^T)L_{r,HH} - \xi L_{r,HH}\right) \quad (34)\\ &+p(r_H^I)\left(r_H^{L\prime}\left(L_H^T\right)L_{r,HH} + r_H^L\left(L_H^T\right) - r_H^{D\prime}(D_H^T)L_{r,HH} - r_H^D(D_H^T) - \xi\right)\\ &-p(r_F^I, a_F)r_H^{D\prime}(D_H^T)L_{r,HF} = 0.\end{aligned}$$

Note that, as higher $L_{r,HH}$ increases interest payments also for deposits used for $L_{r,FH}$, the lender's first order condition can not be separated between markets as it was the case with multinational banks. This generates a *novel trade-off*. On the one hand, as $r_H^D(D_H^T)$ increases with D_H^T, being forced to tap a single market for deposits drives the deposit return up, which by itself would increase the loan rate. On the other hand, the lack of foreign competition for domestic deposits puts downward pressure on the deposit return, which by itself would decrease the loan rate. Hence, for the same number of banks, it is not obvious whether one should expect cross-border lending to lead to more or less risk taking than multinational banking.

For simplicity, we focus on the symmetric deterministic equilibrium with $\mu = 0$. In this case, symmetry implies that in equilibrium the total amount of loans offered by home and foreign banks in a market equals the total amount of deposits raised in the same market ($L^T = D^T$). This is due to the fact that home and foreign banks supply the same amounts of deposits rather than to the fact that banks can finance loans only with local deposits as in the case of multinational banks. Using our functional forms, the first order condition (34) becomes:

$$L^T \left[\frac{1}{\alpha} - (\nu + \gamma) L^T - \xi\right] + \left[\frac{1}{\alpha} - 2(\nu + \gamma) L^T - \xi\right] \ell - \gamma L^T \ell = 0.$$

Hence, after imposing $L^T = N^a \ell$, we can solve for the total amount of loans extended by cross-border lenders in each market:

$$L^T_{cbl} = N^a \ell = \frac{\frac{1}{\alpha} - \xi}{\nu + \gamma} \frac{(N^a + 1) - \frac{1}{2}}{(N^a + 2) + \left(N^a + \frac{\gamma}{\nu+\gamma}\right)}, \tag{35}$$

which shows that, also in the case of cross-border lending, a larger number of active banks raises the total amount of loans, thus reducing risk-taking. Expression (35) can be compared with its analogue in the case of multinational banks:

$$L^T_{mnb} = N^a \ell = \frac{\frac{1}{\alpha} - \xi}{\nu + \gamma} \frac{N^a + 1}{N^a + 2}.$$

Three comments are in order. First, for a given number of active banks N^a, cross-border lenders raise a smaller total amount of deposits and thus supply a smaller total amount of loans ($L^T_{cbl} < L^T_{mnb}$). Second, for a given initial number of active banks N^a, the increase in competition caused by the same increase in the number of active banks leads to a smaller increase in deposits and loans with cross-border lenders than with multinational banks ($dL^T_{cbl}/dN_a < dL^T_{mnb}/dN_a$). Hence, for given N^a, multinational banking generates less risk taking than cross-border lending ($p_{cbl} > p_{mnb}$) and more competition reduces risk by a larger extent ($dp_{cbl}/dN_a < dp_{mnb}/dN_a$). Third, when instead the number of active banks is endogenously determined by free entry, multinational banking still generates less risk than cross-border lending provided that the additional fixed cost of setting up a foreign subsidiary is not too large. Too see this, note that, for given N_a and net of the corresponding overall entry cost, the maximized profit of a cross-border lender evaluates to

$$\Pi_{cbl} = \frac{\alpha\nu\left(\frac{1}{\alpha} - \xi\right)^3}{(\gamma + \nu)^2} \frac{(2N^a + 1)^2 \left(\frac{5\gamma+3\nu}{\gamma+\nu} + 2N^a\right)}{8N^a\left(\frac{3\gamma+2\nu}{\gamma+\nu} + 2N^a\right)^3} - [1 - \beta(1 - \varrho)]\left(\kappa - \kappa^d\right),$$

while the profit of a multinational bank evaluates to:

$$\Pi_{mnb} = \frac{\alpha\nu\left(\frac{1}{\alpha}-\xi\right)^3}{(\nu+\gamma)^2}\frac{(N^a+1)^2}{N^a(N^a+2)^3} - [1-\beta(1-\varrho)]\,\kappa.$$

Both Π_{cbl} and Π_{mnb} are decreasing in N^a and go to zero as N^a goes to infinity. However, it can be shown that the multinational bank's profit gross of the overall entry cost is larger than the cross-border lender's for any value of N^a. It then follows that for $\kappa^d = 0$ the multinational banking free entry condition $\Pi_{mnb} = 0$ holds for a value of N^a that is larger than the one at which the cross-border lending free entry $\Pi_{cbl} = 0$ holds. By continuity, this also holds for $\kappa^d > 0$ provided that κ^d is not too large. Otherwise, when κ^d is large enough, the reverse happens with $\Pi_{mnb} = 0$ holding for a value of N^a that is smaller than the one at which $\Pi_{cbl} = 0$ holds. Higher risk taking associated with cross-border lending is in line with evidence reported by IMF (2015) that the increase in cross-border lending prior to the 2007 produced larger default after the crisis erupted and this was followed by extensive re-trenchment (see also Milesi-Ferretti and Tille, 2011).

D Sample Description

This appendix section is largely based on the appendix section of Faia, Laffitte and Ottaviano (2019).

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 37 destination countries in Europe: Albania, Austria, Belgium, Bulgaria, Bosnia-Herzegovina, Croatia, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Lithuania, Luxembourg, Latvia, Malta, Mon-

tenegro, 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.

E Risk Metrics

This appendix section is largely based on the appendix section of Faia, Laffitte and Ottaviano (2019).

Our empirical analysis looks at the impact of bank expansion in foreign countries on bank risk. In order to capture the fact that bank risk is multidimensional, we use a variety of different risk metrics that can be decomposed between individual risk metrics and systemic risk metrics.

E.1 Individual Risk Metrics

Five individual risk metrics are used: (log) CDS price, loan-loss provisions, (log) standard deviation of returns, leverage and (log) Z-Score.

- **CDS price:** Bloomberg
- **Loan-loss provisions:** Orbis Bank Focus
- **Returns:** Datastream
- **Leverage:** Centre for Risk Management of Lausanne and complemented with data from the V-Lab
- **Z-Score:** The Z-Score is defined as follows: Z-score $= \dfrac{\text{ROA} + \text{Capital Asset Ratio}}{\sigma(returns)}$. The ROA and the Capital Asset Ratio comes from Orbis Bank Focus and the returns come from Datastream.

E.2 Systemic Risk Metrics

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.

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. (2017) and Brownlees and Engle (2017). 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:

$$LRMES_{i,t:t+6} = -\mathbb{E}\left[R_{i,t:t+6}|R_{M,t:t+6} \leq -40\%\right] \tag{36}$$

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.

SRISK This measure has been proposed by Acharya, Engle and Richardson Acharya, Engle and Richardson (2012) and Brownlees and Engle (2017). The SRISK is based on MES but takes into account the liabilities and the size of the bank. Following Acharya, Engle and Richardson (2012), SRISK is defined as:

$$LRMES_{it} = max\Big[0; \left[kL_{it} - 1 + (1-k)LRMES_{it}\right] W_{it}\Big] \tag{37}$$

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.

Δ CoVaR The ΔCoVaR measure has been proposed by Adrian and Brunnermeier Adrian and Brunnermeier (2016). 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:

$$\mathbb{P}(r_i \leq VaR_i(p)) = p \tag{38}$$

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

$$\mathbb{P}(r_i \leq CoVaR^{i|\mathbb{C}(r_i)}(p)|\mathbb{C}(r_i)) = p \tag{39}$$

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):

$$CoVaR^{i|r_{it}=VaR_{it}(p)} - CoVaR^{i|r_{it}=Median(r_{it})} \tag{40}$$

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 (2016). 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 (2016) the ΔCoVaR is not equivalent to the VaR.

Data Sources As for data sources, CDS prices come from Bloomberg and equity prices from Datastream. Both are averaged to obtain monthly (for computing Δ Covar) 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.[46] Concerning the variables used as states in the Δ CoVaR 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.

F Boone Indicator

F.1 Computation

In this section we provide details on the Boone indicator is computed in the model and in the data. For the empirical part we compute the Boone indicator following Schaeck and Čihák (2010).

In industrial organization the Boone indicator is defined as the elasticity of profits to marginal cost in a given market. Schaeck and Čihák (2010) consider the following simple model of oligopolistic competition. Bank i's demand curve is

$$p(q_i, q_{j \neq i}) = a - bq_i - d \sum_{j \neq i} q_j \tag{41}$$

with profits

$$\pi_i = (p_i - c_i)\, q_i. \tag{42}$$

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

The FOC for profit maximization is

$$a - 2bq_i - d\sum_{j\neq i} q - c_i = 0 \tag{43}$$

where $d < b$ measures product differentiation. With N competitors, bank i's profit maximizing size is:

$$q_i(c_i) = \frac{(2b/d - 1)\, a - (2b/d + N - 1)c_i + \sum_{j\neq i} c_j}{[2b + d(N-1)]\,(2b/d - 1)}.$$

Empirically, Schaeck and Čihák (2010) estimate the Boone indicator through a regression base on the reduced form:

$$\pi_{it} = \alpha + \beta \ln c_{it},$$

where π_{it} are the profits of bank i at time t as a proportion of total assets (ROA). As marginal cost is not observed, they use average cost as a proxy and regress π_{it} on it. More precisely, they run the following regression:

$$\pi_{it} = \alpha_i + \sum_{t=1,\ldots,T} \beta_t d_t \ln c_{it} + \sum_{t=1,\ldots,T-1} \gamma_t d_t + u_{it} \tag{44}$$

where π_{it} are the profits of bank i at time t as a proportion of total assets (ROA), c_{it} is average variable costs, d_t is a time dummy and u_{it} is the error term. Profits increase for banks with lower marginal costs ($\beta < 0$). Thus, an increase in competition raises profits of a more efficient bank relative to a less efficient one. The stronger the effect (i.e., the larger the β in absolute value), the stronger is competition.

As for data, they use use average cost of bank i as a share of total income. Average costs comprise interest and personnel expenses, administrative and other operating expenses. Income consists of commission and trading income, interest income, fee income, and other operating income.

Note that Schaeck and Čihák (2010) only consider oligopolistic competition in the loan market, while our model also features oligopsony in the deposit market. Therefore we adapt their definition by replacing the return on loans with the loan to deposit margin.

Recall that we have defined $m(L_t^T) = \left[\frac{1}{\alpha} - (\nu+\gamma)L_t^T - \xi\right]$.

Then, defining $p = \alpha\nu L_t^T/2$, with perfectly correlated projects ex-ante expected and ex-post average domestic profits are:

$$\Pi_t = p\ m(L_t^T)\ \ell_t$$

as the success rate equals p for all banks.

Note that the ex-ante expected and ex-post average *profits as a proportion of total assets* (ROA) are:

$$\pi_t = \frac{\Pi_t}{\ell_t} = \begin{cases} p\ m(L_t^T) & \text{with perfectly correlated shocks} \\ \left(1 - \hat{\varkappa}G(\hat{\varkappa}) - \int_{\hat{\varkappa}}^{1} G(\varkappa, p)dx\right)\ m(L_t^T) & \text{with imperfectly correlated shocks} \end{cases}$$

Using $\pi_t^{CN}(\xi,\mu)$ to denote the corresponding equilibrium values of π_t, the Boone indicator can then be defined as:

$$B_t(\xi,\mu) = \frac{d\ln\pi_t^{CN}(\xi,\mu)}{d\ln\xi}$$

F.2 Descriptive Statistics

Table A1 describes the Boone indicator (BI) across Europe in 2014 revealing substantial variation. With reference to our G-SIBs, the average value in host countries is -1.62, while it is -0.09 in origin countries as the latter tend to be less competitive than the average. This is particularly the case of France, Italy and the Netherlands, while Luxembourg, Spain, Switzerland and United Kingdom have more competitive banking sectors.

Table A2 reports for each origin country the percentage of openings happening in host countries that are more competitive than the origin one according to the Boone indicator. In the third column this percentage is conditioned to a positive entry event in the market. For France, Germany, Italy and the Netherlands more than two thirds of their openings are in more competitive host countries. There is no large difference between the unconditional rate and the conditional rate indicating that there is no systematic bias towards expanding in countries with high or low competition index. Differently, a very small fraction of Spanish openings target more competitive countries, as Spain has a very competitive financial sector according to the BI. Finally, Sweden, Switzerland and the United Kingdom are close to the median BI. However, for these three countries the conditional rate is lower, suggesting that these countries generally tend to expand into less competitive destinations compared with the set of opportunities that contains all bilateral combinations.

Figure 2 illustrates the foreign expansion pattern of the European G-SIBs across time. Using the Boone indicator, we distinguish between expansion in more competitive countries (*i.e* with lower Boone indicator) and expansion in less competitive countries (*i.e* with higher Boone indicator). The figure illustrates that openings follow similar patterns in more and in less competitive countries, but before 2010 more openings are directed towards higher competitive countries.

G Robustness tests

G.1 Generated Regressor Issue

Our baseline specification follows the literature using gravity instrumental variables as common practice.[47] Nonetheless, our instrument is a generated regressor and this may affect the standard errors of our regressions (see Pagan, 1984). Our specification includes three stages: an initial stage, in which we estimate the expansions through gravity, and the two stages of the IV estimation. We checked the robustness of our first-stage IV estimates to bootstrapped standard errors. Specifically, we bootstrapped the estimates of the two first stages (see columns 3 and 4 of Table 3). The bootstrapping procedure takes into account the panel structure of the data by sampling panels instead of observations. See Table A3 for results. The standard errors are computed using 1000 replications. The standard errors of the estimates as well as the Sanderson-Windmeijer F-stats remain close to those obtained without bootstrapping.

[47] See e.g. Goetz, Laeven and Levine (2013), Levine, Lin and Xie (2016) and Faia, Laffitte and Ottaviano (2019) for applications to international finance and banking.

G.2 Identification Strategy

As discussed in the main text, our identification mainly relies on shocks in destination countries. We argued there that these shocks can be considered exogenous as endogeneity would imply that shocks in destination countries affect simultaneously both risk measured at the level of the headquarter and expansion. In this subsection, we provide a robustness test in which we drop destination countries where a bank has a large cross-border exposure, that is, where local shocks are (if at all) most likely to affect the overall risk of the banking group. We extract data on banks' cross-border exposures in 2012 from Duijm and Schoenmaker (2020) and drop from our sample destination countries that represent more than 5% of the cross-border exposure of a bank. This leads us to drop 15 bank-destination country pairs. Our main results are robust to this check. Table A4 and Table A5 for corresponding results.

H Tables

Table 1 – Calibration of parameters (quarterly)

Parameter	Mnemonics	Value
Discount factor	β	0.99
Functional form $p(L^T, a)$	α	31.797
Functional form of r^L	ν	0.01618
Functional form of r^D	γ	0.00597
Monitoring cost	μ	0.004
Exit probability	ϱ	0.01125
Insurance fee	ξ	0.0011
Entry cost	κ	0.10

Table 2 – Long-run values of variables (quarterly)

Description	Variable	Value
Success probability	$p(L^T)$	0.25
Loan return	r^L	0.0158
Deposit return	r^D	0.0058
Project return	r^I	0.0236
Bank profits domestic	Π	0.0017
Bank profits abroad	Π^*	0.0004
Total Number of banks	N	1.7374
Bank value	V	0.1
Deposits domestic	ℓ	0.7779
Deposits abroad	ℓ^*	0.3242
Total deposits	L^T	0.9683

Table 3 – First-stage results

	(1)	(2)	(3)	(4)
	No controls		**Controls**	
Dependant variable	Higher	Lower	Higher	Lower
$\widehat{\text{Higher}}$	1.376***	0.162	1.525***	0.221**
	(0.405)	(0.100)	(0.430)	(0.108)
$\widehat{\text{Lower}}$	0.589	1.333***	0.668	1.430***
	(0.827)	(0.287)	(1.074)	(0.356)
ln(Tot Assets)			6.738*	1.794
			(3.445)	(1.293)
ROA			-2.568	-0.669
			(1.701)	(0.833)
Income diversity			1.453	-0.0453
			(1.283)	(0.492)
Asset diversity			7.154	6.044*
			(5.372)	(3.155)
Tier1/Asset			0.0678	-0.0509
			(0.109)	(0.0659)
Deposits/Asset			0.00744	-0.00273
			(0.0128)	(0.00295)
Average regulation			0.514	-0.0380
			(0.672)	(0.370)
Net interest margin			473.8*	269.7
			(276.1)	(244.6)
Observations	145	145	136	136
F-test	8.43	20.15	7.63	14.74
Sanderson-Windmeijer (SW)	11.52	21.92	11.10	20.07

Robust standard errors in parentheses. Higher (resp. Lower) stands for the observed number of openings in more (resp. less) competitive countries. $\widehat{\text{Higher}}$ (resp. $\widehat{\text{Lower}}$) stands for the predicted number of openings in more (resp. less) competitive countries.

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

Table 4 – Expansion, competition and individual risk metrics

		(1)	(2)	(3)	(4)
		No controls		**Controls**	
		OLS	2SLS	OLS	2SLS
ln(CDS)	Higher Competition	-0.00410	-0.00823	-0.00573*	-0.0151**
		(0.00319)	(0.00524)	(0.00301)	(0.00633)
	Lower Competition	-0.00622	-0.0191	0.000149	-0.00209
		(0.00513)	(0.0135)	(0.00722)	(0.0154)
	Observations	145	145	136	136
	R-squared	0.964	0.961	0.981	0.977
	F-Test 1st		9.327		9.443
LLP	Higher Competition	-0.00437	-0.00388	-0.00435	-0.0295
		(0.00930)	(0.0164)	(0.00959)	(0.0202)
	Lower Competition	-0.0226	-0.0638	0.00731	0.00243
		(0.0260)	(0.0490)	(0.00912)	(0.0402)
	Observations	143	143	135	135
	R-squared	0.288	0.266	0.645	0.605
	F-Test 1st		8.847		9.386
ln(σ returns)	Higher Competition	-0.00390***	-0.00957**	-0.00489**	-0.0148***
		(0.00115)	(0.00384)	(0.00223)	(0.00530)
	Lower Competition	-0.00190	-0.00174	0.00239	0.0117
		(0.00439)	(0.0106)	(0.00418)	(0.0108)
	Observations	145	145	136	136
	R-squared	0.894	0.888	0.923	0.908
	F-Test 1st		9.327		9.443
ln(Z-score)	Higher Competition	0.00384**	0.00646	0.00520***	0.0125***
		(0.00153)	(0.00454)	(0.00140)	(0.00420)
	Lower Competition	0.00562	0.0127	-0.00296	-0.0160*
		(0.00609)	(0.0149)	(0.00497)	(0.00936)
	Observations	135	134	135	134
	R-squared	0.842	0.837	0.910	0.901
	F-Test 1st		8.954		9.222
Leverage	Higher Competition	-0.259*	-0.785***	-0.265	-0.770**
		(0.146)	(0.298)	(0.231)	(0.350)
	Lower Competition	-0.199	0.394	-0.463**	-0.145
		(0.202)	(0.554)	(0.206)	(0.550)
	Observations	145	145	136	136
	R-squared	0.583	0.536	0.680	0.634
	F-Test 1st		9.327		9.443

Robust standard errors in parentheses. We apply a small-sample correction for the instrumental variable estimations. Each regression includes bank and year fixed effects. Control Set: ln(Total Assets), Income Diversity, Asset Diversity, Tier1 ratio and Deposit-to-asset ratio, average regulation, net interest margin and specific time-trend for Italy and Spain. Higher Competition (resp. Lower) stands for openings in host countries more (resp. less) competitive than the origin country according to the Boone index. Kleibergen-Paap rk Wald F statistic are displayed in the "F-Test 1st" line.

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

Table 5 – Expansion, competition and systemic risk metrics

		(1)	(2)	(3)	(4)
		No controls		**Controls**	
		OLS	2SLS	OLS	2SLS
LRMES	Higher Competition	-0.0880	-0.128	-0.121	-0.121
		(0.155)	(0.125)	(0.153)	(0.112)
	Lower Competition	-0.279	-0.398	-0.223	-0.267
		(0.187)	(0.353)	(0.212)	(0.472)
	Observations	145	145	136	136
	R-squared	0.625	0.621	0.704	0.704
	F-Test 1st		9.327		9.443
SRISK	Higher Competition	-0.259	-0.994**	-0.280	-0.931*
		(0.351)	(0.459)	(0.370)	(0.511)
	Lower Competition	-0.500	-0.595	-0.631	-0.943
		(0.371)	(0.825)	(0.380)	(0.871)
	Observations	145	145	136	136
	R-squared	0.665	0.594	0.761	0.697
	F-Test 1st		9.327		9.443
ΔCoVaR CDS	Higher Competition	-0.000298	-0.000981	-8.48e-05	-0.00211
		(0.00191)	(0.00239)	(0.00146)	(0.00217)
	Lower Competition	-0.00203	-0.00280	0.000486	0.00686
		(0.00562)	(0.00586)	(0.00509)	(0.00676)
	Observations	145	145	136	136
	R-squared	0.687	0.686	0.753	0.747
	F-Test 1st		9.327		9.443
ΔCoVaR Equ.	Higher Competition	-0.000349	-0.00109**	-0.000287	-0.00122*
		(0.000321)	(0.000550)	(0.000398)	(0.000667)
	Lower Competition	0.000155	-6.56e-05	-0.000184	0.000290
		(0.000670)	(0.00123)	(0.000429)	(0.00145)
	Observations	145	145	136	136
	R-squared	0.852	0.844	0.866	0.856
	F-Test 1st		9.327		9.443

Robust standard errors in parentheses. We apply a small-sample correction for the instrumental variable estimations. Each regression includes bank and year fixed effects. Control Set: ln(Total Assets), Income Diversity, Asset Diversity, Tier1 ratio and Deposit-to-asset ratio, average regulation, net interest margin and specific time-trend for Italy and Spain. Higher Competition (resp. Lower) stands for openings in host countries more (resp. less) competitive than the origin country according to the Boone index. Kleibergen-Paap rk Wald F statistic are displayed in the "F-Test 1st" line.

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

Table 6 – Regression Coefficients Estimated on Model-Generated Data

	log(probability of default)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Expansion	-0.9976***		-0.6573***	-1.0790***	-0.8703***	-0.9407***	-0.8385***
	(0.0066)		(0.0199)	(0.0159)	(0.0036)	(0.0220)	(0.0043)
|Boone Index|		-0.9920***	-0.3465***	0.0877***		-0.0269	
		(0.0127)	(0.0216)	(0.0164)		(0.0251)	
Expansion×|Boone Index|				-0.1059***		-0.0879***	
				(0.0037)		(0.0093)	
High Competition					0.0255**		0.0117
					(0.0085)		(0.0098)
High Competition×Expansion					-0.2872***		-0.3104***
					(0.0090)		(0.0098)
Obs.	150	150	150	150	150	134	134
ρ	1	1	1	1	1	0.8	0.8

Table 6 displays regression coefficients estimated on data generated by 150 iterations of the model for randomly drawn parameters μ. Expansion are the loans granted by a foreign affiliate in the foreign market (L_t^*), |Boone Index| is the absolute value of the Boone Index and High Competition is a dummy that takes on the value one if the absolute value of Boone Index is above the sample median and zero otherwise. The first 5 columns have as dependent variable the log probability of default with banks' idiosyncratic risk. Data in the last two columns are based on model simulation allowing for the presence of systemic risk by setting the model parameter $\rho = 0.8$. All continuous variables are standardized. Robust standard errors are in parentheses. * p<0.05, ** p<0.01, *** p<0.001.

Table A1 – Boone indicator

Country	Boone	Country	Boone	Country	Boone	Country	Boone
Albania	-.05	Spain	-.61	Italy	0	Russia	-.08
Austria	-.02	Estonia	-.1	Lithuania	0	Serbia	-.11
Belgium	-.02	Finland	.09	Luxembourg	-50.06	Slovakia	-.01
Bulgaria	.21	France	0	Latvia	-.15	Slovenia	11.34
Bosnia Herzegov.	-.03	United Kingdom	-.05	Malta	-.13	Sweden	-.05
Switzerland	-.07	Greece	0	Netherlands	.13	Turkey	-.03
Cyprus	0	Croatia	-.05	Norway	.03	Ukraine	.09
Czechia	-.07	Hungary	-.1	Poland	-.08		
Germany	-.03	Ireland	.65	Portugal	-1.03		
Denmark	-.07	Iceland	-.19	Romania	0		

Table A2 – Expansion and host market competition

Origin country	% of more competitive host countries	% of more competitive host countries (Openings> 0)
France	72	71
Germany	63	66
Italy	73	77
Netherlands	88	89
Spain	4	3
Sweden	46	38
Switzerland	46	32
United Kingdom	47	34

Note: The second column displays the share of host countries that are more competitive that the origin country in the first column. The third columns displays the share of host countries that are more competitive that the origin country in the first column conditional on entry by origin country's banks.

Table A3 – Replication of columns 3 and 4 of Table 3 with bootstrapped standard errors.

	(1) Higher	(2) Lower
$\hat{Higher}$	1.525***	0.221
	(0.365)	(0.211)
$\hat{Lower}$	0.668	1.430***
	(0.646)	(0.442)
ln(Tot Assets)	6.738	1.794
	(8.534)	(1.703)
ROA	-2.568	-0.669
	(3.001)	(1.054)
Income diversity	1.453	-0.0453
	(5.667)	(1.605)
Asset diversity	7.154	6.044
	(10.51)	(5.021)
Tier1/Asset	0.0678	-0.0509
	(0.170)	(0.0657)
Deposits/Asset	0.00744	-0.00273
	(0.0215)	(0.00429)
Av. regulation	0.514	-0.0380
	(0.717)	(0.439)
Net interest margin	473.8	269.7
	(419.5)	(221.3)
Observations	136	136
R-squared	0.548	0.538
Sanderson-Windmeijer F-stat (SW)	10.86	19.64

Bootstrapped standard errors in parentheses (1000 replications).
*** p<0.01, ** p<0.05, * p<0.1

Table A4 – Expansion, competition and individual risk metrics: drop biggest exposure

		(1)	(2)	(3)	(4)
		No controls		**Controls**	
		OLS	2SLS	OLS	2SLS
ln(CDS)	Higher Competition	-0.00710**	-0.0105	-0.00943***	-0.0169***
		(0.00287)	(0.00664)	(0.00244)	(0.00588)
	Lower Competition	-0.00478	-0.0381	0.00387	-0.0121
		(0.00571)	(0.0286)	(0.00795)	(0.0203)
	Observations	145	145	136	136
	R-squared	0.965	0.957	0.982	0.978
	F-Test 1st		3.721		4.085
LLP	Higher Competition	-0.0150	-0.0181	-0.0116	-0.0393**
		(0.0193)	(0.0212)	(0.0108)	(0.0194)
	Lower Competition	0.0126	-0.0528	0.0291	0.0379
		(0.0136)	(0.0709)	(0.0184)	(0.0507)
	Observations	143	143	135	135
	R-squared	0.285	0.245	0.651	0.624
	F-Test 1st		3.840		4.144
ln(σ returns)	Higher Competition	-0.00581***	-0.0112***	-0.00677***	-0.0153***
		(0.00186)	(0.00422)	(0.00220)	(0.00443)
	Lower Competition	0.00119	-0.00743	0.00464	0.00762
		(0.00377)	(0.0191)	(0.00506)	(0.0145)
	Observations	145	145	136	136
	R-squared	0.895	0.887	0.924	0.915
	F-Test 1st		3.721		4.085
ln(Z-score)	Higher Competition	0.00582*	0.00754	0.00648***	0.0121***
		(0.00305)	(0.00610)	(0.00217)	(0.00380)
	Lower Competition	0.00205	0.0231	-0.00334	-0.0122
		(0.00718)	(0.0289)	(0.00711)	(0.0128)
	Observations	135	134	135	134
	R-squared	0.842	0.828	0.910	0.906
	F-Test 1st		3.491		3.843
Leverage	Higher Competition	-0.268**	-0.821***	-0.332	-0.884***
		(0.122)	(0.275)	(0.230)	(0.283)
	Lower Competition	-0.480***	-0.0461	-0.569**	-0.204
		(0.157)	(0.782)	(0.262)	(0.748)
	Observations	145	145	136	136
	R-squared	0.587	0.551	0.685	0.648
	F-Test 1st		3.721		4.085

Robust standard errors in parentheses. We apply a small-sample correction for the instrumental variable estimations. Each regression includes bank and year fixed effects. Control Set: ln(Total Assets), Income Diversity, Asset Diversity, Tier1 ratio and Deposit-to-asset ratio, average regulation, net interest margin and specific time-trend for Italy and Spain. Higher Competition (resp. Lower) stands for openings in host countries more (resp. less) competitive than the origin country according to the Boone index. Kleibergen-Paap rk Wald F statistic are displayed in the "F-Test 1st" line. For all regressions, the the p-value of the Anderson-Rubin test of the significance of the endogenous regressors is lower than 0.006. *** p<0.01, ** p<0.05, * p<0.1

Table A5 – Expansion, competition and systemic risk metrics : drop biggest exposure

		(1)	(2)	(3)	(4)
		No controls		**Controls**	
		OLS	2SLS	OLS	2SLS
LRMES	Higher Competition	-0.160	-0.222	-0.202	-0.218*
		(0.179)	(0.144)	(0.174)	(0.125)
	Lower Competition	-0.447	-0.725	-0.303	-0.539
		(0.271)	(0.497)	(0.320)	(0.521)
	Observations	145	145	136	136
	R-squared	0.644	0.633	0.716	0.711
	F-Test 1st		3.721		4.085
SRISK	Higher Competition	-0.342	-0.975**	-0.415	-0.990**
		(0.356)	(0.404)	(0.377)	(0.424)
	Lower Competition	-0.784**	-1.946	-0.697	-1.804
		(0.363)	(1.182)	(0.454)	(1.331)
	Observations	145	145	136	136
	R-squared	0.673	0.592	0.765	0.698
	F-Test 1st		3.721		4.085
ΔCoVaR CDS	Higher Competition	-0.00133	-0.00462*	-0.000568	-0.00522
		(0.00285)	(0.00250)	(0.00189)	(0.00378)
	Lower Competition	0.00292	0.0191**	0.00492	0.0328**
		(0.00852)	(0.00915)	(0.00653)	(0.0152)
	Observations	145	145	136	136
	R-squared	0.687	0.662	0.756	0.687
	F-Test 1st		3.721		4.085
ΔCoVaR Equ.	Higher Competition	-0.000453	-0.00104**	-0.000420	-0.00124**
		(0.000429)	(0.000513)	(0.000515)	(0.000551)
	Lower Competition	0.000509	-0.00197	9.70e-05	-0.000920
		(0.000868)	(0.00221)	(0.000905)	(0.00215)
	Observations	145	145	136	136
	R-squared	0.852	0.833	0.866	0.855
	F-Test 1st		3.721		4.085

Robust standard errors in parentheses. We apply a small-sample correction for the instrumental variable estimations. Each regression includes bank and year fixed effects. Control Set: ln(Total Assets), Income Diversity, Asset Diversity, Tier1 ratio and Deposit-to-asset ratio, average regulation, net interest margin and specific time-trend for Italy and Spain. Higher Competition (resp. Lower) stands for openings in host countries more (resp. less) competitive than the origin country according to the Boone index. Kleibergen-Paap rk Wald F statistic are displayed in the "F-Test 1st" line. For all regressions, the the p-value of the Anderson-Rubin test of the significance of the endogenous regressors is lower than 0.006. *** p<0.01, ** p<0.05, * p<0.1

I Figures

Figure 1 – Banking globalization

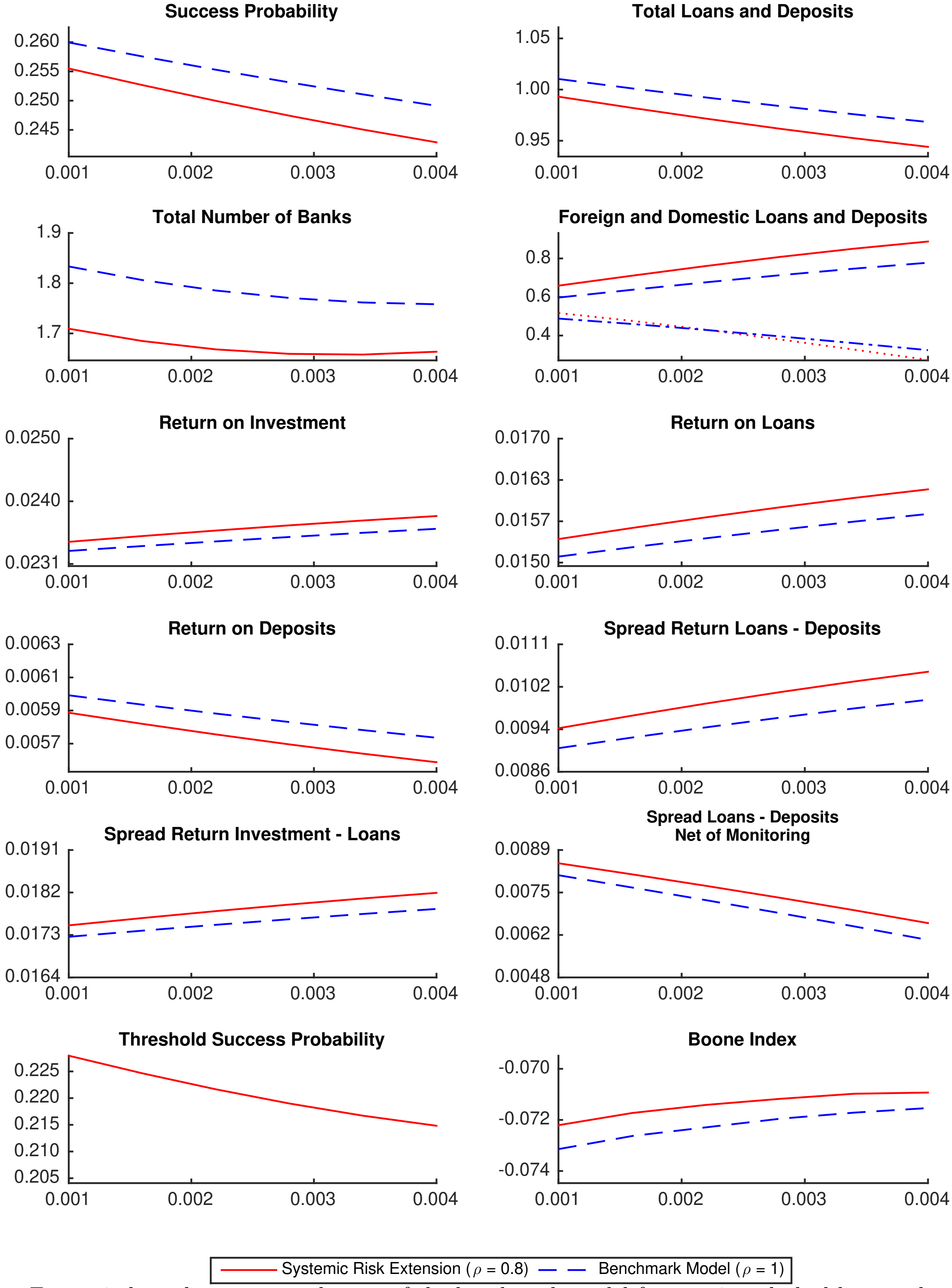

Figure 1 shows long-run simulations of the benchmark model for $\rho = 1$ as dashed lines and simulations for the case of $\rho = 0.8$ in solid lines. In the panel "Foreign and Domestic Loans and Deposits" dashed-dotted lines and dotted lines represent foreign loans/deposits. The variables of interest are reported on the vertical axis, while μ increases rightward on the horizontal axis. The effects of increased banking globalization (i.e. lower μ) can be gauged by moving from right to left on the horizontal axis.

Figure 2 – Foreign expansion of European G-SIBs

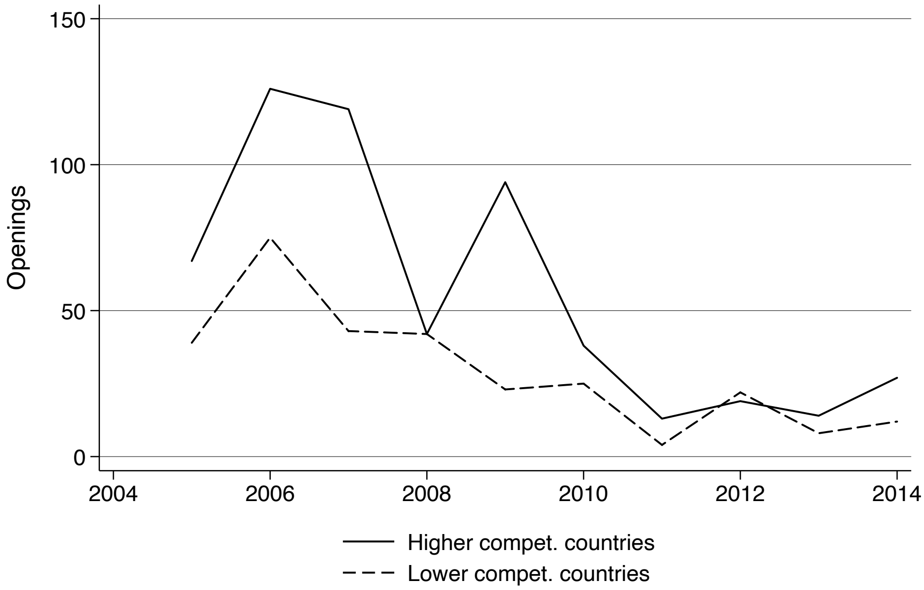

Figure 3 – Impact of increased entry barriers on efficiency

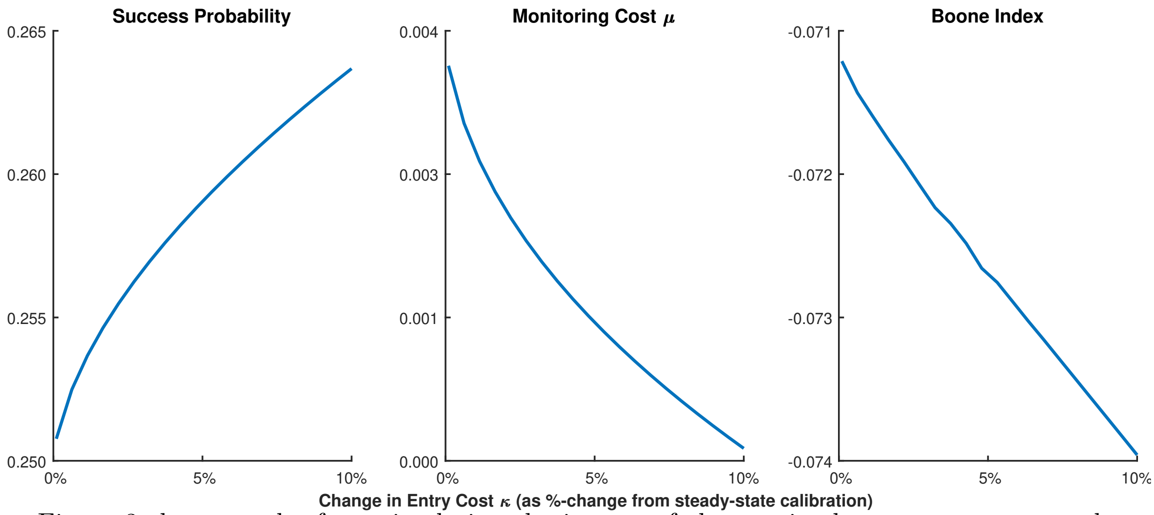

Figure 3 shows results from simulating the impact of changes in the entry cost, κ, on the probability of default, the monitoring cost compatible with the medium term equilibrium and competition.

Figure A1 – Banking globalization with random deposit withdrawals

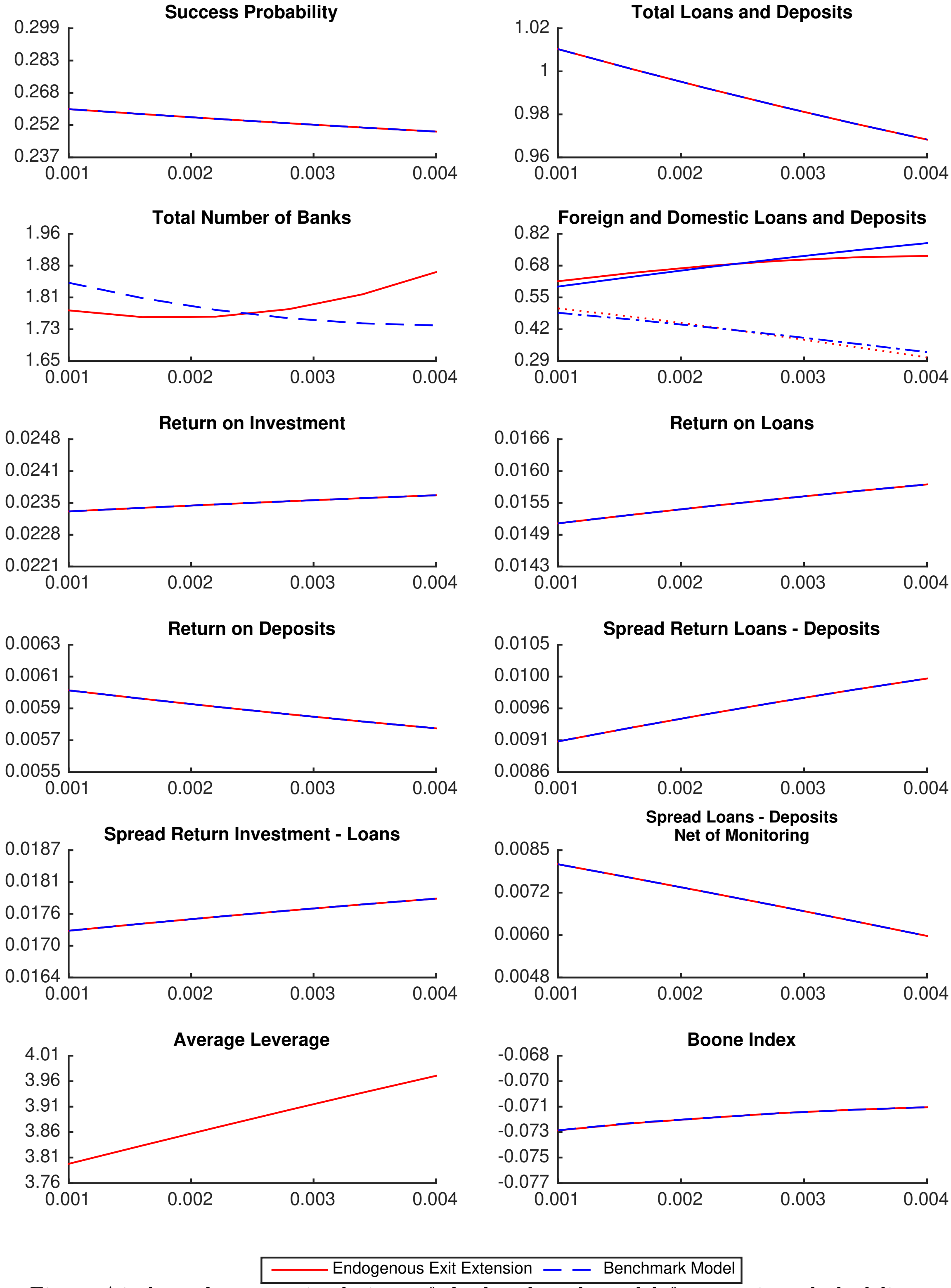

Figure A1 shows long-run simulations of the benchmark model for $\rho = 1$ as dashed lines and simulations for the model with random deposit withdrawals as solid lines. In the panel "Foreign and Domestic Loans and Deposits" dashed-dotted lines and dotted lines represent foreign loans/deposits. The variables of interest are reported on the vertical axis, while μ increases rightward on the horizontal axis. The effects of increased banking globalization (i.e. lower μ) can be gauged by moving from right to left on the horizontal axis.

Figure A2 – Banking globalization with fixed number of Banks

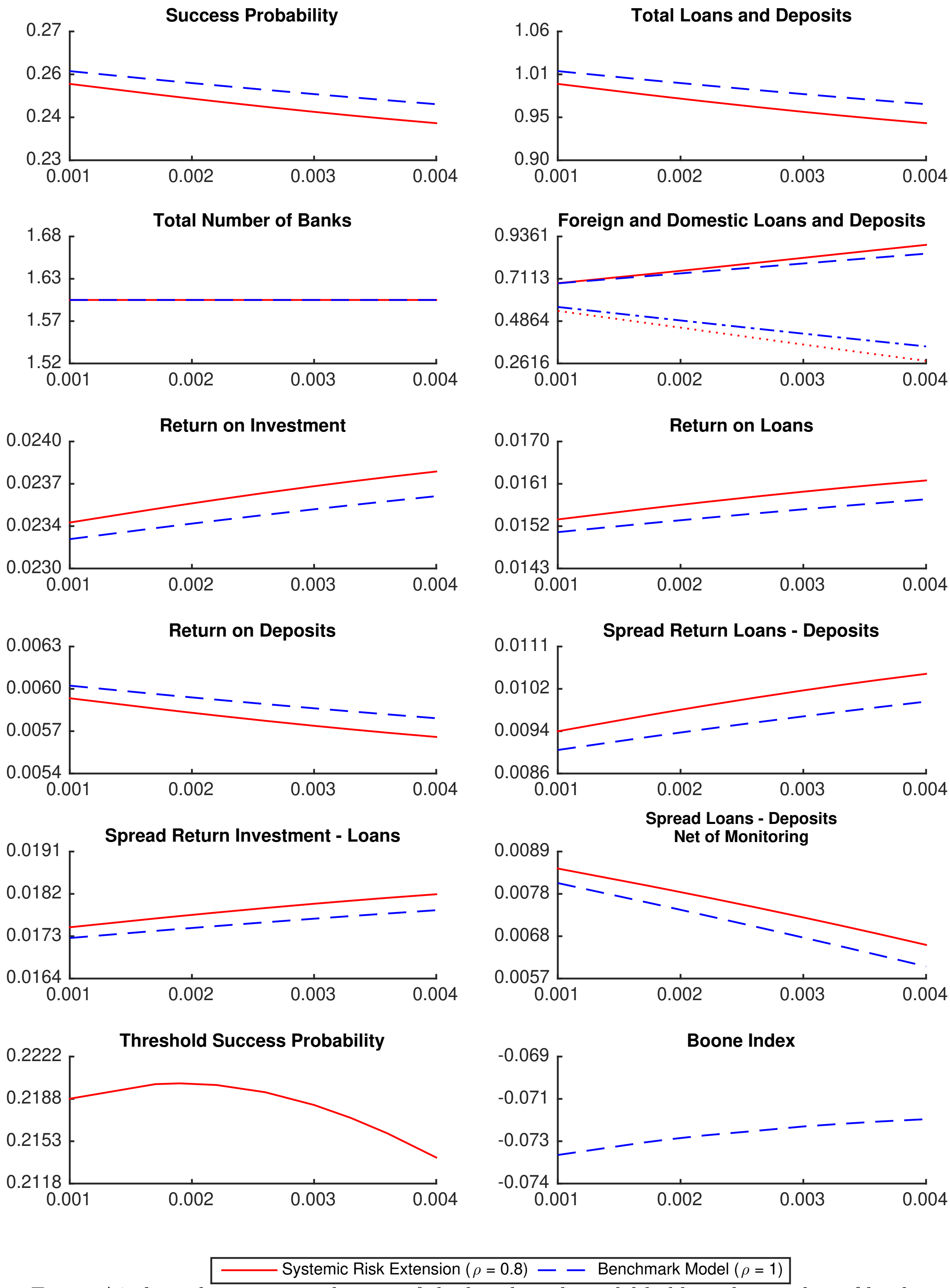

Figure A2 shows long-run simulations of the benchmark model holding the number of banks in the domestic and foreign market fixed. Dashed lines display simulations for $\rho = 1$ and solid lines results for the case of $\rho = 0.8$. In the panel “Foreign and Domestic Loans and Deposits” dashed-dotted lines and dotted lines represent foreign loans/deposits. The variables of interest are reported on the vertical axis, while μ increases rightward on the horizontal axis. The effects of increased banking globalization (i.e. lower μ) can be gauged by moving from right to left on the horizontal axis.