Internationalization, Foreign Complexity and Systemic Risk: Evidence from European Banks

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Abstract

Using a novel cross-European dataset on bank internationalization, the paper accounts for both organizational and geographic complexity and evaluates its impact on systemic risk and how both the 2008–09 global financial crisis and the 2010–11 European sovereign debt crisis might have modified such an impact. Ahead of the crisis (2005–07), results suggest that bank complexity materially reduces systemic risk and enhances stability, as it encourages banks to take on more diversified risks. While such a relation is inverted during the crisis (2008–11) and after the crisis (2012–13), consistent with the view that, during distress times, international banks have less ability to monitor cross-border risks. Furthermore, we document that complexity affects systemic risk via its impact on bank size, activity diversity and foreign expansion strategies. Regardless of the period, the effect of complexity on systemic risk is accentuated for complex 'too-big-too-fail' and banks with strong activity diversity. Conversely, we find that complex banks with merger-acquisition experience and with foreign branching strategy effectively mitigate systemic risk at the acute crisis and the later stage of the crisis, respectively. Findings bear critical policy implications for the implementation of ring-fencing requirements and systemic risk-based capital surcharges.

JEL codes: G11, G21, G28, G32

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1. Introduction

It is by now well established that deregulation and financial innovation have reshaped the structure of international banking and prompted globalization among large financial institutions. Along the way, banks grew substantially in their organizational complexity, incorporating broad and complex network of foreign affiliates (i.e. subsidiaries, branches and interconnected legal entities), encompassing different business types in local and overseas markets (e.g., Dell'Ariccia and Marquez, 2010; McCauley et al., 2010; Berger et al., 2017).[2, 3] These profound changes have spurred banks to become larger and more diversified (business lines/regions) given value-enhancing through consolidation processes, economies of scale and scope, and yet, systemically riskier (e.g., Herring and Carmassi, 2010, Hughes and Mester, 2013; Goetz et al., 2016).[4] Hence, the 2008–09 global financial crisis (GFC) has clearly demonstrated that banks' complexity and size made them systemically more important, which were later recognized as systemically important financial institutions–SIFIs or "too-complex-to-unwind" banks.[5] Consequently, these developments have triggered regulatory debates and active academic on the effects that internationalization, geographical expansion and complexity of the so-called SIFIs have, especially for financial stability (see Claessens and van Horen, 2012; Ceterolli and Goldberg, 2014; Carmassi and Herring, 2016; among others).[6] Regulators have focused on stringent approaches to regulate and supervise such complex SIFI banks, by redesigning existing frameworks for regulatory capital requirements and by advocating size caps, breakups and cross-border activity limits (e.g., IMF-BIS-FSB, 2009; FSB, 2011). Basel Committee for Banking Supervision-BIS (2011, 2013) has proposed stress tests, enhanced capital and liquidity regulations to contain systemic risk, and improved resolution planning. The 'Volcker rule' of the US Dodd–Frank Act, the UK Vickers report (Vickers, 2011) and Liikanen proposals in Europe (Liikanen, 2012) have supported restrictions of certain activities (ring-fencing) deemed especially risky (e.g., insulation of trading from deposit activities into a separate subsidiary).

[2] More evidences on the transformations of bank holding companies (BHCs) and interstate banking are provided by Herring and Carmassi (2010), McCauley et al. (2010), Claessens and van Horen (2012) and Ceterolli et al. (2014). Studies that specifically look on impacts of banking regulations on banks' operations in foreign markets under different organizational structures (foreign branch and/or subsidiary), see e.g., Deng and Elyasiani, (2008) and Dell'Ariccia and Marquez (2010). More details on bank internationalization and complexity, see Cetorelli and Goldberg (2016) and Berger et al. (2017).

[3] Cetorelli and Goldberg (2014) provide three broad measurement concepts of complexity of global banking: (i) organizational complexity (the number of affiliates), (ii) business complexity (the types and variety of activities conducted), and (iii) geographical complexity (the global diversity of operations).

[4] Higher complexity can simultaneously imply a higher degree of diversification. We use the term complexity throughout the paper to implicitly refer to diversification and cross-border activities. See Herring and Santomerro (1990), Laeven and Levine (2007), De Jonghe et al. (2015), Krause et al. (2017) and Berger et al. (2017).

[5] The Financial Stability Board (FSB) defines SIFIs as financial institutions whose distress or disorderly failure, due to their size, complexity, cross-jurisdictional activity and systemic interconnectedness, would cause significant disruption to the wider financial system and negative spillover effect to real economic (FSB, 2011). Size and complexity made SIFIs more important leading to '*too-big-to-fail*' (TBTF) and '*too-complex-to-unwind*' paradigms.

[6] We follow the convention in this literature and use the word '*complexity*' to evaluates how intricate is a network of different activities and legal entities in domestic/foreign markets and the extent of its geographical distribution. See Clarke et al. (2003), Claessens et al. (2010), Claessens and van Horen (2014b) and Krause et al. (2017).

The economic theory in banking provides conflicting views on the effect of bank internationalisation and geographic diversification on risk. The literature argues that such effect can be either good or bad in reducing bank's risk. On the positive side, it is widely recognized that diversification strategies into cross-border activities with returns that are imperfectly correlated might reduce idiosyncratic risks, the so-called *diversification hypothesis*. This makes internationally diversified banks more cost-efficient and less exposed to domestic shocks, and hence reducing their idiosyncratic risks and enhancing stability (see e.g., Laeven and Levine, 2007; Gropp et al., 2011; Goetz et al., 2016; Berger et al., 2017). However, on the negative side, the advocates of the so-called *market risk hypothesis* argue that cross-border expansion might increase overall risk as it make banks holding similar asset portfolios, exposing them to similar risks. This argues that international banks may have higher risk due to market-specific factors that make foreign assets relatively risky, unless this risk is offset by a low correlation with domestic assets (see e.g., Buch et al., 2013; Goetz et al., 2016; Berger et al., 2017). In such a setup, Wagner (2010), Ibragimov et al. (2011) and Allen et al. (2012) argues that geographical and functional diversification in interlinked systems pose international banks to similar risk exposures, and thus systemic shocks might affect the whole financial system.[7] Furthermore, Buch et al. (2013) argue that internationally active banks acquire substantial market power, whereas international activities do not necessarily make them less risky, as long as the costs of monitoring cross-border activities outweigh the benefits in terms of complexity (i.e. *diversification*). While Dell'Ariccia and Marquez (2010) stress that host country risks are the key challenges that can hinder the expansion of a bank's to new overseas markets and the choice of the foreign organizational entity set (subsidiary *versus* branches).[8]

Existing empirical assessments analyse aspects of organizational and geographic complexity of bank holding companies as well as their potential implication for *risk-adjusted returns* and *standalone BHC risk* (Akhigbe and Whyte, 2003; Deng and Elyasiani, 2008; Fang and van Lelyveld, 2014; Goetz et al., 2016; Krause et al., 2017), *diversification* and *financial fragility* (Calomiris, 2000; Barth and Wihlborg, 2016; Carmassi and Herring, 2016), *risk monitoring* and *adverse effects on asset quality* (Berger et al., 2005; Brickley et al., 2003), *loan quality* and *bank fragility* (Berger and Ofek, 1995; Servaes, 1996; Denis et al., 1997), *capital* and *loans* (Demsetz and Strahan, 1997; Laeven et al., 2016; Acharya et al., 2016), and *balance sheet management strategies* (Cetorelli and Goldberg, 2016)[9]. However, the previous literature focusses on analysing *individual aspects* of bank risk. There is still no academic consensus on the effect of bank complexity, both organizational complexity of banks' affiliates and their geographical dispersion on systemic exposure or contagion risk. There is a dearth of empirical evidence on how complexity affects systemic risk, and so financial stability. A partial exception is Carmassi and Herring (2016),

[7] Insights on the '*asset similarity'*, see Allen et al. (2012) and Girardi et al. (2018).
[8] Other empirical support for diversification is the '*correlation puzzle*'. See Aviat and Coeurdacier (2007).
[9] More detailed surveys related to complexity are provided by Clarke et al. (2003) and Carmassi and Herring (2016). For a summary, see also Gropp, et al. (2011), Cetorelli et al. (2014), Berger et al. (2017) and Krause et al. (2017).

who show that the organizational complexity of 29 Global Systemically Important Banks–G-SIBs (8 from the U.S.) has increased in the pre-GFC period, and slightly decreased in the aftermath of the GFC, and argue that large mergers and acquisitions arrangements are the main driver of complexity. They also advocate the importance of economies of scale and scope and tax rules for international banking.

The 2008–09 GFC, followed by the 2010–11 European sovereign debt crisis, provides a legitimate experiment that allow us to investigate whether the effect of bank complexity on systemic risk varies through time (normal *versus* distress times). In this work, we seek to extend the literature on bank internationalization to account for both *organizational* and *geographic* complexity, link it to the strand of literature on systemic risk and aim to examine the effect of bank complexity on systemic risk. For that, we turn our attention to internationally active European banking, and address the following questions: Does bank internationalization enhance financial stability? And at what extent the effect of organizational and geographic complexity on systemic risk might differ during sound and distress period? Specifically, in this paper we disentangle the effect at the normal times (2005–07), from the effect at the peak of the GFC (2008–09) and the highest of the European sovereign debt crisis (2010–11). We concomitantly consider not only the pre-crisis (2005–07) and the acute crisis years (2008–11), but also the post-crisis period (2012–13) to assess whether a different influence of complexity on systemic risk at the height of these crises is more or less persistent, and hence investigate their implications on financial stability. Complex SIFIs are more likely to care about their sensitivity to a sudden market shortfall than to how much their cross-border operations and strategies might jeopardize the real economy in crisis episodes. In addition, we go further by exploring whether bank size, activity diversity and foreign organizational strategies serve as *channels* through which complexity affects systemic risk. To the best of our knowledge, this is the first paper on bank internationalization of European banks that seeks to assess the direct link between foreign complexity and systemic risk, over the peak of GFC (2008–09) the height of the European sovereign debt crisis (2010–11) and the aftermath period (2012–13). To address these questions, we construct a unique hand-collected dataset on parent European banks' networks of foreign affiliates from Bankscope/SNL to define our measures complexity *over time* and relate them to systemic risk. We obtain bank level financial information from Bloomberg and Thomson Reuters. Unlike Carmassi and Herring (2016)' study that is limited to US and non-US G-SIBs, our sample specifically covers 105 listed European banks over the 2005–2013 period. On the one hand, we follow Cetorelli and Goldberg (2014), Carmassi and Herring (2013, 2016) and Barth and Wihlborg (2016, 2017) to build complexity proxies on affiliates structure of ultimate parents. Specifically, we focus on two broad definitions of complexity by using *organizational* complexity – set of proxies encompassing specific aspects of network of foreign subsidiaries – and *organizational* complexity – set of proxies capturing the geographic dispersion and span of these affiliates across different locations – that we construct for each of international European banks. On the other hand, we combine the insights from Anginer et al. (2014), Laeven, et al. (2015), Acharya et al. (2016) and Bakkar et al. (2019), and *mainly* focus on three measures underlining systemic risk, which are their systemic exposures (Marginal Expected Shortfall (MES)), their expected capital shortfall (SRISK) and their systemic risk contributions (delta Conditional Value-at-Risk (ΔCoVaR)).

The key findings reveal that bank internationalization and complexity – both organisational and geographical complexity proxies – lead to a lower systemic risk measured by the systemic exposure (MES), magnitude of capital shortfall (SRISK) and contagion risk (ΔCoVaR). Bank complexity may dampen systemic risk and drive more stability because of diversification advantages. Hence, as active international banks choose to expand geographically and operate foreign affiliates in multiple markets, their asset portfolios might become less similar to each other, making them acquiring substantial diversification benefits and less disadvantages arising from asset similarity (see e.g., Wagner, 2010; Ibragimov et al., 2011; Goetz et al., 2016). However, this stabilizing effect is short-lived. Bank complexity appears to be an important driver of systemic risk and instability during the 2008–11 acute crisis and the 2012–13 post-crisis years. Indeed, the effect is significantly reversed (or dampen with regards to the impact stated in the 2005–07 period) during the distress times (see e.g., Allen et al., 2012; Krause et al., 2017; Girardi et al., 2018). Overall, we show that while complex banks operating foreign affiliates across geographic borders are associated with lower systemic risk in normal times, the effect is reversed when the banking system undergoes global shocks making it more complex for international bank to monitor their cross-border activities and manage risks. These findings suggest that complex banks might be advocated to build capital shortfall buffers during sound years – risk accumulating period – that can be drawn down in the event of a systemic shock.

Deeper cross-sectional investigations assess the following question: What are the channels through which complexity affects systemic risk? We combine insights form Laeven and Levine (2007), Bhagat et al. (2015), Carmassi and Herring (2016) and Goetz et al. (2016) and investigate important aspects of systemic importance, i.e. bank size, activity diversity and foreign expansion strategies. When we dig into these three aspects, we find that the impact of complexity on systemic risk (negative in normal times and positive in stress times) is more pronounced and relevant for TBTF banks as well as banks that experienced M&As activity (and hence strong income diversity) and strong income diversity. In contrast, during the 2008–11 acute crisis years, we find that complex banks that have experienced M&A event (i.e. strong asset growth) contribute effectively to mitigate systemic risk with comparison to their without-M&A-involvement peers. We also find that banks operating exclusively a network of foreign branches might be more effective in mitigating systemic risk during the 2011–13 distress years, and thought to contribute less to the risk of systemic disruptions, compared to their peers operating exclusively a set-up of foreign subsidiaries or a mix corporate structure with both affiliate types. The results remain valid with several robustness checks including alternative systemic risk measures, addressing the acute crisis by detangling the 2008–09 global financial crisis and the 2010–11 European sovereign debt crisis, alternative regression specifications, alternative frequency samples and different sample selection criteria. Our findings carry various policy implications, especially for too-complex and systemically important financial institutions.

The remainder of the paper is structured as follows. Section 2 introduce the dataset and the empirical methodology. Section 3 describes the construction of our bank complexity and systemic risk variables and report some statistics. Section 4 provides univariate analyses, presents the empirical results and discusses the additional analyses. Section 5 presents robustness tests and performs additional estimations. Section 6 concludes the paper with suggestions for policy implications.

2. Sample and model specification

In this section, we first provide the procedures that we follow to construct our sample, and then discuss the empirical setup of our baseline model.

2.1. Sample

The approach presented in this paper relies on market information required to estimate systemic risk measures. Addressing this aspect, we focus exclusively on publicly traded banks headquartered in Europe and analyse the 2005–13 period[10]. We restrict the analysis to commercial, cooperative and savings banks that are internationally active[11]. Also, because of their specific business models, we exclude banks with less than $500 million of total assets[12].

Our methodological approach is based on a two stage procedure that requires both bank-specific stock market data and balance sheet information. From Bloomberg, we retrieve bank stock prices and other market data, which we combine with accounting and structural data from various sources. We extract bank-level annual accounting data from the Bureau Van Djik (BvD) BankScope and Thomsen-Reuters Advanced Analytics (TRAA) databases. Bloomberg is a well-known proprietary database collecting market data across publicly listed companies, while TRAA and BankScope are databases collecting balance sheet statements across a large sample of countries. All banks in our sample report annual financial statements following an accounting period running from January 1 to December 31.[13]

In order to construct a representative and homogenized sample, we apply several selection criteria and restrictions. First, we drop banks with infrequently traded stocks and low variability in stock prices. Then, we restrict the subsample to banks with continuously traded stocks. More specifically, we disregard a stock if daily returns are zero over five rolling consecutive days. Third, we consider bank stocks with more than 70% of the daily returns over the period that are non-zero returns. Finally, for each year we eliminate outliers and extreme values of all variables.

[10] We end the sample period in 2013 in order to avoid the confounding effect of the implementation of the Basel III regulations in Europe that among other things introduced size caps and cross-border activity limits for complex international banks.

[11] We focus on these banks due to similar core business specializations.

[12] Small cooperative banks in Europe are known for their focus on traditional banking activities, i.e. lending, deposit and banking accounts services, with limited market-based operations. We exclude those with total assets less than $500 million, ratio of net loans to total assets above 33% and the ratio of customer deposits to total assets above 50% (see, Distinguin et al., 2013; Bakkar et al., 2020).

[13] December 31 is the end of the fiscal year. We also consider local Generally Accepted Accounting Principles (GAAP) for all banks over the study period.

Moreover, to map the internationalization pattern of banks, we hand-collect a unique database on how banks are present abroad, and the number and locations of banks' foreign affiliates around the world from BankScope and SNL. For each bank and its affiliates, we go through annual reports and websites to match the collected data and refill the missing data, in cases of discrepancies, we extract and add complementary data. Given the built maps of foreign organizational strategies for each bank, we compute degrees of *organizational* complexity (incorporated subsidiaries or/and branches) and *geographic* complexity (dispersion of affiliates around the world) using the method initially proposed by Dell'Ariccia and Marquez (2010), Barth and Wihlborg (2016, 2017) and Krause et al. (2017). For more precise details on bank internationalization, see Section 3.1.

Due to the delisting of many banks, mainly due to merger-and-acquisition activity, our final sample consists of 105 publicly traded banks in 15 European countries: Austria, Czech Republic, Denmark, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Poland, Portugal, Slovakia, Spain, and Sweden from 2005 to 2013.[14] Although we only consider publicly listed banks, our sample conveniently represents the European banking sector. The publicly traded banks included in our sample account for approximately 52% of the total assets of the European banks recorded in BSI/Bloomberg statistics.[15] Sample size varies across regression specifications because not all variables are available for all bank year observations. More information on the sample composition by country and by year can be found in Panels A and B of Table A1 in appendix.

2.2. Empirical methodology

To evaluate the effect of complexity on systemic risk associated with internationally active European banks and investigate whether this relationship differs according to the conjecture, we define a large timeline to include both the GFC and the European sovereign debt crisis. To address these concerns, we estimate the following reduced regression model:

$$Risk_{ijt} = (\alpha_1 + \beta_1 Crisis08\_11 + \beta_2 Post12\_13) * International_{ijt} + \beta_3 Crisis08\_11 + \beta_4 Post12\_13 + \varphi X_{ijt-1} + \gamma Country_{jt-1} + \omega_i + \varepsilon_{ijt}, \quad (1)$$

where $Risk_{i,j,t}$ is a measure of systemic risk of *parent* bank *i* in country *j* computed over year *t*; $International_{i,t}$ is a measure of internationalization and complexity of *parent* bank *i*; *Crisis08_11* is a dummy for the acute crisis (both the GFC and the European sovereign debt crisis), equalling one if the year is 2008, 2009, 2010 and 2011, and zero otherwise[16]; *Post12_13* is a dummy

[14] We focus on European countries for reasons of data availability and cross-countries consistency and homogeneity. Countries like Norway and Iceland were excluded from our analysis because no listed banks provide data consistent with the criteria we used to build and clean the dataset.

[15] We do not include banks that were non-listed (listed) for some years but become listed (delisted). Our approach considers a sample of banks with stable presence abroad and/or low speed of changes of locations of the international banks' affiliates.

[16] Crossing different timelines given by BIS (2010, 2011) and Banque de France (2010, 2012), the financial crisis started in July 2007 in the U.S., intensified after the collapse of Lehman Brothers in September 2008, and turned into

accounting for the post-crisis period, equalling one for the years 2012 and 2013, and zero otherwise; $X_{i,t-1}$ is a vector of lagged bank characteristics (hence time $t-1$) and $Country_{jt-1}$ is control-level control variables; ω_i is the vector of bank fixed effects (which subsume country fixed effects) account for time-invariant unobserved bank heterogeneity such as quality of management, risk preferences and the mix of markets in which the *parent* bank operates; and ε_{ijt} is the error term. In the presence of lagged controls, the inclusion of bank (or firm) fixed effects in systemic risk regressions is econometrically and economically important. We build on the insights of Anginer et al. (2014) and Krause et al. (2017) and use bank fixed effects estimations to mitigate the endogeneity concerns. First, complexity and systemic risk measures can be driven by omitted bank-level heterogeneity, that is, variables that are relatively stable over time such as: ownership structure, business model and/or capital structure (Goetz et al. 2016). Second, the decision to expand overseas might be endogenous as banks may choose an organizational entity set in foreign markets when the benefits outweigh the costs of operating abroad (Buch et al., 2013). Throughout the paper, the reported standard errors are heteroskedasticity robust and adjusted for clustering.

In the baseline specification, we investigate the relationship between five bank internationalization and complexity measures, by detangling between three measures of *organizational complexity*: (i) presence abroad with subsidiaries, (ii) number of host countries where *parent* bank has a foreign subsidiary and (iii) number of subsidiaries, and two measures of *geographical complexity*: (i) geographic dispersion, and (ii) complexity index of the foreign affiliates, and three measures of systemic risk over the whole 2005–13 period: the MES, SRISK and ΔCoVaR. Therefore, the parameters α_1, $(\alpha_1+\beta_1)$, and $(\alpha_1+\beta_2)$ in the Eq. (1) capture the effect of internationalization and complexity on systemic risk during the pre-crisis period (2005–07), the acute years of both the peak of the GFC and the highest of the European sovereign debt crisis (2008–11), and the later stage (2012–13), respectively.

3. Data and variables

We start by presenting the procedures we follow to measure banks' foreign complexity and systemic risk, and then outline the characteristics of control factors specified in the baseline model of the Eq. (1).

3.1. Building bank foreign presence and complexity variables

We evaluate the complexity of parent banks in terms of its presence abroad, the penetration of foreign markets and the widespread of their foreign operations. We adopt two broad definitions of complexity. First, we introduce '*organizational*' complexity measurements to indicate the degree to which the organization is structured through separate affiliated entities (i.e. incorporated

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a global economic crisis in early 2009. In the aftermath of this period, the European sovereign debt crisis started in the late 2009 (mainly in Greece, Ireland, Portugal and Spain) and had profoundly affected all European economies in 2011. In 2012, the agreement of the EU to bailout Greece on February 21st and the adoption of an EU fiscal compact treaty on March 2nd mark the beginning of strong interventionist measures in order to stop the contagion of the crisis and provide stability for all EU countries. Hence, we define crisis times over the 2008–2011 period.

subsidiaries or/and branches). Second, we introduce '*geographic*' complexity, which captures the span of the organization's affiliates across different regions or countries (i.e. dispersion of affiliates around the world). We address the issue of foreign bank penetration and organizational complexity by differentiating three types of penetration strategies: (i) foreign subsidiaries only, (ii) foreign branches only, and (iii) dual strategy with both types of affiliates, (see, Herrero and Martinez Peria, 2007; Dell'Ariccia and Marquez, 2010)[17]. Importantly, subsidiaries need to comply with host country regulatory requirements; while branches are extensions of the parent bank and in general need to abide home country rules[18]. In the baseline results, we exclusively investigate banks' internationalization strategy with foreign presence in the form of subsidiary. For further investigations, we investigate the two subsequent banks' internationalization strategies and disentangle single strategy (exclusive choice of one affiliate type) and a dual strategy (with both affiliate types).[19]

From BankScope we identify banks that have at least one foreign subsidiary and collect data as of the end of 2007, 2010 and 2013. Hence, taking into account the legal procedures and costs related to the opening/closing of foreign affiliates, we assume that these will lead to sticky and lower speed of change of the organizational structure and presence abroad over time. Henceforth, we replay on the internationalization measures constructed for the year 2007, 2010 and 2013, and backfill values for 2006 and 2005, 2009 and 2008, and 2011 and 2012, respectively. Using these dataset, we consider three proxies for *organizational* complexity. First, we create a dummy variable, $Foreign_{ij}$, that takes value of one when the parent bank *i* from country *j* owns at least one subsidiary abroad, and zero otherwise (i.e. either bank is not present abroad or does not have foreign presence in the form of subsidiary, but operates another type of foreign affiliate). Second, given the (economic, political, social and cultural) differences between all host countries, we construct a continuous variable, $NbHost_{ij}$, that measures the international presence of the *parent* bank *i* around the world and gives the exact number of host countries where it owns at least one foreign subsidiary. Third, following Carmassi and Herring (2013, 2016), Laeven et al. (2015) and Barth and Wihlborg (2016, 2017), we introduce the natural *logarithm* of the number of subsidiaries, $NbSubsidiaries_i$, as an indicator of foreign complexity. Overall, international banks that have a large number of subsidiaries across different countries and regions of the world might have more possibilities for

[17] We also follow the insights from Ball and Tschoegl (1982), Fisher and Molyneux (1996) and Breakley and Kaplanis (1996), Cetorelli and Goldberg (2014), among others.
[18] A subsidiary is a majority-owned (>50%) entity that is directly owned by parent bank, competes directly on a local market, abides the regulations of its host country, owns its full accounting statements, and so is totally independent from its parent. On the contrary, a branch is an extension of the parent bank, which undergoes the home country supervision and all its activities, assets, incomes and costs, and is accounted for by the parent bank. A subsidiary operates under limited liability and therefore the parent bank is shielded from great losses, and yet more exposed to expropriation risk. Conversely, with a branch, the parent bank maintains its capital at home and to some extent avoids some of the constraints imposed by foreign regulators.
[19] Unfortunately, it is not possible to identify foreign branches systematically and comprehensively over the study period from publicly available data. We partially corrected this defect using for publicly available data in SNL; but only at the end of year 2010 (see analyses in the subsection 4.3.3).

regulatory arbitrage, as they abide the host country regulations, and thus cause coordination problems among regulators from different countries in case the *parent* bank has to be resolved.

Furthermore, we include two other proxies of *geographical* complexity, by considering: first, geographic dispersion of foreign subsidiaries around different world regions, and second, geographical complexity index. On the basis of the World Bank regional division of countries, we defined the following eight regions: East Asia & Pacific (EAP), Europe (EUR), Central Asia (CA), Latin America & Caribbean (LAC), Middle East & North Africa (MENA), North America (NA), South Asia (SA), and Sub-Saharan Africa (SSA).[20, 21] Against this division, we consider for each *parent* bank *i* the continuous variable $NbRegions\_Sub_{ij}$ that accounts for the number of regions where foreign subsidiaries are located. Besides, following the insights of Cetorelli and Goldberg (2014) and Krause et al. (2017), we construct a normalized Herfindhal (*GeoComplexS*) index that assesses the geographical complexity of foreign subsidiaries. By construction, *GeoComplexS* index ranges from 0 (lowest complexity) to 1 (highest complexity), the lowest complexity indicates a presence in a unique region and the highest complexity describes a presence in all regions with the same number of subsidiaries. We use the eight previously defined regions *r* to build an index for each bank that has established subsidiaries abroad, as follows:

$$GeoComplexS_{ij} = \frac{R}{R-1}\left(1 - \sum_{r=1}^{R}\left(\frac{NbSubsidiaries_{i,r}}{NbSubsidiaries_{i}}\right)^2\right), \qquad (2)$$

where R is the total number of r world regions; $NbSubsidiaries_{i,r}$ is the number of subsidiaries of *parent* bank i in region r; and $NbSubsidiaries_i$ is the total number of subsidiaries of *parent* bank i. Therefore, although, higher geographical complexity might help withstand local shocks, it can increase agency problems and exposure to global systemic shocks and spillovers. This would result into increased risk-taking policy before crisis times and higher vulnerability during instability times.

Table 1 reports the distribution of the 105 parent banks by country and foreign activities over three sub-periods: 2005–07, 2008–10 and 2011–13. The dataset indicates that the while most of publicly listed banks are from Denmark (21.90%), France (17.14%) and Italy (16.19%), whereas Czech Republic (0.95%), Hungary (0.95%), and Ireland (0.95%) have the fewest representatives in the sample. We also observe that on average 50 European banks in the sample own at least one foreign subsidiary. Comparing the number of subsidiaries, we find that during both the 2005–07 (and the 2008–10) periods French, German and Italian banks operate most of the foreign subsidiaries in

[20] The World Bank regional division of countries consists of seven groups with Europe and Central Asia (ECA) representing a unique group. Considering the countries and their economic, cultural, and political specificities we divide ECA into: (i) Europe (EUR) for countries in ECA located in Europe continent and (ii) Central Asia (CA) for the rest. Similarly, we remove Malta and Gibraltar from MENA region, as defined by the World Bank, and move them in the newly created Europe (EUR) region.

[21] Figure A1 in appendix displays the map of the World regional division of the World Bank.

Europe, with respectively 586, 431 and 350 (434, 349 and 163) affiliates. However, this organizational structure and representativeness in the 2011–13 period differ from those in the two previous periods. Thus, French (140), Spanish (72) and Swedish (68) banks hold the largest networks of foreign subsidiaries around the world.

Concerning, the bank foreign expansion (of their network of subsidiaries), French and German banks over the whole period are with the wider international presence in terms of the number of host countries [and world regions]. Data shows that network of foreign subsidiaries of French banks are present in 63 host countries [8 regions] for the 2005–07 period, then in 57 [8] for the 2008–10 period and in 47 [8] for the 2011–13 period. Similarly, we find that foreign subsidiaries of German banks are dispersed in 57 foreign countries [8 regions] for the 2005–07 period, then in 47 [8] for the 2008–2010 period and in 24 [6] for the 2011–13 period.

Considering the index of geographic complexity of foreign subsidiaries, we find that the average complexity index decreases from 0.33 in the 2005–07 period to 0.31 in the 2008–10 period (as the dispersion of geographical regions of banks' subsidiaries has generally decreased), before increasing back to 0.34 in the 2011–13 period. Results also highlight that Portuguese banks are operating the most regionally diversified network of foreign subsidiaries (with an average index of 0.69, 0.71 and 0.82 over the 2005–07, 2008–10 and 2011–13 periods, respectively) among all banks in the sample.[22]

Subsequently, these findings suggest that banks are highly concerned about readjusting quickly their organizational structure and operations abroad towards their main markets. Investigations on the observed drops in number of foreign subsidiaries, specifically for French and German banks between the data extraction at end of 2010 and 2013, might have different causes. First, according to IMF (2015), the pre-crisis level of cross-border operations reflected a temporary unsustainable boom[23]. Hence, one implication of the 2008–09 global financial crisis on banks' organizational network of affiliates was a shift away from international activities to more local lending via domestic branches and subsidiaries. Thus, since 2008, many international banks have significantly retrenched from international business, by reducing number of foreign affiliates, in order to refocus on core markets, rebalance their business models away from market-based to bank-based activities/markets, refocus their geographical presence on fast-growing markets and adjust their risk exposures (Claessens and van Horen 2014a). Second, IMF (2015) also explains this changes of cross-border affiliates/operations by a combination of regulatory and supervisory changes, weaknesses in banks' affiliates balance sheets (consolidation and cash pooling issues) and some macroeconomic factors (e.g. monetary policy factors, exchange rates) leading up to the global financial crisis. In sum, ring-fencing of cross-border banks is achieved by reducing number of foreign affiliates, closing foreign representations and legal entities, restricting and refocusing

[22] It is not striking that Danish and Polish banking systems present similar characteristics as they both comprise large listed cooperative/regional banks with comparison to **French**, Italian and German systems.
[23] See chapter 2 of the Global Financial Stability Report (IMF, 2015).

operations in the main markets, and reducing geographical dispersion of the foreign network of affiliates. [24]

[Insert Table 1 about here]

Table 2 shows the distribution of foreign subsidiaries by country in the eight different world regions. Regardless of the region, the total number of subsidiaries has significantly decreased throughout the three sub-periods, from 1838 in the 2005–07 period to 1429 in the 2008–10 period (i.e., a change of –22.25%, with regards to the 2005–07 period), and then to 484 (i.e., a change of –66.13%, with respect to the previous sub-period). Going through the downfall of the GFC and European debt crisis, banks have faced numerous losses which might have forced them to close some of their counterparts abroad. Conspicuous, we ascertain that most of the foreign subsidiaries are located in Europe (1001, 753 and 202) and North America (372, 297 and 78).

[Insert Table 2 about here]

3.2. Bank systemic risk measures

Our empirical methodology devotes a special attention to market-based time-varying systemic risk measures. Although there is no common definition of systemic-wide risk, as suggested by Borio (2011) and Bisias et al. (2012), our study builds on consistent frameworks for systemic risk analyses that have been applied in a number of recent studies (see e.g., Weiss et al., 2014; Anginer et al., 2014; Laeven et al., 2015; Bakkar et al., 2020).[25] In this step, we estimate three systemic risk–*maker* measures: the Marginal Expected Shortfall (MES), the systemic capital shortfall (SRISK) and the delta Conditional Value-at-Risk (ΔCoVaR). We also compute two additional systemic risk–*taker* measures: the Merton's probability-of-default and quantile Tail-β, for robustness check. All measures are estimated at time t given information available in t–1 on one-day bank/market tail-risk, and then averaged on the yearly-basis over the period January 2000 to December 2013.

3.2.1. Bank-level systemic risk: MES, SRISK and ΔCoVaR

We consider three main systemic risk measures: the MES, SRISK and ΔCoVaR. The first measure follows and Brownlees and Engle (2012), Acharya et al. (2016) and Bakkar et al. (2019a). It corresponds to the expected return stock return for bank i conditional on the market return when

[24] In case the drop might come from databases' issues, we conducted additional checks of our sample. Going through all filtering procedures, controlling and comparing them with other extractions, we were not able to find any discrepancies. Bankscope does not give information about what might explain these changes. We followed instead several policy reports (e.g., Cetorelli et al., 2014; Ceterolli and Goldberg, 2014) and/or previous studies (e.g., Carmassi and Herring, 2016) to have a closer look.

[25] Barth and Schnabel (2013) argue that idiosyncratic risk measures are not sufficient to capture banks' systemic risk, as they neglect aspects such as interconnectedness within financial markets, underlying tail risks and economic conditions.

the latter declines substantially[26]. The MES identifies the bank's system risk participation in a systemic event. It takes the following form:

$$MES_{i,t}^{q=5\%} \equiv E\left(R_{i,t} | R_{M,t} \leq VaR_{R_{M,t}}^{q}\right), \tag{3}$$

where $R_{i,t}$ is one-day stock return for bank i, $R_{M,t}$ is one-day market return[27], q-percent is a pre-specified quantile and $VaR_{R_{M,t}}^{q}$ stands for Value-at-Risk, which is the critical threshold that equals the worst expected market loss given the p-percent quantile of the market return $R_{M,t}$ distribution. Herewith, we set q to be equal to 5-percent, the term $R_{M,t} \leq \mathrm{VaR}_{\mathrm{R_{M,t}}}^{\mathrm{q}}$ reflects the set of days when the daily market return is being at or below the 5-percent tail outcomes.

The second measure of systemic risk is SRISK index, estimated based on the MES. For the purpose of macroprudential regulations, we quantify SRISK to measure the extent of bank i's capital shortfall to systemic-wide distress when the market performs poorly, as proposed by Brownlees (2012) and Engle et al. (2015). SRISK explicitly takes into account the size, equity and capital ratio of the bank. Formally, Brownlees and Engle (2017), Laeven et al. (2015) and Acharya et al. (2012) define SRISK as:

$$SRISK_{i,t} = E_{t-1} \times (Capital\ Shortfall_i | Crisis) = \left(kD_{i,t}\right) - \left(VE_{i,t} \times (1 - k) \times \left(1 - LRMES_{i,t}\right)\right), \tag{4}$$

where k is the minimum prudential capital ratio each bank has to hold (we set k equal to the equity-to-total *unweighted* asset ratio of 8 percent), $VE_{i,t}$ is market value of its equity and $D_{i,t}$ is book value of its debts (proxied by total liabilities). Following Acharya et al. (2012), we use an approximation to compute long-run MES ($LRMES_{i,t}$) based on one-day MES loss expected if market returns are less than −2-percent: $LRMES_{i,t} = (1-k)exp^{(-18\ MES_{i,t})}$.[28] Unlike Acharya et al. (2012) and Laeven et al. (2015), we do not limit SRISK from below to zero. Here, we allow SRISK to take negative values, with a view that highly capitalized banks with large buffers can easily absorb systemic shocks and subtract systemic risk from the financial system.[29]

[26] Economically, the term '*marginal*' refers to the bank's capital shortfall stemming from each unit variation in the equity value. The $\mathrm{MES}_{\mathrm{i,t}}^{\mathrm{q}}$ measures variation in systemic risk induced by a marginal increase/decrease in bank i's exposure to the system.

[27] We either refer to the financial sector index or the broad market index, as market portfolio benchmark; so as to, catch bank's contribution to the economy stability.

[28] LRMES is an approximation of the tail expectation of the stock return for bank i in a crisis, i.e., when the mark drops by 40 percent over the next 180 days. In these market conditions, SRISK is based on the assumption that the bank's debt $D_{i,t}$ will remain constant over the 180 days horizon, while its market capitalization $VE_{i,t}$ will decrease by its 180 days return in a crisis.

[29] See Engle et al. (2015) and Black et al. (2016) for analysis of SRISK on a larger sample of European banks.

The third systemic risk measure is ΔCoVaR. Following Adrian and Brunnermeier (2016), we estimate CoVaR based on the VaR of one-day market return $\mathrm{R_{M,t}}$ conditional on a tail event observed for bank *i*. $CoVaR^{q}_{R_{M|i,t}}$is the *q*-percent quantile of a conditional probability distribution which is defined as follows[30]:

$$Prob_{t-1}\left(R_{M,t} \leq CoVaR^{q}_{R_{M|i,t}} \mid R_{i,t} = VaR^{q}_{R_{i,t}}\right) = q, \tag{5}$$

where $\mathrm{VaR^{q}_{R_{i,t}}}$corresponds to the critical threshold equal to the *p*-percent quantile of the bank return $R_{i,t}$ distribution. Explicitly, we follow Adrian and Brunnermeier (2016) to define bank's contribution to the systemic risk: ΔCoVaR as the difference between the VaR of the financial market conditional on bank *i* being in distress and the VaR of the system conditional on the bank *i* being in its median value. It catches the externality a bank causes to the entire financial system. Correspondingly, $\Delta\mathrm{CoVaR^{q}_{R_{M|i,t}}}$ refers to the difference between $\mathrm{CoVaR^{q}_{R_{M|i,t}}}$of the market when bank *i* is in distress (i.e. the bank stock return is at its bottom *q*-percent probability level) and $\mathrm{CoVaR^{q=median}_{R_{M|i,t}}}$ of the market when bank *i* is in its median return value (i.e. the inflection point at which bank performance starts becoming at risk) (see Hautsch et al., 2014; Mayordomo et al., 2014; Black et al., 2016; Bakkar et al., 2019a). Setting *q* at 1-percent, ΔCoVaR of bank *i* is expressed as:

$$\Delta CoVaR^{q=1\%}_{R_{M|i,t}} = CoVaR^{q=1\%}_{R_{M|i,t}} - CoVaR^{q=50\%}_{R_{M|i,t}}. \tag{6}$$

The Eq. (6) can be written as:

$$\Delta CoVaR^{q=1\%}_{R_M|R_i=VaR^{1\%}_{R_{i,t}},t} = \hat{\lambda}^{1\%}_{R_{M|i,t}}\left(VaR^{1\%}_{R_{i,t}} - VaR^{50\%}_{R_{i,t}}\right), \tag{7}$$

where $\hat{\lambda}^{1\%}_{R_{M|i,t}}$ is the slope of the 1-percent quantile regression estimating $\mathrm{CoVaR^{q=1\%}_{R_{M|i,t}}}$ when bank *i* is in financial distress[31].

Our paper derives systemic risk based on two standalone measures of tail risk: value- at-risk (VaR) and expected shortfall (ES). Several differences between the MES, SRISK and ΔCoVaR should be taken into consideration for the purposes of our analyses. First, the MES and ΔCoVaR are

[30] Quantile regression estimates the functional relationship among variables at different quantiles (Koenker and Hallock, 2001) and allows risk co-dependence during stress periods by taking into account nonlinear relationships when there is a negative shock.

[31] We define Conditional VaR $\{\mathrm{CoVaR^{q}_{R_{M|i,t}}=VaR^{q}_{R_{M,t}}|VaR^{q}_{R_{i,t}}}\}$ as follows: $\mathrm{CoVaR^{q}_{R_{M|i,t}}} = \hat{\alpha}_{\mathrm{R_{M|i}}} + \hat{\lambda}^{\mathrm{q}}_{\mathrm{R_{M|i,t}}}\mathrm{VaR^{q}_{R_{i,t}}} + \hat{\varepsilon}_{\mathrm{M|i,t}}$. For bank's $\mathrm{VaR^{q}_{R_{i,t}}}$, we run 1-percent and 50-percent quantile regressions, using one-day bank's stock prices as: $\mathrm{VaR^{q}_{R_{i}}} = \hat{\mathrm{R}}_{\mathrm{i,t}} = \hat{\alpha}_{\mathrm{i}} + \widehat{\gamma_{\mathrm{i}}^{\mathrm{q}}}\mathrm{R_{M,t-1}} + \hat{\varepsilon}_{\mathrm{i,t}}$. See Mayordomo et al. (2014) and Adrian and Brunnermeier (2016).

expressed as percentages, while SRISK is expressed in billions of US dollars. Second, the main difference between these concepts is the directionality. The MES and SRISK assesses the extent to which a bank's stock will lose value when financial systemic is in distress, whereas ΔCoVaR identifies the extent to which distress at a bank contributes to system-wide stress. Hence, SIFIs are more likely to care about their sensitivity to a sudden market shortfall (as well as the capital shortfall proportion) than to how much their operations might jeopardize the financial system in times of crisis. Third, neither the MES nor ΔCoVaR incorporates *ex-ante* bank size, capital and equity in estimating systemic risk, while SRISK does. Fourth, MES and ΔCoVaR are positive and given in absolute risk value. I.e., an increase in these bank's systemic risk measures is thus given by a positive change.

3.2.2. Systemic risk as measured by probability of default and Tail-β

For further analyses and robustness check, we suggest also two additional measures of bank systemic risk: probability of default and Tail-β.

We follow Merton (1974) contingent claim framework to measure probability-of-default. This model considers bank equity as a single-period European call option on bank's assets. The probability of default is computed using the distance-to-default metric, which is the difference between the asset value of the firm and the face value of its debt, scaled by the standard deviation of bank's asset value. Bartram et al (2007), Anginer et al. (2014) and Hovakimian et al. (2015), among others, have used the Merton model to measure probability of default as proxy of systemic risk of commercial banks. Formally, we follow Hillegeist et al. (2004) and Campbell et al. (2008) to compute the Merton's distance-to-default (dtd) for each bank i at the end of year t as:

$$dtd_{i,t} = \frac{log\left(\frac{VA_{i,t}}{D_{i,t}}\right)+\left(r_f-0.5\times(\sigma^A_{i,t})^2\right)\times T}{\sigma^A_{i,t}\sqrt{T}}, \quad (8)$$

where $VA_{i,t}$ is the market value of bank's assets; $D_{i,t}$ is book value of its debts (proxied by total liabilities) maturing at time T; r_f is risk-free rate (10-year government bond in given country) and $\sigma_{A,i,t}$ is the volatility of the bank's assets.

The $dtd_{i,t}$ requires to estimate $VA_{i,t}$ and $\sigma_{A,i,t}$, neither of which are directly observed. Following the option pricing model of Black and Scholes (1973), equity can be modelled as a call option on the underlying bank's assets. Therefore, market value of equity and volatility are estimated from observed stock prices ($VE_{i,t}$) and their volatility ($\sigma^E_{i,t}$), by solving simultaneously the following system of nonlinear equations:

$$VE_{i,t} = VA_{i,t}N(d_1) - X_t e^{-r_f T} N(d_2), \qquad \sigma^E_{i,t} = \left(\frac{VA_{i,t}}{VE_{i,t}}\right). N(d_1). \sigma^A_{i,t}, \quad (9a)$$

where $VA_{i,t} = VE_{i,t} + D_{i,t}$ and N is the cumulative normal distribution function and d_1 and d_2 are given by:

$$d_1 = \frac{log\left(\frac{VA_{i,t}}{D_{i,t}}\right) + \left(r_f + 0.5.\left(\sigma_{i,t}^A\right)^2\right) \times T}{\sigma_{A,it}\sqrt{T}}, \qquad d_2 = d_1 - \sigma_{A,it}\sqrt{T}. \tag{9b}$$

For that, we *quadratically* extrapolate the book value of bank's debts over the period; so as to, match them with the daily market value of its assets[32].

In this paper, we focus specifically on the Merton's probability of default (PD) defined as the normal transformation of the dtd, computed as: $PD_{i,t} = F(-dtd_{i,t})$, where F is the cumulative distribution function of a standard normal distribution. Thus, default happens when the market value of assets $VA_{i,t}$ of bank i at year t falls below the book value of the debt $D_{i,t}$. The larger the $dtd_{i,t}$, the greater is the distance of bank i from the default point and the lower is the $PD_{i,t}$; and thus contribute less to the entire financial instability.

Following Koenker and Hallock (2001), Engle and Manganelli (2004), De Jonghe (2010) and Bakkar et al. (2020), we measure quantile Tail-*βs* (spillover coefficients) for each bank to captures its sensitivity to extreme movements. For that, we estimate Tail-*βs* using q-percent quantile regression at 1% and using $R_{i,t}$ one-day stock returns for bank i's and $R_{M,t}$ one-day market returns as follows:

$$\hat{R}_{i,t} = \hat{\alpha}_i + \widehat{\beta_i^q} R_{M,t-1} + \hat{\varepsilon}_{i,t}. \tag{10}$$

The larger is Tail-β ($\widehat{\beta_i^{1\%}}$), the higher is bank i's spillover effect and the more is its vulnerable to financial downturns.

3.3. Control variables

In examining the relationship between complexity and systemic risk, we include in our estimations a vector of control variables (matrix X in Eq. (1)) which are expected to affect individual systemic risk indicators. We follow previous studies in the literature and compute for each *parent* bank i over each year t, a set of bank-level controls (see e.g., Anginer et al., 2014; Weiß et al., 2014 and Laeven et al., 2015). We account for bank *size* per se, defined as the natural logarithm of total assets in the U.S. dollars; *leverage*, measures the ratio of equity-to-total unweighted assets to control for capital ratio; *diversification*, indicates the reliance on non-interest income activities (income diversity ratio), *deposit*, considers bank's involvement in market-based activities (deposits to total assets), *loan* funding (net loans over total assets), *efficiency*, stands for cost income ratio (non-interest expense over total income) and *ROA*, stands for return on assets ratio (net income to total assets). In addition, we control at the country-level for the growth rate of real gross domestic product (GDP Growth Rate) to account for macroeconomic conditions in the *paren*t bank' country.

[32] Interpolation method has the advantage of producing smooth implied values and avoids jumps in the implied default probabilities at year-end. See Anginer et al., 2014.

All variables are winsorized at the top and bottom 1 percent level to eliminate the adverse effects of outliers and misreported data.[33]

4. Empirical findings

In this section, we begin by displaying and discussing the main univariate analyses. We use univariate mean tests to look into foreign presence and banks' characteristics for the entire period versus the three considered periods (2005–07, 2008–11 and 2012–2013). We then present the empirical analyses to investigate the dynamics in the relationship between banks' complexity and systemic risk during normal vis-à-vis distress times.

4.1. Descriptive statistics and univariate analysis

Table 3 displays the descriptive statistics of the key financial characteristics of banks and compares them throughout the 2005–07, 2008–11 and 2012–13 periods. We observe that on average measures of systemic risk (the MES and SRISK) are at the lowest levels (resp., 1.17 and 4.83) during the 2005–07 period, prior to the crisis years, while their averages values increase significantly over the subsequent sub-periods (resp., 3.30, 12.43 vs. 3.32, 13.32 during the 2008–11 and 2012–13 periods, respectively). These measures are also disperse with respect to standard deviations and mini-max values. Such stylized facts are also consistent for ΔCoVaR, probability of default and Tail-β. We hence point out that maximum levels of ΔCoVaR (6.85) and probability of default (0.57) were reached during the 2008–11 crisis period, whereas Tail-β was in its maximum (3.17) during the post-crisis period. Overall, statistics reveal that banks vary in terms of systemic importance, and the average bank is systemically riskier during and after the severe crisis years.

With regards to the controls across banks, different evidences are observed throughout these three sub-periods. For instance, the average bank is well-capitalization (average leverage ratio observed in the 2005–07 period is 9.09%), but this level reduces significantly (to 8.68% in the 2008–13 period vs. 8.01% in the 2012–13 period) suggesting that the average bank becomes less-capitalized during and after the crisis (with regards to the pre-crisis period). We also observe that the average bank has high profitability in the 2005–07 period (average ROA of 1.17%), however, during the 2008–11 and 2012–13 periods, banks dramatically lose in profitability (resp., from 0.35% to 0.06%). In terms of retail market funding (deposit) and operational efficiency (cost-to-income share), the average bank is strongly liquid and more cost-efficient in the pre-crisis period (res. 48.52%, 40.08%) than in the subsequent 2008–11 and 2012–13 sub-periods (resp., 49.36%, 42.33% vs. 49.58%, 45.20%). Regarding diversification and loans, the average bank is moderately diversified in terms of revenue (29.82%) and assets (69.19%) over the pre-crisis period, however during the acute crisis period, average bank becomes strongly reliant on traditional activities (average loan and diversification of: 26.10%, 72.61%), before it regains its initial levels in the later 2012–13 period (resp., 28.80%, 69.23%).

[33] More information on the definitions, the sources and the summary statistics of these variables are presented in appendix A1 (Tables A1 and A2) and the papers referenced therein.

[Insert Table 3 about here]

In Table 4, we compare the systemic risk measures and the key financial characteristics for subsamples of banks without and with foreign subsidiaries over the full period of time and across 2005–07, 2008–11 and 2012–13 periods. Results point out that irrespective of the period, banks with foreign subsidiaries exhibit a significantly higher exposure to systemic risk and are larger in size per se compared to the other banks without foreign affiliates. However, they are significantly less capitalized, less liquid, diversified in terms of assets and less profitable than other banks.

Considering the changes over the three sub-periods for banks without and with foreign presence, the statistics suggest that the difference is greater during the crisis times (2008–11) than during the pre-crisis (2005–07) and post-crisis (2012–13) periods. Overall, considering the severe crisis years (2008–11), results show that multinational banks with foreign affiliates exhibit significantly higher systemic risks, are very large in absolute size (natural log of total assets), are undercapitalized (leverage ratio), rely less on deposits and loans and perform less (ROA) compared to their peers during the 2005–07 and 2012–13 periods.[34]

A possible explanation could be that large and complex banks, such as parents that tie together a large count of different affiliates, might take on excessive risks and engage in multiple cross-border activities and diversification strategies (e.g., combining domestic and foreign business types/regions), when they expect government bailouts in case of distress. Alternatively, such banks could be regarded as sufficiently complex and opaque to justify the costs associated with the agency frictions, as suggested by their higher cost-efficiency and poor performance, specifically during distress times (i.e. lower efficiency and ROA), that can translate into systemic risk. Such stylized facts are jointly consistent with the *unstable banking hypothesis* (e.g., Gennaioli et al., 2013; Boot and Ratnovski, 2012) and the *agency cost hypothesis* (e.g., Laeven et al, 2016; Laeven and Levine, 2007).

[Insert Table 4 about here]

We display in Table 5 the correlation matrix for the main variables employed in the analysis over the 2005–13 period at the bank level. Variables of internationalization and foreign complexity are observed only for bank with a presence abroad, and hence the statistics indicate a positive and significant correlation between *Foreign* and *NbHost*, *NbSubsidiaries*, *NbRegions_Sub* and *GeoComplexS*, which unable us to use them simultaneously in the regressions. The correlation matrix also suggests that there is a structural reason why some banks become large (size per-se), undercapitalized (leverage ratio), diversified (asset mix) and systemically risky at the same time. Yet, the statistics reveal no major collinearity issues among the rest of the variables that would

[34] Although we picture tremendous changes in banks' cross-border operations through the period of study, we do not analyze the drivers of these changes. This could be a scope of a future research.

prevent us from using them simultaneously in the regressions. We determine the variance inflation factor for each of the models, results suggest that multicollinearity does not affect our results.

[Insert Table 5 about here]

4.2. Regression results

We first examine the effect of banks' foreign complexity on the estimated measures of systemic risk of listed European banks depending on the state and soundness of the financial system. Specifically, we determine whether the relationship between bank international activities (i.e. organizational and geographical complexity) and systemic risk is different during the GFC and European sovereign debt crisis and at the later stage of these crises. We run the regression specified in Eq. (1) and include complexity variables and their interactions with times dummies.

4.2.1. Bank internationalization and stability: impact of organizational and geographic complexity on systemic risk

Table 6 (Panels A and B) displays the coefficient estimates for the bank fixed effect regressions. In Panel A, we primarily analyse the baseline relationship between the organizational complexity measured using a dummy indicating if the bank is operating *exclusively* foreign subsidiaries (*Foreign*) and systemic risk measured using the MES, SRISK and ΔCoVaR, over the normal pre-crisis times (2005–2007), the acute crisis (2008–2010) and the post-crisis years (2012–2013). Panel B displays the results of the other measures of foreign organizational complexity: number of host countries (*NbHost*) and number of subsidiaries (*NbSubsidiaries*), and geographical complexity measures: geographical complexity (geographic dispersion (*NbRegions_Sub*) and complexity index of foreign affiliates (*GeoComplexS*).

Across Columns (1a–3a) of Panel A, we start by including only the dummy variable *Foreign* to account for the complexity organisational as explanatory variable for bank systemic risk. We do not find clear-cut results as the relationship between *Foreign* and systemic risk is not significant. Next, in Columns (2a), (2b) and (2c) of Panel A, we allow for non-linearity in the relationship by including only the complexity dummy (*Foreign*) as explanatory variable and its interactions with time dummies, since our control variable are correlated between each other. Then, in Columns (3a), (3b) and (3c) of Panel A, we report the regression results including bank and country level control variables. The baseline results suggest that before the crisis (2005–07), banks with foreign presence (*Foreign*) exhibit a negative and statistically significant effect on the three systemic risk measures (Columns 2a–3a, 2b–3b, 2c–3c), suggesting that international banks, operating foreign subsidiaries, reduce individual systemic risk and pose less adverse effects on financial instability. Internationalization would then incentivize banks to control risk-taking and help to reduce systemic risk –in terms of systemic exposure and contagion risk– and hence enhances stability.
Subsequently, we investigate differences in such relationship with regards the 2008–11 and 2012–13 periods. The first observation about the results in Panel A is that all interaction variables are significant. Results reveal that with respect to the pre-crisis period, the negative effect of

internationalization on systemic risk is either lessened (during the acute crisis 2008–11) or reversed (in the post crisis 2012–13). When significant, the Wald test indicates that while the effect of internationalization and complexity on the MES (SRISK) is reversed during the 2008–11 period ($\alpha_1+\beta_1$ carries a positive and statistically significant at the 1% (5%) level), the negative effect on ΔCoVaR is not reversed (but lessened) ($\alpha_1+\beta_1$ carries a negative and statistically significant effect at the 10% level) (Columns 3a, 3b, 3c). Looking at the post-crisis period (2012–13), the positive effects derived during the acute crisis episodes continue and become substantially larger. By summing the coefficients in all Columns, the Wald test shows positive and statically significant for all risk models, indicating that the effect of bank presence abroad on systemic risk is completely reversed during the pre-crisis episode (α1+β2 is significant and carries the opposite sign to α1). The Wald test also suggests that the extent of such effect on systemic risk is more sizable during the post-crisis years (2012–13) with regards to the acute-crisis period (2008–11). Indeed, this negative effect between foreign bank penetration and systemic risk during the pre-crisis years is not persistent (i.e. short-lived) because such impact is either lessen or reversed at the acute crisis period.

The results are not only statistically significant but also economically telling. During the pre-crisis (post-crisis) years, a one standard deviation (0.50) increase in complexity proxy (*Foreign*) decreases (increases) the MES, SRISK and ΔCoVaR by around 49% (9%), 31% (7%) and 30% (9%) of its mean respectively.[35] Overall, the evidence in Panel A of Table 6 suggests that operating foreign subsidiaries enhances stability only during the pre-crisis years, and amplifies instability during the later periods.

In Panel B of Table 6, we include the other complexity measures. Columns (4b) and (5b) illustrate that the relationship between the other two organizational complexity measures (namely the number of host countries of foreign subsidiaries, *NbHost*, and number of subsidies in banks, *NbSubsidiaries*) and systemic capital shortfall (SRISK) are negative and statistically significant at the 1% level. Whereas, we find that *NbHost* is negatively and statistically significant at the 1% (10%) level related to the MES (ΔCoVaR) (Columns 4a, 4c), while *NbSubsidiaries* is negatively and statistically significant at the 5% level related to ΔCoVaR (Column 5c). The results implies the number of subsidiaries per se and its network abroad dull international banks to reduce systemic risk, and thus enhance financial stability. By the same token, geographical complexity measures (namely widespread in different world regions, *NbRegions_Sub*, and Herfindhal complexity index, *GeoComplexS*) are negatively and statistically significant at a 1% level associated with SRISK (Columns 6b, 7b). Results suggest that geographic complexity – in terms of geographical dispersion and diversification – is economically beneficial in reducing banks' exposure to the deterioration of the capitalization of the financial system. Columns (6a vs. 7a) indicate the existence

[35] Based on Columns 2a, 2b and 2c of Panel A, the effect of complexity proxy (*Foreign*) on systemic risk (MES, SRISK and ΔCoVaR) before the crisis is computed as follows:
$\frac{\partial Risk}{\partial \text{Foreign}}(Crisis_{08\_11} = Post_{12\_13} = 0)$= [0.50*–1.268]=–0.63; [0.50*–10.95]=–5.48, and [0.50*–0.659]=–0.33. This is associated with 49%, 31% and 30% standard deviation reduction in the individual bank's systemic risk exposure (MES), capital shortfall (SRISK) and contagion risk (ΔCoVaR), respectively.

of a negative and significant relationship only for *NbRegions_Sub* and the exposure to systemic risk (MES) at 5% level. However, both organizational complexity measures do not appear to be an important driver of contagion risk (ΔCoVaR) (Columns 6c, 7c). These results are in line with the estimations reported in Panel A.

We go further in investigation, and repeat the Wald test to assess the stability of these relationships and track possible changes during the 2008–11 and 2012–2013 sub-periods. The estimated coefficients of the interaction terms (β1 and β2) have mostly positive intuitive signs, though not always statistically significant. Our results again find that bank complexity is an important determinant of the change in systemic risk across time, highlighting that the negative effect during the pre-crisis years (2007–08) is short-lived. Hence, consistent with our previous results as regards to the 2008–10 period, the Wald test ($\alpha_1+\beta_1$) documents that the negative effect is ether significantly reversed (Columns 4b, 5a–5c, 6b, 7a–7b), strongly lessened (Columns 4a, 4c, 6a) or non-existent (Column 6c, 7c). With respect to the post-crisis period (2012–13), the Wald test ($\alpha_1+\beta_2$) indicates a reversed effect for all risk measures, except for ΔCoVaR (Column 7c), and show that the relationship between complexity and systemic risk becomes positive and statistically significant. This implies that complexity of banks' network of foreign affiliates and its geographic dispersion pose greater systemic risk, which undermines financial stability. Our investigations confirm that the negative effect of complexity on individual systemic risk, carried during the pre-crisis years, is short-lived, with respect to the adverse effect of complexity on systemic risk at the later periods.

Our results are not only statistically significant but also economically meaningful. For instance, during the pre-crisis (post-crisis) years, a one standard deviation (1.40 unit) increases in the number of host countries around the world (*NbHost*) decreases (increase) the MES and SRISK by around 66% (6%), 102% (12%) and 33% (14%) of its mean (Columns 4a, 4b and 4c in Panel B). While, a one standard deviation (2.36 unit) increases in the number of host countries around the world (*NbRegions_Sub*) decreases the MES and SRISK by around 53% and 90% of its mean respectively, during the pre-crisis years; and increase the MES, SRISK and by around 13%, 12% and 18% of its mean respectively, during the post-crisis years (Columns 4a, 4b and 4c in Panel B).

Among the remaining controls in both Panels A and B of Table 6, most of them carry the signs obtained in previous studies. Importantly, coefficients of both the acute crisis dummy and the post-crisis dummy show mostly an increase in the bank systemic risk (Bakkar et al., 2020). To account for unweighted regulatory capital ratio, we use leverage which we expect to have a positive effect on systemic risk. Highly leveraged banks are generally more engaged in market-based activities and untable funding, which we found to be associated with higher systemic risk (see e.g., Farhi and Tirole, 2012; Bhagat et al., 2015; Laeven et al, 2016). With respect to loans, the effect is expected to be negative, as loans are usually more stable than non-interest activities (Berger et al., 2017). Whereas, diversified banks, engaged in risky market-based activities, are generally found to be associated with higher systemic risk (De Jonghe, 2010; Bertay et al., 2013). Operational efficiency is expect to have a negative effect on bank systemic risk. That is cost-effective banks are systemically riskier (De Jonghe et al., 2015). We control for differences in the macroeconomic environment by controlling for the growth rate of the real gross domestic product. Results expect a higher GDP growth rate to lower systemic risk (Distinguin et al., 2013; Bakkar et al., 2020). Overall, these evidences suggest that international banks (that are systemically riskier) have more fragile business model: overleveraged, less-stable funding, more non-interest-based activities, less-cost-effective, and more complex.

To summarize, evaluating the relationship between bank complexity and stability over different time periods shows a heterogeneous picture. Overall, results in Panel A and B of Table 6, together with those of Goetz et al. (2016), confirm that organizational/geographic complexity is seen as detrimental for systemic risk. Our evidences suggest that complexity enhances stability during normal times (2005–07), but strongly undermines stability during distress times, specifically during the 2012–13 period. Many might argue that during normal times, complexity – in term of subsidiaries' network and geographic dispersion – sizes up the diversification of business activities across geographic borders, which incentivizes banks to take on diverse risks, and hence leads to lessen systemic risk and higher systemic stability (Wagner, 2010; Gropp et al., 2011; Goetz et al., 2016; Carmassi and Herring, 2016). In contrast, during financial shock, higher complexity increases agency problems and exposure to system-wide shock spillovers. This explains the steady downward trend in international banking (diversification) in order to mitigate systemic exposure (Cetorelli et al., 2014; Krause et al., 2017). Indeed, international SIFI banks are likely to care about their complexity to a sudden market shortfall, pointing the adverse effect of complexity on systemic risk and banking system stability in times of crisis. Overall, our results lend support to the theoretical prediction in Wagner (2010) and Ibragimov et al. (2011) that bank diversification may result in higher bank systemic risk and instability concurrently.

[Insert Table 6 about here]

4.2.2. Deeper exploration of alternative systemic risk measures

We examine whether our results for the three considered periods are robust across alternative measures of systemic risk. Likewise, we run the Eq. (1) and present in Table 7 the coefficient estimates for bank fixed effect regressions. In Column (1a) of Table 7, results suggest that bank internationalization (*Foreign*) strongly mitigates probably-of-default (PD) and thus increases financial stability before the period of crisis (negative α_1), while its effect on sensitivity to extreme shocks (Tail-β) is not statistically significant (Column 1b). Such relation is reversed during the later periods (positive β_1 and β_2), we expect it to be statically stronger in increasing default and tail risks during the 2011‒13 years. More precisely, as shown by the Wald test, we find operating foreign subsidiaries to be positively and statically significant linked to default and tail risks during financial distress times (α_1+ β_1 and α_1+ β_2 are positive and statistically significant), such positive effect is significantly stronger during the 2011–13 period.
Regarding the four other indicators of complexity, we find operating large network of subsidiaries in different geographical regions to carry a negative and statistically significant effect on default risk during the pre-crisis years (Columns 3a, 4a), but not significant regarding tail risk. These

results suggest that complexity – larger and disperse network of subsidiaries – reduces probability of default and contributes to enhance stability. However, such an effect is short-lived, the Wald test highlights the existence of either a reversed or a reduced –to a lesser extent– effect during the 2008–10 period ($\alpha_1 + \beta_1$, in Columns 2a, 3a, 4a, 5a) only on default risk, or a completely reversed effect during the 2012–13 period ($\alpha_1 + \beta_2$, in Columns 2a, 2b, 4b, 5b) on both default and tail risks. Results suggest that, in the presence of bad economic conditions or financial shocks, complex banks – operating large network of subsidiaries and spanning multiple borders – become strongly riskier, because of their higher probability of defaults (and their Tail-βs to a lesser extent), which poses greater probability of crash and undermines stability. Overall, the obtained results are consistent with our main results in Table 6, and with evidences lent by Goetz et al. (2016), Berger et al. (2017) and Laeven and Valencia (2018).

[Insert Table 7 about here]

In what follows, we further investigate the potential determinants that might affect the non-linear relationship between complexity and systemic risk for international banks.

4.3. Further investigations of the impact of complexity on systemic risk

In this section, we go deeper by investigating the possible factors that encourage SIFIs to become increasingly *too-complex*. Specifically, we test whether differences in size, activity diversity – including merger-and-acquisition activity (M&A) and income diversity – and organizational expansion strategies serve as channels through which complexity affects systemic risk. For simplicity and consistency, we restrict our analyses into using lonely our main regressor: foreign complexity through subsidiaries (*Foreign*).

4.3.1. Deeper exploration of the effect of bank size in the nonlinear relationship between complexity and systemic risk

We investigate whether the impact of complexity on bank systemic risk may depend on the extent of parent's bank size. We hypothesize that as banks gain advanced management skills and economies of scale and scope from their size, the effect of complexity might differ depending on the bank-level size (see, Bhagat et al., 2015; Laeven et al., 2015; Oldfather et al., 2016; among other)[36]. Hence, combining the insights from Barth and Schnabel (2013), Bertay et al. (2013) and Bhagat et al. (2015) as well as the European Central Bank criteria, we focus on two distinguishing aspects regarding SIFIs and G-SIBs, namely size per se (i.e. parent bank' absolute total assets) and relative size (i.e. parent bank's market share in the total assets of the domestic banking industry).[37]

[36] The Basel Committee on Banking Supervision (BIS, 2013) recommends against the use of assets size as a measure of complexity of large banks, but acknowledges that large banks behave differently from the other peers.

[37] The ECB identifies four criteria to define SIFIs: (i) size (total assets>€30 billion); (ii) economic importance (for the specific country or the EU economy as a whole); (iii) cross-border activities (total assets> €5 billion and ratio of cross-border assets/liabilities in more than one other participating member state to its total assets/liabilities>20%) and (iv) public financial assistance (requested or received funding from the European Stability Mechanism or the European Financial Stability Facility). https://www.bankingsupervision.europa.eu/banking/list/criteria/html/index.en.html

To investigate the effects of bank size per se on the effect of complexity on systemic risk, we break down the full sample into two groups: subsample of larger banks (recognised as TBTF, if absolute total assets is strictly above \$40 billion) and subsample of small banks (absolute total assets less than or equal to \$40 billion)[38]. Subsequently, with respect to their economic importance, we differentiate also between two subsamples: group of TBTF relative-sized banks (parent bank's market strictly above 5-percent) and group of small relative-sized banks (parent bank's market share strictly less than or equal 5-percent) (see, De Jonghe et al., 2015; Bakkar et al., 2020). For each subgroup of banks (TBTF vs. small), we run alternately Eq. (1) and look into the changes in the effect of complexity on systemic risk during the three considered periods (instead of augmenting Eq. (1) with interaction terms). Based on regulatory scrutiny, we expect it to be more acute and persistent for large-sized (vis-à-vis small-sized) banks, since SIFIs are more likely to be larger and complex.

Table 8 (Panels A and B) reports the results for subsamples of large (TBTF) versus small banks, constructed using the absolute and the relative parent's bank size cut-offs, respectively. During the acute financial crisis years, operating foreign subsidiaries is negatively associated with the MES and SRISK (α_1 statistically significant), and mainly hold for the subsamples of large banks (Columns 1a–1b in Panel A, Columns 3a–3b in Panel B). While, it does not alter uniformly ΔCoVaR. However, for the subsamples of small banks, such a negative relationship is mainly significant for ΔCoVaR (Columns 2c, 4c), and only significant (but economically lesser) for the MES and SRISK for relatively small-sized banks (Columns 4a, 4b). Subsequently, as shown by the Wald test, we find that operating foreign subsidiaries exhibits a strong positive and statistically significant effect on systemic risk for mainly subsamples of large-sized banks during the 2008–11 period ($\alpha_1 + \beta_1$ of Panels A and B in Table 8), while results for subsamples of small-sized banks show, notably, a significant negative effect on ΔCoVaR (and mixed evidences for the other systemic risk measures). Thus, the short-lived effect only hold for subsamples of large-sized banks. Similarly, at the later stage (2012–13), the observed positive relationship between foreign complexity on systemic risk hold for both subsamples of small- and large-sized banks ($\alpha_1 + \beta_2$ of Panels A and B in Table 8). However, the economic relevance is substantial for large-sized vis-à-vis small-sized banks. Generally, regardless of the period, bank size (absolute or relative) may indeed exacerbate the extent at which bank complexity affect systemic exposure and contagion risk and hence financial stability. Our findings thereby demonstrate that the adverse effect of complexity on systemic risk is effectively relevant for larger international banks during distress times.

[Insert Table 8 about here]

[38] 43% of banks in our sample have a total of assets greater than \$40 billion. We use the corresponding threshold to define the sub-samples of large TBTF/small banks. We use the average exchange rate on the 2005–13 period (€1=\$1.334946, World Bank–World Development Indicators database) to reset bank size threshold.

4.3.2. Activity diversity, complexity and systemic risk

In this section, we go deeper by investigating other factors that might lead to enhance complexity of European banking firms and hence affect the complexity-systemic risk nexus. One way in which banks can became more complex over time is growth through activity diversity. Asset diversity, mainly substantial M&A activity, and/or income diversity lead to an increase in the number of subsidiaries, that persists over time, and endure greater impact on corporate complexity (Laeven and Levine, 2007; Cetorelli et al., 2014; Carmassi and Herring, 2016). We hence concomitantly account for the extent of both asset diversity and income diversity – M&A activity and activity mix, respectively – of each parent's bank financial activities to focus on the independent impact of complexity on systemic risk.

Following Carmassi and Herring (2016), we use M&A activity dummy, as a proxy of asset diversity, to account for banks that experienced a merger-acquisition event during the period of study. A long history of M&As might have a greater impact on parent's bank complexity and hence its systemic importance[39]. We follow Laeven and Levine (2007) and Goetz et al. (2016) and use the income diversity ratio to account for the degree to which the bank's income is diversified between major activities: net-interest income and noninterest income[40]. Formally, to address the effects of these factors on the nonlinear relationship between complicity and systemic risk, we rearrange our Eq. (1) and estimate the following model:

$$\begin{aligned} Risk_{ijt} = {} & [\alpha_1 + \alpha_2 Factor + (\beta_1 Crisis08\_11 + \beta_2 Post12\_13) \times Factor] * Foreign_{ijt} + \\ & \beta_3 Crisis08\_11 + \beta_4 Post12\_13 + \varphi X_{ijt-1} + \gamma Country_{jt-1} + \omega_i + \varepsilon_{ijt}, \end{aligned} \tag{11}$$

where *Factor* is a dummy variable that stands alternately for one of the two activity diversity, (i) asset diversity, d(M&A), which takes a value of one if the parent's bank experienced a merger-acquisition arrangement and strong asset growth, and zero otherwise; (ii) income diversity, d(IncDiversity), which takes a value of one if the parent's bank in the top quartile of income diversity (i.e., income diversity >Q3: 3rd quartile of the income diversity ratio), and zero otherwise. We include the same set of controls as in Eq. (1).

Table 9 displays the results of estimating Eq. (11). During the normal times, we find that both M&A activity and income diversity lead international banks operating foreign subsidiaries to lower individual systemic risk to a larger extent, across the three different risk measures (as shown by the Wald test, $\alpha_1+\alpha'_1$ are negative and significant in all regressions). During the acute crisis (2008–11), in the presence of foreign complexity, asset diversity is found to have a similar sizable negative effect in reducing systemic risk (as in the previous period) by reversing the positive extent of

[39] This dummy implicitly considers banks pursuing higher growth strategies. M&As arrangements lead parent's bank to growth in size by at least 15%.

[40] We define this measure in term of activity-mix as: $Income\ diversity = 1 - \left|\frac{\text{Net interest income} - \text{Total non-interest income}}{\text{Total operating income}}\right|$, where net interest income equals total interest income minus total interest expenses. Other operating income includes net fee income, net commission income, and net trading income.

foreign complexity on systemic risks (as shown by the Wald test, $\alpha_1+\beta_1+\alpha'_1+\beta'_1$ are negative and significant in all regressions in Columns 1a–1c). However, international banks that have stronger income diversity exhibit a significantly larger systemic risk exposure (as shown by the Wald test, $\alpha_1+\beta_1+\alpha'_1+\beta'_3$ are positive and significant in Columns 2a–2b). At the later stage of the financial crisis (2012–13), the results show that such international banks exhibit a significantly higher systemic risk when they experience M&A activity and/or stronger income diversity, specifically for SRISK (as shown by the Wald test, $\alpha_1+\beta_2+\alpha'_1+\beta'_2$ and $\alpha_1+\beta_2+\alpha'_1+\beta'_4$ are positive and significant in Columns 1b and 2b, respectively). [41]

[Insert Table 9 about here]

4.3.3. Do expansion strategies affect differently systemic risk and stability?

For deeper insights, we further investigate organizational complexity by looking more closely at the effect of the organizational expansion choice/strategy of foreign affiliates – foreign subsidiaries versus branches, with respect to a strategy-mix (with both affiliate types) – on systemic risk. For this purpose, we finetune our main organisational complexity regressor, by detangling strategies of internationalization (i.e. single vis-à-vis dual strategy of affiliate forms), rather than considering foreign complexity *exclusively* through subsidiaries. Because of limited data availability on foreign branching strategy (Bankscope only provides information on subsidiaries and SNL database has limited data on branches), we were only able to hand-collect branch data from SNL as of end of 2013, and match it with information on subsidiary already collected from Bankscope[42]. Similarly to data on foreign subsidiaries, we apply the values of year 2013 and backfill the values for 2011 and 2012. We hence restrict our investigations for the 2011–13 period.

Besides, *Foreign* dummy, we construct two other dummies: $Bank\_Brh_i$ equals to one if bank i operates a network of foreign branches exclusively (with at least one foreign branch and no foreign subsidiary) and zero otherwise; and $Bank\_Both_i$ takes the value one if bank i has a network of both subsidiary and branch, and zero if not. Thus, we slightly adjust Eq. (1), such that the vector of variables of interest is replaced by these three foreign complexity dummies, and estimate ordinary least squares (OLS) regressions. The regression model is specified as follow:

$$Risk_{ijt} = \beta_1 OrgComplex_{ijt} + \varphi X_{ijt-1} + \gamma Country_{jt-1} + \varepsilon_{ijt}, \tag{12}$$

where, $Risk_{i,j,t}$ represents systemic risk measures of parent's bank i in country j over the year t. $OrgComplex_{ijt}$ corresponds to three dummies representing the choice of the foreign organizational

[41] Alternately, we consider the top quartile of total asset growth over the study period as proxy of M&A activity *factor* and the highest quartile of the Herfindahl-Hirschman Index (HHI) income-based, computed by summing the squared percentage of each operational activities (net-interest and non-interest incomes) to the bank's total operating income, as proxy of income diversity *factor*, and obtain similar results.

[42] SNL only provides data on branches for the latest accounting exercise (2012 and 2013). Unfortunately, since we lost our access to the database in 2014 and were not able to find additional as detailed data elsewhere, the sample of branches is limited to the year 2013.

structure and foreign penetration strategy: an exclusive strategy with foreign subsidiaries ($Foreign_{ijt}$) or with branches only ($Branch_{ijt}$), or a dual strategy with both types of affiliates ($Dual\_Str_{ijt}$).

Table 10 present the estimation results of Eq. (12) examining whether the relationship between complexity and systemic risk depends on the foreign organizational complexity strategies. Results show that organizational complexity and foreign strategies might affect differently systemic importance of international banks. Specifically, organizational complexity of foreign affiliates through an exclusive (single) business strategy of subsidiaries and/or a mix (dual) strategy with both types of affiliates are found to pose greater systemic risk, and hence undermining financial stability during distress times (Columns 1a–1c, 3b, 3c). In contrast, results show that international banks establishing an exclusive (single) business strategy with branches only exhibit a significantly lower systemic risk during distress times (Columns 2a, 2b). Overall, bank internationalization (branching vis-à-vis subsudiaring) strategies plays a double-edged sword for financial stability. The preferred foreign affiliate structure (*with* branches or/and subsidiaries) might indeed jeopardize the financial system and specifically to even a more extent in times of crisis when bank expand abroad with (*only*) subsidiaries or with dual strategy combining both types of affiliates.

[Insert Table 10 about here]

5. Robustness checks

In this section, we perform additional regressions to check for the robustness and the validity of our main results. First, to ensure that our results are not affected by the definition and the length of the acute crisis period (2008–11), we decompose it into two subperiods to disentangle the individual effect of the acute years of the 2008–09 global financial crisis and of the 2010–11 sovereign debt crisis (and hence two dummies: *Fin08_09* and *Sov10_11*). In Table A3 in Appendix, we introduce these two dummies in Eq. (1) and revisit the effects of complexity on systemic risk. In this robustness check, we find that with the exception of the negative and significant effect of organizational complexity on systemic risk during the peak of the GFC (Columns 1a, 1c, 2a, 3a of Table A3 in Appendix) and during the highest of the European sovereign debt crisis (Column 2a, 2c of Table A3 in Appendix), the effects of *Fin08_09* and *Sov10_11* on the complexity-systemic risk nexus are consistent, in sign and significance, with our findings. As shown by the Wald test, the obtained interacted terms do not find that the effects of the GFC and the European sovereign debt crisis differ from our main results. Overall, regardless the definition of the crisis period, shocks increase the systemic risk of internationally active banks with cross-border activities and geographic complex structure (see Table A3 in appendix).

In addition, Panel A of Table A4 in Appendix consider alternative regression specification. First, we build on the insights of Laeven et al. (2015) and use ordinary least squares (OLS) estimation with robust standard-errors to estimate the baseline regression model with all dependent variables resulting from previous estimation methodologies. Second, following Beck et al. (2013) and Angenier et al. (2014), we use a time varying country fixed effect to capture time varying country-specific regulation or business cycle effects on systemic risk of banks. Third, as the number of observations varies widely across the European countries, we also use weighted least squares (WLS), with robust standard errors to correct for heteroscedasticity, to estimate the baseline model using equal weight to each country in the pooled approach. In particular, we take the inverse of the number of country observations for each country as the weight for each individual bank. Forth, to tackle differently the possible endogeneity issues, we use the two-stage least squares (2SLS) instrumental variables method with fixed effects. We reports second stage coefficient estimates from a 2SLS regression, where we use lagged regressor, asset growth and HHI assets-based as instruments for complexity proxy in the first stage. The obtained results are reported in Panel A of Table A4 in Appendix. Overall, our main finding remain unchanged and portray similar conclusions, suggesting that for results are not driven by the empirical specifications.

Furthermore, we conduct a battery of robustness checks using different sample selection criteria. First, we remove banks that operate foreign affiliates in less than six different foreign countries. Second, we restrict our sample to banks that operate strictly more than ten foreign subsidiaries. Third, we exclude banks present in less than three different world regions. Forth, we keep banks with Herfindhal geographical complexity index strictly higher than 0.33. The regression results are presented in Panel B of Table A4 in Appendix. Our results remain unchanged and robust to these alternative sample selection criteria.

We conclude that our results on bank internationalization and geographical complexity and systemic risk are robust to all these alternative regression specifications. The results are by and large in line with our main findings.

6. Conclusion

The persistent liberalization and interstate banking deregulation have changed bank organizational structure and expansion across geographic borders. The global financial crisis as well as the European sovereign debt crisis have also surged the issues of bank complexity and systemic risk on the top position of the agenda of policymakers. Hence, the Basel III Accord has, among other things, introduced stringent systemic risk-based capital requirements for too-complex SIFI banks and outright limits including size caps, breakups and cross-border activity limits.

In this paper, we assemble a unique hand-collected database on bank internationalization of European banking to construct a time-varying and bank-specific proxies for organizational and geographic complexity and empirically investigate its effect on systemic risk. Specifically, we look at whether this observed relationship is different across normal and distress times by examining how the 2008–09 global financial crisis and the 2010–12 European sovereign debt crisis might have modified such relationship. For this purpose, we consider a pre-Basel III period from 2005 to

2013 and construct a data set on bank complexity –foreign affiliate structure and expansion– and quantify systemic risk measures of 105 publicly traded banks headquartered in 15 European countries. Our findings show that, before the crisis, bank complexity – organizational and geographical – leads to significantly lower systemic risk measured by the systemic exposure (MES), magnitude of capital shortfall (SRISK) and contagion risk (ΔCoVaR) and hence higher stability. Moreover, the results suggest that complexity might size up bank diversification advantages of cross-border activities during normal times, resulting in financial stability. These findings lend support to diversification hypothesis. However, our investigations show the existence of a reversed effect during stress periods, attesting that the effect during the 2005–07 pre-crisis years was short-lived. The results show that complexity positively (or strongly lessened the negative effect in the pre-crisis years) affects systemic risk during the 2008–11 acute crisis years, while it leads to significantly higher systemic risk during the 2012–13 post-crisis years. Distress times matters in inverting such relationship as it is more complex for banks to monitor effectively their international activities and manage risk. Although international banks have significantly reduced their number of foreign affiliates (and state/region borders), during crisis times, in order to refocus on core markets, the findings suggest that higher complexity lead to higher systemic risk, resulting in unstabilizing effects.

Subsequently, this paper examines several aspects characterizing SIFI banks, that is, size importance, activity diversity and foreign expansion strategies, to explore whether they serve as channels through which complexity impacts systemic risk across sound and distress periods. We pay a special attention to differences in absolute/relative bank size, asset/income diversity and exclusive/dual foreign business model on such relationships. The investigations demonstrate that, regardless of the period, such relationships are substantially enhanced in internationally active banks that (i) are "too-big-to-fail", be it absolute or relative, (ii) experienced a history of M&As activity (and hence high level of asset growth) and (iii) benefited from strong income diversity. A closer look into asset diversity during the 2008–11 acute crisis years indicates that M&As activity has contributed to significantly lower systemic risk of internationally active banks, with comparison to their peers without M&As activity. Further investigations of foreign organizational strategies demonstrate that operating a network of branches might be more effective in mitigating systemic risk and thus enhancing system-wide stability during the 2011–13 distress years, while corporate structure with exclusively foreign subsidiaries or dual strategy combining both branches and subsidiaries leads to significantly higher systemic risk.

Overall, we find that bank internationalization is significantly matter in explaining cross-variation in bank systemic risk and financial stability during calm periods and when banking system undergoes global shocks. Our paper has direct policy implications. First, our findings are expected to be particularly useful for the ongoing debate on the merits of imposing systemic risk-based capital requirements on too-complex and SIFI banks, as outlined in the Basel III Accords (Pillar 2). According to our results, regulators and supervisors should be aware that although such institutions might contribute to greater stability in banking system in normal times –including

TBTF banks–, they might impose higher systemic risk and jeopardize international banking system during distress times. Second, our results lend support to the views that conservation buffers and total loss-absorbing capacity introduced by the Basel III Accord may not be enough to guarantee bank stability. These constraints are expected to push international SIFIs to regulatory arbitrages in cross-border banking. Furthermore, our in-of-sample results show that supervisory monitoring should closely account for the procyclical behaviour in operating foreign affiliates, specifically of SIFI banks, when they gauge and advocate outright limits on bank size and scope, and ring-fence cross-border banking.

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Table 1. Distribution of European banks by foreign activities and complexity, across the 2007–2005, 2010–2008 and 2013–2011 periods

The table shows the breakdown of the 105 listed banks by country, and the indicator of geographic complexity for foreign subsidiaries (*GeoComplex**S***), (the detailed method of calculation can be found in Section 2) for the three sets of extraction in BankScope [(2005–2007), (2008–2010) and (2011–2013)] of international observations. Delta measures in percentage the variation between (2010–2008) and (2007–2005) and between (2013–2011) and (2010–2008) for the variable in the column at the left side. We extract most of the information on banks, and number and locations of foreign from BankScope and we complete them with data from annual reports and bank web site. "/" indicates unavailable or unknown data.

	Listed banks	Banks with a foreign activity	Number of foreign subsidiaries	Delta %	Number of host countries	Delta %	Number of world regions	GeoComplexS [Mean]
				2013–2011				
Austria	6	6	15	–75.00	6	–64.71	2	0.05
Czech Republic	1	1	1	0.00	1	0.00	1	/
Denmark	23	4	38	–35.59	20	–13.04	7	0.35
Finland	2	/	/	/	/	/	/	/
France	18	6	140	–67.74	47	–17.54	8	0.48
Germany	7	4	43	–87.68	24	–48.94	6	0.43
Greece	6	4	23	–43.90	7	–22.22	2	0.06
Hungary	1	1	6	–57.14	5	–58.33	2	0.51
Ireland	1	/	/	/	/	/	/	/
Italy	17	10	62	–61.96	20	–25.93	7	0.20
Poland	10	2	2	–33.33	2	100.00	1	0.00
Portugal	2	2	14	–56.25	8	–27.27	5	0.82
Slovakia	2	/	/	/	/	/	/	/
Spain	6	6	72	–36.84	28	7.69	6	0.45
Sweden	3	3	68	–55.56	26	0.00	8	0.82
N	**105**	**49**	**484**	**-66.13**				**0.34**
				2010–2008				
Austria	6	5	60	275.00	17	70.00	3	0.05
Czech Republic	1	1	1	0.00	1	0.00	1	0.00
Denmark	23	4	59	–30.59	23	–4.17	6	0.26
Finland	2	1	5	0.00	4	0.00	2	0.54
France	18	6	434	–25.94	57	–9.52	8	0.47
Germany	7	4	349	–19.03	47	–17.54	8	0.53
Greece	6	5	41	–16.33	9	0.00	3	0.08
Hungary	1	1	14	0.00	12	0.00	2	0.28
Ireland	1	1	1	–80.00	1	–75.00	1	0.00
Italy	17	10	163	–53.43	27	–50.00	8	0.20
Poland	10	3	3	50.00	1	0.00	1	0.00
Portugal	2	2	32	–3.03	11	0.00	6	0.71
Slovakia	2	/	0	/	/	/	/	/
Spain	6	4	114	–9.52	26	–18.75	6	0.65
Sweden	3	3	153	13.33	26	4.00	7	0.60
N	**105**	**50**	**1429**	**-22.25**				**0.31**
				2007–2005				
Austria	6	4	16		10		1	0.00
Czech Republic	1	1	1		1		1	0.00
Denmark	23	3	85		24		6	0.31
Finland	2	1	5		4		2	0.36
France	18	6	586		63		8	0.56
Germany	7	4	431		57		8	0.47
Greece	6	5	49		9		3	0.15
Hungary	1	1	14		12		2	0.28
Ireland	1	1	5		4		2	0.36
Italy	17	12	350		54		8	0.25
Poland	10	2	2		1		1	0.00
Portugal	2	2	33		11		6	0.69
Slovakia	2	/	0		/		/	/
Spain	6	5	126		32		7	0.66
Sweden	3	3	135		25		6	0.45
N	**105**	**50**	**1838**					**0.33**

Table 2. Geographic distribution of foreign subsidiaries of European banks over the world regions
The table shows the distribution of the foreign subsidiaries in the eight World Bank regional divisions: East Asia & Pacific (EAP); Central Asia (CA); Europe (EUR); Latin America & Caribbean (LAC); Middle East & North Africa (MENA); North America (NA); South Asia (SA); Sub-Saharan Africa (SSA).

2011–2013	Total	EAP	EUR	CA	LAC	MENA	NA	SA	SSA
Austria	15	0	14	1	0	0	0	0	0
Czech Republic	1	0	1	0	0	0	0	0	0
Denmark	38	9	20	2	1	0	1	2	3
Finland	/	/	/	/	/	/	/	/	/
France	140	23	58	7	10	11	15	1	15
Germany	43	9	16	3	5	0	9	0	1
Greece	23	0	22	0	0	1	0	0	0
Hungary	6	0	4	2	0	0	0	0	0
Ireland	/	/	/	/	/	/	/	/	/
Italy	62	5	21	1	0	2	27	3	3
Poland	2	0	2	0	0	0	0	0	0
Portugal	14	1	4	0	4	1	0	0	4
Slovakia	/	/	/	/	/	/	/	/	/
Spain	72	2	16	0	39	2	12	0	1
Sweden	68	13	25	4	5	1	14	2	4
N	484	62	202	20	64	18	78	8	31
2010–2008	Total	EAP	EUR	CA	LAC	MENA	NA	SA	SSA
Austria	60	1	55	4	0	0	0	0	0
Czech Republic	1	0	1	0	0	0	0	0	0
Denmark	59	4	45	2	2	0	2	0	4
Finland	5	0	2	3	0	0	0	0	0
France	434	55	224	11	23	20	57	25	19
Germany	349	29	103	5	12	4	176	11	9
Greece	41	0	39	0	0	1	1	0	0
Hungary	14	0	12	2	0	0	0	0	0
Ireland	1	0	1	0	0	0	0	0	0
Italy	163	15	106	5	1	4	27	4	1
Poland	3	0	3	0	0	0	0	0	0
Portugal	32	1	17	0	3	1	3	0	7
Slovakia	/	/	/	/	/	/	/	/	/
Spain	114	5	43	0	44	3	17	0	2
Sweden	153	12	102	14	3	0	14	7	1
N	1429	122	753	46	88	33	297	47	43
2007–2005	Total	EAP	EUR	CA	LAC	MENA	NA	SA	SSA
Austria	16	0	16	0	0	0	0	0	0
Czech Republic	1	0	1	0	0	0	0	0	0
Denmark	85	3	76	3	1	0	1	0	1
Finland	5	0	4	1	0	0	0	0	0
France	586	59	299	20	19	36	119	8	26
Germany	431	45	160	7	14	6	184	12	3
Greece	49	0	43	0	0	4	1	0	1
Hungary	14	0	12	2	0	0	0	0	0
Ireland	5	0	4	0	0	0	1	0	0
Italy	350	77	209	9	8	5	39	1	2
Poland	2	0	2	0	0	0	0	0	0
Portugal	33	1	20	0	4	2	3	0	3
Slovakia	/	/	/	/	/	/	/	/	/
Spain	126	4	48	2	52	1	17	0	2
Sweden	135	6	107	11	3	0	7	1	0
N	1838	195	1001	55	101	54	372	22	38

Table 3. Summary of descriptive statistics, across the 2005–2007, 2008–2011 and 2012–2013 periods

MES= Marginal Expected Shortfall, marginal participation of a bank to the Expected Shortfall (ES) of the financial system, a measure of bank equity sensitivity to market crashes; SRisk= Systemic risk, expected capital shortfall; ΔCoVaR= ΔConditional Value-at-Risk of a bank to an entire financial system or benchmark/reference market conditional on an extreme event leading to the fall of a bank stock return beyond its critical threshold level; PD= Probability of default; Tail-beta= quantile-beta, a measure of the sensitivity to extreme movements of beta. *Foreign*= a dummy that takes the value one when the listed bank owns at least one subsidiary abroad; *NbHost*= continuous variable that accounts the number of host countries of the foreign subsidiaries; *NbSubsidiaries*= continuous variable that accounts the exact number of foreign subsidiaries a listed bank operate abroad; *NbRegions_Sub*= the number of regions where all foreign subsidiaries are located; *GeoComplexS*= the geographic complexity indicator of the dispersion of all subsidiaries in different world regions. *Size*= natural logarithm of the total assets; *Leverage(%)*= ratio of total equity to total assets ; *Deposits(%)*= ratio of customer deposits to total assets; *Diversification (%)* = ratio of noninterest income to total income; *Loans(%)*= ratio of net loans to total assets ; *Efficiency(%)*= cost to income ratio defined as non-interest expense divided by total income; *ROA(%)*= return on assets is the ratio of net income to total assets.

	Pre-Crisis 2005–2007					**Crisis 2008–2011**					**Post-Crisis 2012–2013**				
	N	Mean	SD	Min	Max	N	Mean	SD	Min	Max	N	Mean	SD	Min	Max
Bank complexity measures															
Foreign	261	0.47	0.50	0.00	1.00	348	0.48	0.50	0.00	1.00	175	0.49	0.50	0.00	1.00
NbHost	131	13.21	16.38	1.00	63.00	175	10.75	13.36	1.00	57.00	88	9.55	13.05	1.00	54.00
NbSubsidiaries	127	37.21	70.39	1.00	378.00	169	23.78	49.30	0.00	289.00	85	9.47	13.49	0.00	60.00
NbRegions_Sub	127	3.06	2.36	1.00	8.00	169	2.84	2.27	1.00	8.00	85	2.79	2.23	1.00	8.00
GeoComplex**S**	127	0.34	0.31	0.00	0.87	169	0.31	0.34	0.00	0.95	85	0.34	0.37	0.00	0.95
Systemic risk measures															
MES	261	1.17	1.30	–1.21	5.74	348	3.30	2.26	–1.64	9.63	175	3.32	2.32	–1.56	9.17
SRISK	261	4.83	17.57	–6.12	165.21	348	12.43	34.03	–6.21	223.80	175	13.32	35.84	–5.02	202.98
ΔCoVaR	261	1.12	1.11	–2.80	4.08	348	2.61	1.46	–2.01	6.85	175	2.02	1.50	–1.57	6.16
PD	261	0.00	0.01	0.00	0.21	348	0.03	0.07	0.00	0.57	175	0.06	0.10	0.00	0.53
Tail-β	261	0.69	0.81	–1.46	3.05	348	1.01	0.77	–1.57	3.07	175	1.02	0.92	–1.41	3.17
Bank characteristics															
Size	261	-3.69	2.14	–8.18	0.16	348	-3.40	2.12	–7.99	0.16	175	–3.32	2.12	–7.97	0.16
Leverage	261	9.09	5.80	0.78	44.82	348	8.68	5.05	0.78	35.68	175	8.01	4.79	0.78	30.35
Deposits	261	48.52	19.66	5.69	88.91	348	49.36	18.91	5.69	88.68	175	49.58	20.78	5.69	91.43
Diversification	261	29.82	10.95	1.06	66.54	348	26.10	12.16	1.06	66.54	175	28.80	12.37	1.06	66.54
Loans	261	69.19	16.66	13.02	90.28	348	72.61	15.30	23.37	91.60	175	69.23	17.12	13.02	91.05
Efficiency	261	40.08	12.73	14.87	79.52	348	42.33	13.77	14.87	89.93	175	45.20	13.44	14.87	84.41
ROA	261	1.17	0.92	–2.09	5.85	348	0.35	1.06	–4.58	3.61	175	0.06	1.32	–4.58	3.24

Table 4. General financial characteristics by foreign presence across the 2005–2007, 2008–2011 and 2012–2013 periods

This table compares the characteristics of banks that operate at least one subsidiary abroad and banks that do not across the 2005–2007, 2008–2011, and 2012–2013 periods. T-statistics test the null hypothesis: "bank characteristics are not different between international and non-international banks during the 2005–2007, the 2008–2011, and the 2012–2013 periods." * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ indicate the significance of p-value for a bilateral test. *MES*= Marginal Expected Shortfall, marginal participation of a bank to the Expected Shortfall (ES) of the financial system, a measure of bank equity sensitivity to market crashes; *SRISK*= Systemic risk, expected capital shortfall; Δ*CoVaR*= ΔConditional Value-at-Risk of a bank to an entire financial system or benchmark/reference market conditional on an extreme event leading to the fall of a bank stock return beyond its critical threshold level; *PD*= Probability of default; *Tail-beta* = quantile-beta, a measure of the sensitivity to extreme movements of beta. *Foreign*= a dummy that takes the value one when the listed bank owns at least one subsidiary abroad; *TA*= the bank total assets; *Size*= natural logarithm of the total assets; *Leverage(%)*= ratio of total equity to total assets; *Deposits(%)*= ratio of customer deposits to total assets; *Diversification(%)*= ratio of noninterest income to total income; *Loans(%)*= ratio of net loans to total assets; *Efficiency(%)*= cost to income ratio defined as non-interest expense divided by total income; *ROA(%)*= return on assets is the ratio of net income to total assets.

	All 2005–2013			**Pre-Crisis 2005–2007**			**Crisis 2008–2011**			**Post-Crisis 2012–2013**		
	Foreign = 0	Foreign = 1	t-statistics	Foreign = 0	Foreign = 1	t-statistics	Foreign = 0	Foreign = 1	t-statistics	Foreign = 0	Foreign = 1	t-statistics
Systemic risk measures												
MES	1.75	3.51	-13.05***	0.77	1.62	-6.15***	2.27	4.41	-11.01***	2.22	4.48	-8.09***
SRISK	0.59	20.46	-10.67***	0.43	9.73	-4.86***	0.75	25.15	-7.85***	0.51	26.88	-5.72***
ΔCoVaR	1.50	2.51	-10.78***	0.85	1.42	-4.7***	2.11	3.16	-7.86***	1.28	2.8	-8.54***
PD	0.02	0.04	-2.79***	0.00	0.00	1.20	0.03	0.04	-2.79***	0.05	0.07	-1.49*
Tail-β	0.61	1.22	-12.08***	0.45	0.95	-5.70***	0.71	1.33	-9.09***	0.66	1.40	-6.32***
Bank characteristics												
Size	-4.82	-2.01	-26.95***	-5.02	-2.20	-15.49***	-4.81	-1.85	-19.89***	-4.54	-2.04	-10.56***
Leverage	11.06	6.06	16.54***	11.83	6.04	10.20***	10.91	6.24	10.64***	10.17	5.72	7.57***
Deposits	54.59	43.38	9.08***	54.1	42.29	5.52***	54.46	44.3	5.65***	55.61	43.18	4.49***
Diversification	27.40	28.53	-1.44*	29.19	30.51	-1.06	26.56	25.6	0.80	26.35	31.41	-2.99***
Loans	74.21	67.25	6.51***	73.52	64.8	4.64***	75.91	69.35	4.34***	71.81	66.71	2.11**
Efficiency	42.62	41.81	0.89	40.79	39.36	0.96	42.81	41.85	0.69	45.06	45.33	-0.14
ROA	0.73	0.37	4.73***	1.44	0.86	5.80***	0.50	0.19	3.00***	0.11	0.02	0.50

Table 5. Correlation Matrix

Table presents the pairwise correlation matrix for foreign presence and complexity variables and systemic risk measures. Definitions of all variables are listed in section 3 (also see in Table A2 in Appendix).

	Foreign	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Bank complexity measures																
NbHost (1)		1														
NbSubsidiaries (2)		0.818***	1													
NbRegions_Sub (3)		0.862***	0.687***	1												
GeoComplexS (4)		0.640***	0.433***	0.866***	1											
Systemic risk measures																
MES (5)	0.380***	0.158**	0.037	0.190***	0.217***	1										
SRISK (6)	0.326***	0.712***	0.577***	0.651***	0.500***	0.355***	1									
ΔCoVaR (7)	0.313***	0.049	-0.013	0.048	0.056	0.647***	0.168***	1								
PD (8)	0.173***	0.056	0.000	0.013	0.009	0.583***	0.176***	0.437***	1							
Tail-β (9)	0.386***	0.256***	0.104*	0.261***	0.283***	0.671***	0.248***	0.429***	0.475***	1						
Bank characteristics																
Size (10)	0.644***	0.690***	0.505***	0.678***	0.614***	0.396***	0.626***	0.215***	0.168***	0.373***	1					
Leverage (11)	-0.479***	-0.302***	-0.238***	-0.286***	-0.233***	-0.037	-0.241***	0.050	-0.217***	-0.075	-0.309***	1				
Deposits (12)	0.038	0.295***	0.225***	0.302***	0.239***	0.033	0.271***	-0.148**	-0.025	0.061	0.160***	0.096*	1			
Diversification (13)	-0.253***	-0.367***	-0.276***	-0.397***	-0.333***	-0.008	-0.301***	0.097*	-0.049	-0.052	-0.310***	0.461***	-0.184***	1		
Loans (14)	-0.215***	-0.500***	-0.450***	-0.471***	-0.389***	-0.023	-0.419***	0.090	0.008	-0.108*	-0.328***	0.333***	-0.284***	0.522***	1	
Efficiency (15)	-0.036	0.061	0.013	0.040	0.001	0.127***	0.221***	-0.080	0.013	0.041	-0.129**	0.101*	0.555***	0.029	-0.202***	1
ROA (16)	-0.136***	0.020	0.032	0.045	0.063	-0.308***	-0.107*	-0.107*	-0.388***	-0.185***	-0.070	0.521***	0.228***	0.185***	-0.011	-0.149**

Table 6. Bank internationalization and systemic risk

This table displays the results of the estimation of Eq. (1) regarding the effects of bank internationalization on listed banks systemic risk over the 2005-2013 period. *MES*= Marginal Expected Shortfall, marginal participation of a bank to the Expected Shortfall (ES) of the financial system, a measure of bank equity sensitivity to market crashes; *SRISK*= Systemic risk, expected capital shortfall; Δ*CoVaR*= ΔConditional Value-at-Risk of a bank to an entire financial system or benchmark/reference market conditional on an extreme event leading to the fall of a bank stock return beyond its critical threshold level. Panel A presents results of: *Foreign*= a dummy that takes the value one when the listed bank owns at least one subsidiary abroad. Panel B presents results of: *NbHost*= continuous variable that accounts the number of host countries of the foreign subsidiaries; *NbSubsidiaries*= natural logarithm of the continuous variable that accounts the exact number of foreign subsidiaries a listed bank operate abroad; *NbRegions_Sub*= the number of regions where all foreign subsidiaries are located; *GeoComplexS*= the geographic complexity indicator of the dispersion of all subsidiaries in different world regions; Crisis08_10 is a dummy equal to one if the year is 2008, 2009,2010, or 2011, and zero otherwise; Post12_13 is a dummy equal to one if the year is 2012 or 2013, and zero otherwise; *Size*= natural logarithm of the total assets; *Leverage(%)*= ratio of total equity to total assets; *Deposits(%)*= ratio of customer deposits to total assets; *Diversification(%)*= income diversity ratio; *Loans(%)*= ratio of net loans to total assets; *Efficiency(%)*= cost to income ratio defined as non-interest expense divided by total income; *ROA(%)*= return on assets is the ratio of net income to total assets; *GDP growth (%)*= growth rate of the real gross domestic product. Variables were winsorized at 1% and 99% levels to limit the influence of extreme values. ***, **, and * indicate significance of the p-value respectively at the 1%, 5%, and 10% levels. We do not face muticollinearity problems (VIF test is less than 10 basis points, not reported).

Panel A: Foreign complexity through subsidiaries and systemic risk: baseline results

	MES	SRisk	ΔCoVaR	MES	SRisk	ΔCoVaR	MES	SRisk	ΔCoVaR
	(1a)	(1b)	(1c)	(2a)	(2b)	(2c)	(3a)	(3b)	(3c)
Foreign (α_1)	-0.084	0.236	-0.080	-1.395***	-11.89***	-0.709**	-1.268***	-10.95***	-0.659**
	(-0.22)	(0.28)	(-0.24)	(-4.50)	(-4.05)	(-2.47)	(-3.87)	(-4.28)	(-2.35)
Foreign×Crisis08_11 (β_1)				1.448***	16.28***	0.528***	1.388***	14.25***	0.425**
				(6.64)	(4.48)	(2.87)	(6.09)	(5.07)	(2.20)
Foreign×Post12_13 (β_2)				1.848***	18.16***	1.069***	1.705***	15.97***	0.932***
				(5.84)	(4.41)	(4.55)	(5.47)	(4.85)	(3.88)
Crisis08_11				1.438***	-0.130	1.247***	1.182***	0.385	1.139***
				(12.71)	(-0.34)	(9.56)	(7.65)	(0.44)	(7.65)
Post12_13				1.263***	-0.183	0.386**	1.192***	0.730	0.449**
				(7.29)	(-0.46)	(2.57)	(7.11)	(0.72)	(2.43)
Size							-0.318	-1.844	-0.0402
							(-1.22)	(-0.92)	(-0.21)
Leverage							-8.165**	3.262	-5.752**
							(-2.32)	(0.19)	(-2.07)
Deposit							-1.995	-9.333	-0.125
							(-1.44)	(-0.91)	(-0.16)
Diversification							-0.750	-15.55*	-0.279
							(-0.66)	(-1.71)	(-0.39)
Loans							0.744	20.10	1.157*
							(0.69)	(1.57)	(1.90)
Efficiency							-0.611	14.96**	-0.678
							(-0.73)	(2.06)	(-1.00)
ROA							6.042	88.35**	17.76**
							(0.70)	(2.05)	(2.14)
GDP growth							-0.0655***	-0.0506	0.00946
							(-3.19)	(-0.34)	(0.59)
Constant	2.969***	11.530***	2.288***	1.834***	10.45***	1.455***	6.936***	17.32	2.054
	(15.59)	(26.94)	(13.36)	(13.07)	(17.71)	(10.04)	(2.73)	(1.12)	(1.09)
Observations	784	784	784	784	784	784	784	784	784
Banks	98	98	98	98	98	98	98	98	98
R-squared	0.041	0.028	0.014	0.477	0.244	0.312	0.442	0.289	0.265
Adjusted R-squared	0.019	0.018	0.014	0.474	0.240	0.309	0.433	0.276	0.253
Wald tests: $\alpha_1 + \beta_1$				0.053***	4.390*	-0.181*	0.120***	3.300**	-0.234*
$\alpha_1 + \beta_2$				0.453***	6,270***	0.360***	0.437***	5.020**	0.273**

Panel B: Organizational and geographical complexity and systemic risk

	MES	SRisk	ΔCoVaR	MES	SRisk	ΔCoVaR	MES	SRisk	ΔCoVaR	MES	SRisk	ΔCoVaR
	(4a)	(4b)	(4c)	(5a)	(5b)	(5c)	(6a)	(6b)	(6c)	(7a)	(7b)	(7c)
Organizational Complexity												
NbHost (α1)	-0.0523***	-1.093***	-0.0056*									
	(-4.09)	(-4.65)	(-1.13)									
NbHost×Crisis08_11 (β1)	0.0315***	1.200***	0.00128									
	(3.57)	(6.38)	(0.16)									
NbHost×Post12_13 (β2)	0.0611***	1.360***	0.0181*									
	(4.39)	(7.07)	(1.85)									
NbSubsidiaries (α1)				-0.283	-6.181***	-0.0103**						
				(-1.45)	(-3.53)	(-1.98)						
NbSubsidiaries×Crisis08_11 (β1)				0.329***	9.751***	0.0403						
				(3.36)	(6.37)	(0.51)						
NbSubsidiaries×Post12_13 (β2)				0.455**	12.24***	0.327***						
				(2.47)	(5.95)	(3.01)						
Geographical Complexity												
NbRegions_Sub (α1)							-0.294**	-6.729***	-0.0230			
							(-2.12)	(-3.56)	(-0.23)			
NbRegions_Sub×Crisis08_11 (β1)							0.236***	7.407***	0.0147			
							(3.38)	(6.66)	(0.30)			
NbRegions_Sub×Post12_13 (β2)							0.424***	8.506***	0.138*			
							(3.82)	(7.10)	(2.00)			
GeoComplexS (α_1)										-0.630	-28.84***	0.0235
										(-0.53)	(-2.92)	(0.04)
GeoComplexS×Crisis08_11 (β_1)										1.179**	38.41***	0.231
										(2.23)	(3.91)	(0.65)
GeoComplexS×Post12_13 (β_2)										2.268***	45.13***	0.518
										(3.33)	(4.33)	(1.09)
Crisis08_11	1.855***	-3.617*	1.451***	1.648***	-7.214***	1.615***	1.636***	-9.240***	1.505***	2.044***	2.464	1.494***
	(7.93)	(-1.92)	(8.24)	(5.44)	(-2.92)	(7.83)	(5.77)	(-3.50)	(7.53)	(8.08)	(1.46)	(8.06)
Post12_13	1.802***	-2.537	1.102***	1.780***	-6.876**	1.007***	1.366***	-9.943***	0.850***	1.954***	2.603	1.099***
	(5.49)	(-1.51)	(5.16)	(4.11)	(-2.66)	(3.74)	(3.14)	(-3.63)	(3.11)	(5.61)	(1.50)	(4.71)
Size	-0.184	1.208	0.0746	-0.254	-0.472	0.0223	-0.336	-2.256	0.0199	-0.510	-6.355**	-0.00818
	(-0.59)	(0.74)	(0.38)	(-0.78)	(-0.26)	(0.12)	(-1.08)	(-1.25)	(0.11)	(-1.49)	(-2.16)	(-0.04)
Leverage	-10.48**	-33.79	-19.93***	-7.131	4.149	-17.48***	-8.510	-21.55	-18.78***	-7.956	-17.41	-18.50***
	(-2.38)	(-1.13)	(-4.69)	(-1.31)	(0.14)	(-3.72)	(-1.62)	(-0.84)	(-3.70)	(-1.46)	(-0.46)	(-3.60)
Deposit	0.612	-3.342	0.913	0.306	-9.860	0.954	0.458	-6.305	0.722	-0.108	-16.45	0.630
	(0.32)	(-0.31)	(0.84)	(0.16)	(-0.80)	(0.91)	(0.24)	(-0.57)	(0.67)	(-0.05)	(-1.05)	(0.56)
Diversification	-0.248	-12.76	-0.106	-0.734	-16.59*	0.410	-0.419	-13.11*	0.0303	-0.872	-20.82**	-0.0594
	(-0.18)	(-1.50)	(-0.12)	(-0.56)	(-1.84)	(0.50)	(-0.35)	(-1.74)	(0.04)	(-0.69)	(-2.18)	(-0.06)
Loans	0.919	17.04	2.410***	1.155	24.04*	2.332***	1.239	22.92*	2.129***	1.677	28.10*	2.126***
	(0.65)	(1.65)	(3.11)	(0.82)	(1.68)	(3.14)	(0.98)	(1.87)	(2.96)	(1.30)	(1.69)	(2.86)
Efficiency	-2.746***	-3.953	-1.043	-1.811**	12.28	-0.651	-2.334**	1.593	-0.701	-1.589*	18.36*	-0.552
	(-2.86)	(-0.50)	(-1.23)	(-2.06)	(1.55)	(-0.80)	(-2.62)	(0.22)	(-0.81)	(-1.82)	(1.99)	(-0.63)
ROA	-7.223	63.95	21.19	-4.828	43.43	5.230	-10.14	1.137	8.886	-6.760	74.70	10.68
	(-0.49)	(0.94)	(1.51)	(-0.27)	(0.58)	(0.44)	(-0.58)	(0.02)	(0.75)	(-0.39)	(0.93)	(0.89)
GDP growth	-0.0977***	-0.247	-0.00469	-0.0867***	0.0410	0.0202	-0.0942***	-0.228	0.00568	-0.0943***	-0.192	0.00527
	(-4.58)	(-1.02)	(-0.24)	(-3.65)	(0.16)	(0.96)	(-4.10)	(-0.98)	(0.27)	(-3.95)	(-0.81)	(0.25)
Constant	5.906	10.61	0.466	6.164*	19.13	-0.0137	7.514**	51.33**	1.169	8.506**	81.93**	1.381
	(1.66)	(0.57)	(0.21)	(1.69)	(0.99)	(-0.01)	(2.04)	(2.38)	(0.55)	(2.12)	(2.58)	(0.66)
Observations	394	394	394	382	382	382	382	382	382	382	382	382
Banks	55	55	55	53	53	53	53	53	53	53	53	53
R-squared	0.558	0.686	0.380	0.551	0.604	0.421	0.566	0.638	0.400	0.553	0.485	0.393
Adjusted R-squared	0.543	0.675	0.359	0.535	0.590	0.401	0.550	0.625	0.379	0.538	0.467	0.372
Wald tests: $\alpha_1 + \beta_1$	-0.021*	0.107**	-0.004*	0.046***	3.570***	0.030*	-0.058**	0.678***	-0.008	0.549***	9.570**	0.255
$\alpha_1 + \beta_2$	0.009***	0.267***	0.013**	0.172***	6.059***	0.317***	0.130***	1.777***	0.115*	1.638***	16.290***	0.542

Table 7. Bank internationalization and systemic risk: alternative measures of risk

This table displays the results of the estimation of Eq. (1) regarding the effects of bank internationalization on listed banks systemic risk over the 2005-2013 period. *PD*= Probability of default; *Tail-β* = quantile-beta, a measure of the sensitivity to extreme movements of beta. *Foreign* = a dummy that takes the value one when the listed bank owns at least one subsidiary abroad; *NbHost*= continuous variable that accounts the number of host countries of the foreign subsidiaries; *NbSubsidiaries*= natural logarithm of the continuous variable that accounts the exact number of foreign subsidiaries a listed bank operate abroad; *NbRegions_Sub*= the number of regions where all foreign subsidiaries are located; *GeoComplexS*= the geographic complexity indicator of the dispersion of all subsidiaries in different world regions; *Crisis08_10* is a dummy equal to one if the year is 2008, 2009,2010, or 2011, and zero otherwise; *Post12_13* is a dummy equal to one if the year is 2012 or 2013, and zero otherwise; *Size*= natural logarithm of the total assets; *Leverage(%)*= ratio of total equity to total assets; *Deposits(%)*= ratio of customer deposits to total assets; *Diversification(%)*= income diversity ratio; *Loans(%)*= ratio of net loans to total assets; *Efficiency(%)*= cost to income ratio defined as non-interest expense divided by total income; *ROA(%)*= return on assets is the ratio of net income to total assets; *GDP growth (%)*= growth rate of the real gross domestic product. Variables were winsorized at 1% and 99% levels to limit the influence of extreme values. ***, **, and * indicate significance of the p-value respectively at the 1%, 5%, and 10% levels. We do not face muticollinearity problems (VIF test is less than 10 basis points, not reported).

	PD	Tail-β	PD	Tail-β	PD	Tail-β	PD	Tail-β	PD	Tail-β
	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)	(4a)	(4b)	(5a)	(5b)
Organizational Complexity										
Foreign (α_1)	-2.453**	0.204								
	(-2.47)	(1.34)								
Foreign×Crisis08_11 (β_1)	3.359***	0.123								
	(5.03)	(1.16)								
Foreign×Post12_13 (β_2)	4.259***	0.347**								
	(4.08)	(2.26)								
NbHost (α_1)			-0.0543	0.00571						
			(-1.17)	(0.85)						
NbHost×Crisis08_11 (β_1)			0.104***	0.00363						
			(3.15)	(0.86)						
NbHost×Post12_13 (β_2)			0.145***	0.0159***						
			(3.36)	(3.04)						
NbSubsidiaries (α_1)					-1.374**	-0.120				
					(-2.14)	(-1.66)				
NbSubsidiaries×Crisis08_11 (β_1)					0.940***	-0.00285				
					(3.36)	(-0.08)				
NbSubsidiaries×Post12_13 (β_2)					0.917**	0.0364				
					(2.06)	(0.60)				
Geographic Complexity										
NbRegions_Sub (α_1)							-0.824***	-0.0410		
							(-2.73)	(-0.83)		
NbRegions_Sub×Crisis08_11 (β_1)							0.567***	0.0156		
							(3.10)	(0.65)		
NbRegions_Sub×Post12_13 (β_2)							0.535*	0.0634		
							(1.90)	(1.61)		
GeoComplexS (α_1)									-2.261	0.324
									(-0.88)	(1.00)
GeoComplexS×Crisis08_11 (β_1)									2.830	0.105
									(1.59)	(0.55)
GeoComplexS×Post12_13 (β_2)									2.017	0.365
									(0.98)	(1.16)
Crisis08_11	1.285*	0.0742	3.704**	0.149	2.537*	0.132	3.162**	0.131	4.098***	0.146
	(1.80)	(0.80)	(2.39)	(1.39)	(1.71)	(1.02)	(2.05)	(1.01)	(2.92)	(1.26)
Post12_13	2.267**	-0.0454	4.909**	0.0740	4.073*	0.0692	4.871*	0.0276	6.043***	0.0940
	(2.57)	(-0.38)	(2.25)	(0.54)	(1.92)	(0.40)	(1.92)	(0.17)	(2.69)	(0.67)
Size	-6.227***	-0.0321	-7.774***	-0.0232	-7.188***	-0.0553	-7.482***	-0.0707	-7.681***	-0.0856
	(-4.79)	(-0.37)	(-2.81)	(-0.24)	(-2.77)	(-0.54)	(-2.79)	(-0.73)	(-2.93)	(-0.83)
Leverage	-35.04**	0.362	-95.35***	0.678	-114.7***	0.779	-109.1***	0.951	-104.7***	0.964
	(-2.57)	(0.38)	(-2.99)	(0.32)	(-3.72)	(0.36)	(-3.60)	(0.44)	(-3.40)	(0.43)
Deposit	-20.88***	-0.331	-20.69***	-0.261	-20.22***	-0.275	-19.97***	-0.231	-20.69***	-0.322
	(-4.94)	(-0.65)	(-3.08)	(-0.44)	(-2.92)	(-0.49)	(-2.95)	(-0.40)	(-3.11)	(-0.56)
Diversification	-1.585	0.0170	-1.554	0.239	-2.667	-0.00381	-1.678	0.187	-2.449	0.0526
	(-0.31)	(0.05)	(-0.23)	(0.60)	(-0.40)	(-0.01)	(-0.24)	(0.42)	(-0.33)	(0.11)
Loans	0.695	-0.514	0.900	-0.301	0.993	-0.411	1.017	-0.360	1.550	-0.157
	(0.24)	(-1.26)	(0.23)	(-0.56)	(0.25)	(-0.70)	(0.25)	(-0.67)	(0.36)	(-0.32)
Efficiency	-8.531**	-0.169	-10.38*	-0.415	-7.889	-0.314	-8.338*	-0.364	-6.964	-0.280
	(-2.29)	(-0.52)	(-1.98)	(-1.21)	(-1.64)	(-0.87)	(-1.78)	(-0.93)	(-1.45)	(-0.74)
ROA	-191.7***	-2.949	-232.1***	-14.81**	-176.8***	-13.37**	-191.8***	-16.59**	-188.4***	-16.23**
	(-5.14)	(-0.78)	(-3.69)	(-2.15)	(-3.21)	(-2.04)	(-3.46)	(-2.51)	(-3.43)	(-2.45)
GDP growth	-0.253***	-0.0277***	-0.323***	-0.0182*	-0.371***	-0.0227**	-0.362***	-0.0185*	-0.355***	-0.0200*
	(-3.32)	(-3.52)	(-3.61)	(-1.79)	(-3.51)	(-2.25)	(-3.78)	(-1.80)	(-3.70)	(-1.91)
Constant	81.86***	1.699*	110.0***	1.807	105.9***	2.636**	108.1***	2.577**	107.9***	2.420*
	(5.74)	(1.79)	(3.21)	(1.52)	(3.16)	(2.12)	(3.20)	(2.13)	(3.28)	(1.91)
Observations	784	784	394	394	382	382	382	382	382	382

Banks		98	98	55	55	53	53	53	53	53	53
R-squared		0.396	0.0713	0.498	0.151	0.493	0.148	0.488	0.146	0.479	0.160
Adjusted R-squared		0.385	0.0556	0.481	0.122	0.475	0.118	0.469	0.116	0.461	0.130
Wald tests:	$\alpha_1 + \beta_1$	0.906***	0.327*	0.050***	0.009	-0.434**	-0.120	-0.257*	-0.025	0.569**	-0.219
	$\alpha_1 + \beta_2$	1.806***	0.551***	0.100***	0.022***	-0.457	-0.084	-0.289	0.022*	-0.244	0.041*

Table 8. Effect of bank absolute/relative size in the nonlinear relationship between complexity (through subsidiaries exclusively) and systemic risk over the entire period

This table displays the results of the estimation of Eq. (1) regarding the effects of bank size internationalization and organizational complexity on listed banks systemic risk over the 2011-2013 period. *MES* = Marginal Expected Shortfall, marginal participation of a bank to the Expected Shortfall (ES) of the financial system, a measure of bank equity sensitivity to market crashes; *SRISK*= Systemic risk, expected capital shortfall, Δ*CoVaR*= ΔConditional Value-at-Risk of a bank to an entire financial system or benchmark/reference market conditional on an extreme event leading to the fall of a bank stock return beyond its critical threshold level. *Foreign*= a dummy that takes the value one when the listed bank owns at least one subsidiary abroad; *Crisis08_10* is a dummy equal to one if the year is 2008, 2009,2010, or 2011, and zero otherwise; *Post12_13* is a dummy equal to one if the year is 2012 or 2013, and zero otherwise; *Size*= natural logarithm of the total assets; *Leverage(%)*= ratio of total equity to total assets; *Deposits(%)*= ratio of customer deposits to total assets ; *Diversification(%)*= income diversity ratio; *Loans (%)*= ratio of net loans to total assets; *Efficiency(%)*= cost to income ratio defined as non-interest expense divided by total income; *ROA(%)*= return on assets is the ratio of net income to total assets; *GDP growth (%)*= growth rate of the real gross domestic product. Variables were winsorized at 1% and 99% levels to limit the influence of extreme values. Panel A presents subsamples of banks based on the absolute size: larger banks (TBTF with total assets strictly above $40 billion) and small banks (with assets strictly less $40 billion). Panel B presents subsamples of banks based on the relative size (to banking industry): larger relative-sized banks (TBTF with a market share strictly above 5-percent) and of small relative-sized banks (with market share strictly below 5-percent). ***, **, and * indicate significance of the p-value respectively at the 1%, 5%, and 10% levels. We do not face muticollinearity problems (VIF test is less than 10 basis points, not reported).

	Panel A: Effect of absolute size						**Panel B: Effect of relative size**					
	Subsample of large banks			Subsample of small banks			Subsample of large banks			Subsample of small banks		
	MES	SRISK	ΔCoVaR	MES	SRISK	ΔCoVaR	MES	SRISK	ΔCoVaR	MES	SRISK	ΔCoVaR
	(1a)	(1b)	(1c)	(2a)	(2b)	(2c)	(3a)	(3b)	(3c)	(4a)	(4b)	(4c)
Foreign (α_1)	-1.576**	-18.14***	-0.0175	-0.208	-0.222	-0.677*	-1.748***	-20.01***	-0.374	-0.937**	-3.620***	-0.736**
	(-2.68)	(-3.54)	(-0.05)	(-0.54)	(-0.65)	(-2.00)	(-4.14)	(-3.63)	(-0.90)	(-2.00)	(-3.76)	(-2.50)
Foreign×Crisis08_11 (β_1)	1.910***	21.60***	-0.374	0.606*	0.584*	0.509*	1.770**	25.71***	0.885	0.920***	4.113***	0.453**
	(3.49)	(3.73)	(-1.00)	(1.76)	(1.85)	(1.76)	(2.66)	(4.55)	(1.63)	(3.17)	(3.51)	(2.12)
Foreign×Post12_13 (β_2)	1.427*	25.53***	0.345	0.364	0.361	0.508	2.617***	32.70***	1.721***	1.289***	5.036***	0.512**
	(1.80)	(3.94)	(0.71)	(1.08)	(1.30)	(1.39)	(3.55)	(4.43)	(2.85)	(3.29)	(3.61)	(2.05)
Crisis08_11	0.845	-1.913	1.790***	1.479***	0.611***	1.247***	1.163*	-4.147	0.264	1.217***	0.248	1.399***
	(1.47)	(-0.39)	(5.71)	(11.24)	(3.16)	(5.91)	(1.76)	(-1.01)	(0.48)	(7.82)	(0.74)	(8.23)
Post12_13	1.641**	-1.367	1.043**	1.467***	0.711***	0.553**	0.427	-6.109	-0.318	1.370***	0.382	0.786***
	(2.11)	(-0.26)	(2.48)	(8.68)	(3.56)	(2.06)	(0.69)	(-1.59)	(-0.53)	(8.37)	(1.10)	(3.63)
Size	-0.119	-2.314	0.0460	-0.959***	-0.558	-0.0459	0.393	-0.720	0.406	-0.423	-0.0209	-0.141
	(-0.34)	(-0.74)	(0.20)	(-3.85)	(-1.46)	(-0.12)	(0.60)	(-0.12)	(0.78)	(-1.45)	(-0.03)	(-0.76)
Leverage	-6.612	-3.959	-9.497**	-8.551*	-5.483***	-3.076	-10.06	13.06	-22.89***	-5.373	-4.438	-0.817
	(-1.66)	(-0.08)	(-2.15)	(-1.71)	(-2.77)	(-1.20)	(-1.12)	(0.20)	(-3.79)	(-1.47)	(-1.53)	(-0.37)
Deposit	-0.651	-26.20	-0.584	-3.262***	-0.167	0.150	-2.122	-20.88	-1.878	-2.305	-0.483	0.688
	(-0.28)	(-1.23)	(-0.38)	(-2.98)	(-0.39)	(0.18)	(-0.84)	(-0.70)	(-1.11)	(-1.45)	(-0.17)	(0.88)
Diversification	0.109	-29.96	0.971	-1.565	-0.276	-0.951	-3.406	-51.61**	-0.478	-0.579	-2.298	-0.225
	(0.05)	(-1.64)	(0.90)	(-1.38)	(-0.85)	(-0.99)	(-1.53)	(-2.16)	(-0.29)	(-0.59)	(-1.20)	(-0.30)
Loans	1.341	32.51	2.552***	0.101	0.0472	0.207	1.362	71.76***	3.774***	0.909	-3.656	0.599
	(0.79)	(1.43)	(2.74)	(0.09)	(0.09)	(0.25)	(0.74)	(2.91)	(3.00)	(0.76)	(-1.09)	(0.89)
Efficiency	-1.307	34.54**	-1.957*	-0.422	-0.122	0.00865	1.152	55.78***	-1.306	-0.820	-0.554	-0.525
	(-0.94)	(2.38)	(-1.76)	(-0.39)	(-0.50)	(0.01)	(0.73)	(3.65)	(-0.77)	(-0.96)	(-0.47)	(-0.71)
ROA	-4.600	338.9***	17.80	7.491	4.139	20.38**	19.65	370.7**	31.01*	3.676	-3.340	21.26**
	(-0.34)	(2.68)	(1.09)	(0.65)	(1.41)	(2.53)	(0.98)	(2.68)	(1.88)	(0.38)	(-0.37)	(2.62)
GDP growth	-0.0679***	-0.266	-0.0370**	-0.0543*	-0.00934	0.0545**	-0.101***	0.0907	-0.0268	-0.0485**	-0.0582*	0.0362*
	(-2.94)	(-0.81)	(-2.25)	(-1.78)	(-1.24)	(2.24)	(-2.73)	(0.22)	(-1.24)	(-2.30)	(-1.88)	(1.69)
Constant	5.301	39.27	0.771	12.23***	5.127	1.632	0.711	-5.058	-1.913	6.669**	7.120	1.839
	(1.42)	(1.23)	(0.29)	(4.56)	(1.65)	(0.47)	(0.09)	(-0.07)	(-0.31)	(2.60)	(1.27)	(1.09)
Observations	339	339	339	445	445	445	250	250	250	534	534	534
Banks	51	51	51	65	65	65	37	37	37	79	79	79
R-squared	0.522	0.402	0.378	0.351	0.352	0.224	0.550	0.488	0.396	0.405	0.334	0.277
Adjusted R-squared	0.503	0.379	0.353	0.332	0.332	0.201	0.525	0.460	0.363	0.390	0.317	0.259
Wald tests: $\alpha_1 + \beta_1$	0.334***	3.460***	-0.392	0.398*	0.362*	-0.168**	0.048**	5.700***	0.511*	-0.017**	0.493*	-0.283**
$\alpha_1 + \beta_2$	-0.149	7.390***	0.328**	0.156*	0.139*	-0.169	0.422***	12.690***	1.347***	0.352***	1.416***	-0.224*

Table 9. Effect of activity diversity in the nonlinear relationship between complexity (through subsidiaries exclusively) and systemic risk over the entire period

This table displays the results of the estimation of Eq. (11) regarding the effects of bank internationalization and organizational complexity on listed banks systemic risk over the 2011-2013 period. *MES* = Marginal Expected Shortfall, marginal participation of a bank to the Expected Shortfall (ES) of the financial system, a measure of bank equity sensitivity to market crashes; *SRISK*= Systemic risk, expected capital shortfall, Δ*CoVaR*= ΔConditional Value-at-Risk of a bank to an entire financial system or benchmark/reference market conditional on an extreme event leading to the fall of a bank stock return beyond its critical threshold level. *Foreign*= a dummy that takes the value one when the listed bank owns at least one subsidiary abroad; *Crisis08_10* is a dummy equal to one if the year is 2008, 2009, 2010, or 2011, and zero otherwise; *Post12_13* is a dummy equal to one if the year is 2012 or 2013, and zero otherwise; d(M&A) = merger-and-acquisition dummy, takes value of one if banks have experienced a M&A event during the period, zero otherwise. d(IncDiversity) = high-income diversity dummy, equals to one if banks are in the fourth quartile of the diversity income ratio, and zero otherwise. *Size*= natural logarithm of the total assets; *Leverage(%)*= ratio of total equity to total assets; *Deposits(%)*= ratio of customer deposits to total assets; *Diversification(%)*=income diversity ratio; *Loans (%)*= ratio of net loans to total assets; *Efficiency(%)*= cost to income ratio defined as non-interest expense divided by total income; *ROA(%)*= return on assets is the ratio of net income to total assets; *GDP growth (%)*= growth rate of the real gross domestic product. Variables were winsorized at 1% and 99% levels to limit the influence of extreme values. ***, **, and * indicate significance of the p-value respectively at the 1%, 5%, and 10% levels. We do not face muticollinearity problems (VIF test is less than 10 basis points, not reported).

	M&A			**Income diversity**		
	MES	SRisk	ΔCoVaR	MES	SRisk	ΔCoVaR
	(1a)	(1b)	(1c)	(2a)	(2b)	(2c)
Foreign (α_1)	-1.248***	-10.61***	-0.571**	-1.171***	-11.26***	-0.317*
	(-3.80)	(-4.05)	(-2.07)	(-2.82)	(-3.01)	(-1.73)
Foreign×Crisis08_11 (β_1)	1.407***	14.31***	0.417**	1.250***	14.28***	0.0468
	(6.27)	(4.87)	(2.18)	(3.84)	(3.72)	(0.18)
Foreign×Post12_13 (β_2)	1.650***	15.94***	0.901***	1.702***	17.81***	0.479
	(5.24)	(4.64)	(3.68)	(3.96)	(3.84)	(1.58)
Foreign×d(M&A) (α'_1)	-0.137	-1.303	-0.0295			
	(-0.16)	(-0.20)	(-0.06)			
Foreign×d(IncDiversity) (α'_2)				-0.223	-0.601	-0.608**
				(-0.59)	(-0.11)	(-2.10)
Foreign×d(M&A)×Crisis08_11 (β'_1)	**-2.628****	**-9.259**	**-3.149*****			
	(-2.24)	(-1.42)	(-3.79)			
Foreign×d(M&A)×Post12_13 (β'_2)	**0.439**	**0.432**	**-0.642**			
	(0.37)	(0.06)	(-0.79)			
Foreign×d(IncDiversity)×Crisis08_11 (β'_3)				**0.397**	**1.838**	**0.736****
				(0.87)	(0.29)	(2.22)
Foreign×d(IncDiversity)×Post12_13 (β'_4)				**-0.0599**	**-3.756**	**0.893***
				(-0.10)	(-0.58)	(1.72)
d(M&A)×Crisis08_11	2.134***	0.407	0.509			
	(2.79)	(0.25)	(0.98)			
d(M&A)×Post12_13	-0.589	0.654	-0.643			
	(-1.11)	(0.54)	(-1.32)			
d(IncDiversity)×Crisis08_11				-0.0281	1.878*	-0.415*
				(-0.10)	(1.81)	(-1.69)
d(IncDiversity)×Post12_13				-0.0654	2.361*	-0.254
				(-0.19)	(1.95)	(-0.83)
d(M&A)	-0.0441	-1.025	0.252			
	(-0.18)	(-0.86)	(0.85)			
d(IncDiversity)				-0.102	-1.950*	0.192
				(-0.43)	(-1.98)	(0.86)
Crisis08_11	1.124***	0.373	1.126***	1.191***	-0.466	1.362***
	(7.50)	(0.45)	(7.25)	(5.62)	(-0.42)	(7.71)
Post12_13	1.220***	0.814	0.490***	1.231***	-0.343	0.616**
	(7.19)	(0.82)	(2.71)	(5.09)	(-0.28)	(2.57)
Size	-0.264	-2.090	0.0442	-0.354	-2.149	-0.0552
	(-1.10)	(-1.06)	(0.25)	(-1.29)	(-1.05)	(-0.29)
Leverage	-8.318**	6.605	-5.020	-8.407**	-3.707	-5.906**
	(-2.38)	(0.37)	(-1.56)	(-2.56)	(-0.26)	(-2.11)
Deposit	-1.912	-9.158	-0.184	-1.952	-6.859	-0.209
	(-1.41)	(-0.87)	(-0.23)	(-1.38)	(-0.72)	(-0.27)
Diversification	-0.693	-14.93	-0.158			
	(-0.61)	(-1.65)	(-0.22)			
Loans	0.863	20.12	1.165*	0.742	20.03	1.185*
	(0.80)	(1.56)	(1.88)	(0.69)	(1.57)	(1.94)
Efficiency	-0.691	14.43*	-0.741	-0.889	8.342*	-0.664
	(-0.82)	(1.98)	(-1.07)	(-1.37)	(1.80)	(-1.25)
ROA	6.519	89.09**	17.46**	4.758	59.62	17.02**
	(0.78)	(2.03)	(2.11)	(0.55)	(1.57)	(2.08)

GDP growth	-0.0688***	-0.0581	0.00668		-0.0675***	-0.0603	0.00934
	(-3.37)	(-0.38)	(0.41)		(-3.20)	(-0.41)	(0.60)
Constant	6.317***	19.33	1.124		7.261***	19.44	2.019
	(2.70)	(1.27)	(0.63)		(2.72)	(1.39)	(1.02)
Observations	784	784	784		784	784	784
Banks	98	98	98		98	98	98
R-squared	0.449	0.290	0.277		0.445	0.295	0.272
Adjusted R-squared	0.435	0.273	0.259		0.432	0.272	0.254
Wald tests: $\alpha_1 + \beta_1$	0.159	3.700***	-0.154	**Wald tests**: $\alpha_1 + \beta_1$	0.079	3.020**	-0.248
$\alpha_1 + \beta_2$	0.402*	5.330***	0.330*	$\alpha_1 + \beta_2$	0.531*	6.550**	0.162
$\alpha_1 + \alpha'_1$	-1.385**	-11.913**	-0.342*	$\alpha_1 + \alpha'_1$	-1.394***	-11.861***	-0.925***
$\alpha_1 + \beta_1 + \alpha'_1 + \beta'_1$	-2.606***	-6.862**	-0.498***	$\alpha_1 + \beta_1 + \alpha'_1 + \beta'_3$	0.253*	4.257**	-0.142
$\alpha_1 + \beta_2 + \alpha'_1 + \beta'_2$	0.704	4.459**	-0.342	$\alpha_1 + \beta_2 + \alpha'_1 + \beta'_4$	0.248	2.193**	0.447

Table 10. Effect of organizational expansion strategy on systemic risk ─ OLS regressions

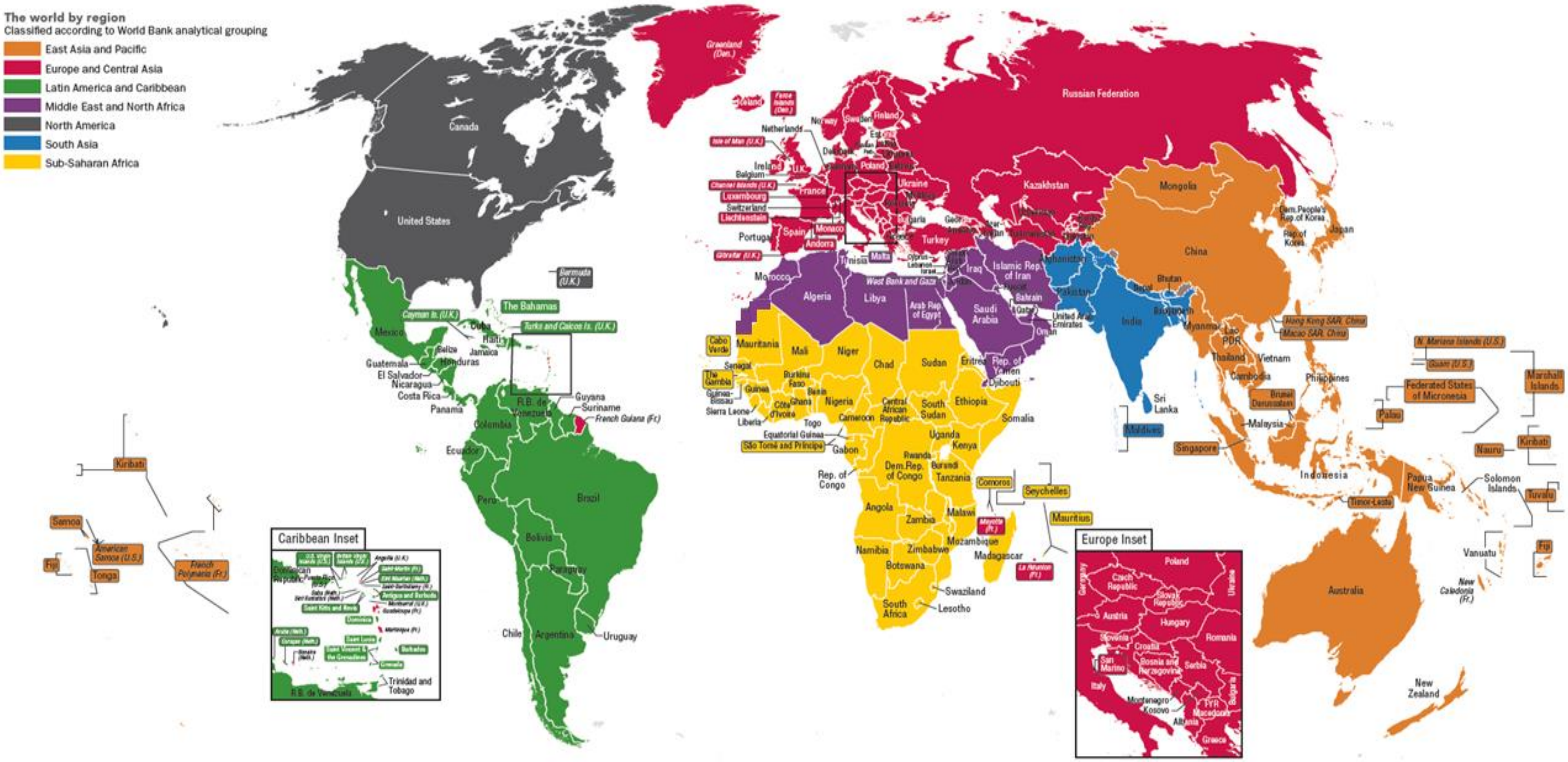
This table displays the results of the estimation of Eq. (12) regarding the effects of bank foreign organizational strategy (branches and/or subsidiaries) on systemic risk over the 2011–13 period. *MES* = Marginal Expected Shortfall, marginal participation of a bank to the Expected Shortfall (ES) of the financial system, a measure of bank equity sensitivity to market crashes; *SRISK*= Systemic risk, expected capital shortfall, Δ*CoVaR*= ΔConditional Value-at-Risk of a bank to an entire financial system or benchmark/reference market conditional on an extreme event leading to the fall of a bank stock return beyond its critical threshold level. *Size*= natural logarithm of the total assets; *Leverage(%)*= ratio of total equity to total assets ; *Deposits(%)*= ratio of customer deposits to total assets ; *Diversification(%)*= income diversity ratio; *Loans (%)*= ratio of net loans to total assets ; *Efficiency(%)*= cost to income ratio defined as non-interest expense divided by total income; *ROA(%)*= return on assets is the ratio of net income to total assets; *GDP growth (%)*= growth rate of the real gross domestic product. Variables were winsorized at 1% and 99% levels to limit the influence of extreme values. ***, **, and * indicate significance of the p-value respectively at the 1%, 5%, and 10% levels.

	MES			SRISK			ΔCoVaR		
	(1a)	(2a)	(3a)	(1b)	(2b)	(3b)	(1c)	(2c)	(3c)
Bank_Sub	0.192			8.740*			0.198		
	(0.56)			(1.95)			(1.33)		
Bank_Brh		-1.260**			0.753			-0.100**	
		(-2.72)			(0.18)			(0.81)	
Bank_Both			-0.233			11.84*			0.150*
			(-0.49)			(1.32)			(1.28)
Size	0.580***	0.585***	0.615***	13.68***	13.63***	11.90***	0.174***	0.284***	0.154***
	(4.48)	(4.54)	(3.90)	(4.23)	(4.32)	(5.04)	(0.90)	(0.40)	(1.17)
Leverage	0.679	0.361	0.412	97.44	109.7	109.6	3.261	14.24	6.135
	(0.19)	(0.11)	(0.12)	(1.55)	(1.72)	(1.71)	(0.54)	(0.89)	(1.29)
Deposits	1.139	1.297*	1.162	33.61	34.77*	32.29	1.537	-3.929	0.642
	(1.61)	(1.84)	(1.64)	(1.60)	(1.78)	(1.71)	(1.14)	(-0.85)	(0.58)
Diversification	3.228**	3.096**	3.153**	29	30.01	32.70	2.423***	15.78	1.018
	(2.39)	(2.25)	(2.36)	(0.66)	(0.73)	(0.80)	(1.25)	(1.38)	(0.50)
Loans	-1.358*	-1.247*	-1.439**	-19.25	-22.44	-14.78	-0.333	-7.259	-4.563**
	(-2.03)	(-1.98)	(-2.32)	(-1.36)	(-1.66)	(-1.28)	(-0.14)	(-1.28)	(-2.60)
Efficiency	-0.716	-0.582	-0.692	68.26**	68.02**	67.05**	-6.548***	-7.229	0.892
	(-0.58)	(-0.51)	(-0.56)	(2.41)	(2.23)	(2.45)	(-4.13)	(-1.12)	(0.49)
ROA	-27.33***	-26.13***	-26.48***	-346.8***	-384.0***	-385.6***	-25.61	-31.13	-5.425
	(-3.75)	(-3.86)	(-3.87)	(-4.31)	(-4.47)	(-4.50)	(-1.64)	(-0.94)	(-0.43)
GDP growth	-0.0167	-0.351**	-0.0553	-0.817	-0.251**	-0.033	-0.967	-0.651**	-0.753
	(-1.64)	(-0.94)	(-0.43)	(-0.23)	(-2.09)	(-0.97)	(-0.174)	(-0.284)	(-0.154)
Constant	-4.515**	-4.453**	-4.609**	-174.1***	-175.7***	-169.1***	9.710***	45.43***	-2.199
	(-2.56)	(-2.66)	(-2.56)	(-3.33)	(-3.31)	(-3.40)	(3.58)	(3.60)	(-1.06)
Observations	294	294	294	294	294	294	294	294	294
R-squared	0.720	0.724	0.720	0.620	0.613	0.620	0.168	0.166	0.145
Adjusted R-squared	0.698	0.701	0.697	0.589	0.581	0.589	0.121	0.119	0.0967

Appendix

Figure A1. **Map of all world countries into seven world regions**

Source: World Bank – World Development Indicator (2017) – http://databank.worldbank.org/data/download/site-content/wdi/maps/2017/world-by-region-wdi-2017.pdf



Note: These regions include economies at all income levels, and may differ from common geographic usage or from regions defined by other organizations. For more information see https://datahelpdesk.worldbank.org/knowledgebase/articles/906519-world-bank-country-and-lending-groups.

Table A1. Sample composition

Panel A shows the sample country composition. It presents the distribution of 105 listed banks from 15 European countries, Austria, Czech, Denmark, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Poland, Portugal, Slovakia, Spain, and Sweden, totaling 945 bank-year observations.

Country	Number of banks	Number of Bank-Year observations
Austria	6	40
Czech Republic	1	9
Denmark	23	165
Finland	2	18
France	18	140
Germany	7	53
Greece	6	44
Hungary	1	9
Ireland	1	9
Italy	17	133
Poland	10	75
Portugal	2	16
Slovakia	2	16
Spain	6	39
Sweden	3	18
Total	105	784

Panel B shows the distribution of the number of observations (banks) by year, both in absolute numbers as well as frequencies.

Year	Freq.	Percent
2005	85	10.84
2006	89	11.35
2007	87	11.10
2008	87	11.10
2009	87	11.10
2010	87	11.10
2011	87	11.10
2012	87	11.10
2013	88	11.22
Total	784	100

Table A2. Definition of variables, Sources and summary statistics over 2005–2013

This table reports the descriptive of variables used in the paper for our sample of publicly traded banks over the whole period 2005–2013.

Variable Name	Definitions	Sources	Obs.	Mean	SD	Min	Max
Bank complexity measures							
Foreign	Dummy equal to one when the bank owns at least one foreign subsidiary, and zero if not.	BankScope	784	0.48	0.50	0.00	1.00
NbHost	Number of foreign countries where a bank has a foreign presence with subsidiary.	BankScope	394	11.29	14.40	1.00	63.00
NbSubsidiaries	Number of foreign subsidiaries per bank.	BankScope	382	24.98	53.38	0.00	378.0
NbRegions_Sub	Number of world regions where a bank has established its foreign subsidiaries, among eight world regions.	World Bank	382	2.90	2.29	1.00	8.00
GeoComplex**S**	Indicator of the geographic dispersion of a bank foreign subsidiary (ies) in different world regions.	BankScope – World Bank	382	0.33	0.33	0.00	0.95
Systemic risk measures							
MES	Marginal Expected Shortfall, marginal participation of a bank to the Expected Shortfall of the financial system, a measure of bank equity sensitivity to market crashes (Eq. (3)).	Bloomberg	784	2.59	2.24	–1.64	9.63
SRisk	Systemic risk, expected capital shortfall (Eq. (4)).	Bloomberg	784	10.09	30.25	–6.21	223.8
ΔCoVaR	Conditional Value-at-Risk of a bank to an entire financial system or benchmark/reference market conditional on an extreme event leading to the fall of a bank stock return beyond its critical threshold level (Eq. (6)).	Bloomberg	784	1.98	1.51	–2.80	6.85
PD	Merton's probability of default (Eq. (7)).	Bloomberg	784	0.03	0.07	0.00	0.57
Tail-β	Measure of the sensitivity to extreme movements of beta, quantile-beta.	Bloomberg	784	0.90	0.83	–1.57	3.17
Bank characteristics							
Size	Natural logarithm of total assets (USD billion).	TRAA	784	–3.48	2.13	–8.18	0.16
Leverage (%)	Ratio of total equity to total assets, measure of leverage/bank capitalization level.	Bloomberg	784	8.67	5.27	0.78	44.82
Deposits (%)	Ratio of customer deposits to total assets.	BankScope – TRAA	784	49.23	19.58	5.69	91.43
Diversification (%)	Income diversity ratio. Degree of non-interest in total income (see subsection 4.3.2).	BankScope – TRAA	784	27.94	11.93	1.06	66.54
Loans (%)	Ratio of net loans to total assets.	BankScope – TRAA	784	70.72	16.25	13.02	100
Efficiency (%)	Cost to income ratio. Non-interest expense divided by total income.	BankScope – TRAA	784	42.22	13.48	14.87	89.93
ROA (%)	Return on assets ratio. Net income to total assets.	BankScope – TRAA	784	0.56	1.17	–4.58	5.85
Instruments							
Asset Growth	Change in total assets over the study period divided by the average total assets over the same period.	TRAA	784	0.39	0.21	0.13	0.78
HHI–Assets	Herfindahl-Hirschman Index (HHI) asset-based, calculates market concentration as the sum of the square of each banks' share in the overall local banking industry.	BankScope – TRAA	696	9.57	18.78	–79.89	196.53

Table A3. Effect of bank internationalization on listed banks systemic risk — Global Financial Crisis *versus* European Sovereign Debt Crisis

This table reports regression results of the model: $Risk_{ijt} = (\alpha_1 + \beta_1 Fin08\_09 + \beta_2 Sov10\_11 + \beta_3 Post12\_13) * Foreign_{ijt} + \beta_4 Fin08\_09 + \beta_5 Sov10\_11 + \beta_3 Post12\_13 + \varphi X_{ijt-1} + \gamma Country_{jt-1} + \omega_i + \varepsilon_{2ijt}$, regarding the effects of bank internationalization on systemic risk over the 2005–13 period. Definitions of all variables are listed in Appendix Table A2.

	MES	SRISK	ΔCoVaR	MES	SRISK	ΔCoVaR	MES	SRISK	ΔCoVaR	MES	SRISK	ΔCoVaR	MES	SRISK	ΔCoVaR
	(1a)	(1b)	(1c)	(2a)	(2b)	(2c)	(3a)	(3b)	(3c)	(4a)	(4b)	(4c)	(5a)	(5b)	(5c)
Foreign (α_1)	-1.258***	-10.89***	-0.623**												
	(-3.83)	(-4.28)	(-2.25)												
Foreign×Fin08_09 (β_1)	1.238***	14.75***	0.559**												
	(5.18)	(4.78)	(2.54)												
Foreign×Sov10_11 (β_2)	**1.531*****	**13.71*****	**0.270**												
	(5.39)	(5.19)	(1.26)												
Foreign×Post12_13 (β_3)	1.641***	15.85***	0.840***												
	(5.16)	(4.82)	(3.57)												
NbHost (α1)				-0.0526***	-1.084***	-0.0076									
				(-3.92)	(-4.82)	(-0.79)									
NbHost×Fin08_09 (β_1)				0.0410***	1.317***	-0.0077									
				(3.18)	(6.34)	(-0.91)									
NbHost×Sov10_11 (β_2)				**0.0162**	**1.078*****	**0.0033**									
				(1.65)	(6.06)	(0.37)									
NbHost×Post12_13 (β_3)				0.0581***	1.352***	0.0156*									
				(4.27)	(7.09)	(1.68)									
ln(NbSubsidiaries) (α_1)							-0.418*	-5.993***	0.139						
							(-1.97)	(-3.25)	(1.17)						
ln(NbSubsidiaries)×Fin08_09 (β_1)							0.407***	10.37***	-0.0462						
							(3.86)	(5.84)	(-0.57)						
ln(NbSubsidiaries)×Sov10_11 (β_2)							**0.134**	**9.126*****	**0.0494**						
							(1.15)	(5.95)	(0.58)						
ln(NbSubsidiaries)×Post12_13 (β_3)							0.391**	12.28***	0.275**						
							(2.21)	(5.74)	(2.62)						
NbRegion_Sub (α1)										-0.307**	-6.727***	-0.0443			
										(-2.38)	(-3.57)	(-0.47)			
NbRegion_Sub×Fin08_09 (β_1)										0.310***	7.943***	-0.0286			
										(4.23)	(6.25)	(-0.57)			
NbRegion_Sub×Sov10_11 (β_2)										**0.129**	**6.783*****	**0.0295**			
										(1.53)	(6.43)	(0.52)			
NbRegion_Sub×Post12_13 (β_3)										0.407***	8.456***	0.126*			
										(3.84)	(7.11)	(1.90)			
GeoComplexS (α_1)													-0.462	-28.30***	0.0149
													(-0.39)	(-2.91)	(0.03)
GeoComplexS×Fin08_09 (β_1)													1.862***	40.67***	0.0401
													(3.51)	(3.72)	(0.11)
GeoComplexS×Sov10_11 (β_2)													**0.472**	**36.09*****	**0.353**
													(0.71)	(3.91)	(0.80)
GeoComplexS×Post12_13 (β_3)													2.143***	44.73***	0.507
													(3.06)	(4.33)	(1.10)
Fin08_09	1.457***	0.371	1.290***	1.911***	-5.003**	1.786***	1.589***	-8.756***	1.918***	1.609***	-10.45***	1.846***	2.010***	2.260	1.771***
	(8.33)	(0.49)	(7.14)	(7.74)	(-2.29)	(8.98)	(4.83)	(-2.86)	(8.20)	(5.53)	(-3.50)	(8.39)	(7.29)	(1.24)	(8.37)
Sov10_11	0.589***	0.111	0.680***	1.577***	-1.996	0.769***	1.373***	-5.134**	0.971***	1.468***	-7.975**	0.812***	1.801***	1.922	0.803***

	(3.08)	(0.09)	(3.49)	(4.27)	(-0.93)	(3.16)	(3.26)	(-2.07)	(3.34)	(3.59)	(-2.66)	(2.94)	(4.71)	(0.83)	(3.20)
Post12_13	0.977***	0.533	0.240	1.562***	-2.223	0.717***	1.421***	-6.247**	0.629**	1.128**	-10.09***	0.487*	1.723***	1.994	0.707***
	(5.31)	(0.49)	(1.27)	(3.89)	(-1.22)	(3.06)	(2.74)	(-2.36)	(2.08)	(2.23)	(-3.49)	(1.75)	(3.95)	(0.93)	(2.90)
Size	-0.0788	-1.610	0.199	-0.00932	1.241	0.306	-0.0480	-0.790	0.229	-0.147	-1.930	0.241	-0.321	-5.828*	0.224
	(-0.33)	(-0.78)	(1.14)	(-0.03)	(0.72)	(1.53)	(-0.13)	(-0.40)	(1.20)	(-0.43)	(-1.02)	(1.34)	(-0.85)	(-1.93)	(1.22)
Leverage	-7.102**	5.654	-4.095*	-6.889	-41.26	-13.65***	-2.739	-6.044	-12.31***	-4.268	-19.17	-12.22***	-2.938	-3.453	-12.21***
	(-2.17)	(0.33)	(-1.88)	(-1.48)	(-1.39)	(-4.02)	(-0.49)	(-0.20)	(-3.24)	(-0.84)	(-0.73)	(-3.18)	(-0.54)	(-0.08)	(-3.15)
Deposit	-1.689	-9.175	0.119	0.851	-2.226	1.028	0.377	-9.818	0.992	0.671	-5.384	0.796	0.0776	-15.90	0.743
	(-1.29)	(-0.89)	(0.17)	(0.48)	(-0.20)	(1.17)	(0.21)	(-0.78)	(1.13)	(0.38)	(-0.49)	(0.90)	(0.04)	(-1.03)	(0.81)
Diversification	0.180	-14.36	0.770	0.528	-12.24	0.850	-0.160	-17.41*	0.972	0.466	-10.89	0.847	-0.139	-18.76**	0.817
	(0.17)	(-1.56)	(1.05)	(0.44)	(-1.48)	(0.95)	(-0.14)	(-1.93)	(1.14)	(0.45)	(-1.52)	(0.93)	(-0.13)	(-2.04)	(0.85)
Loans	0.940	20.30	1.354**	1.264	19.23*	2.468***	1.388	24.68	2.345***	1.500	24.10*	2.203***	1.832	28.55*	2.278***
	(0.90)	(1.58)	(2.36)	(0.94)	(1.72)	(3.62)	(1.02)	(1.67)	(3.47)	(1.25)	(1.88)	(3.32)	(1.52)	(1.69)	(3.37)
Efficiency	0.287	16.21**	0.386	-1.702	-3.737	0.334	-0.574	10.45	0.574	-1.196	3.273	0.727	-0.577	21.11*	0.883
	(0.30)	(2.13)	(0.56)	(-1.51)	(-0.46)	(0.40)	(-0.55)	(1.24)	(0.70)	(-1.18)	(0.44)	(0.90)	(-0.51)	(1.97)	(1.08)
ROA	4.067	86.09**	15.64**	-12.14	77.35	12.01	-8.610	55.76	-0.0103	-16.29	-3.266	-0.327	-13.49	56.30	1.364
	(0.50)	(2.01)	(2.12)	(-0.83)	(1.13)	(0.84)	(-0.48)	(0.72)	(-0.00)	(-0.91)	(-0.05)	(-0.03)	(-0.75)	(0.64)	(0.12)
GDP growth	-0.109***	-0.100	-0.0372**	-0.130***	-0.216	-0.0540**	-0.138***	0.101	-0.0271	-0.126***	-0.250	-0.0424*	-0.125***	-0.274	-0.0428*
	(-4.74)	(-0.65)	(-2.03)	(-4.79)	(-0.87)	(-2.66)	(-4.79)	(0.38)	(-1.04)	(-4.65)	(-0.98)	(-1.86)	(-4.35)	(-1.05)	(-1.87)
Constant	3.701	13.85	-1.319	2.863	8.182	-3.212	3.205	23.17	-2.871	4.309	45.05*	-2.354	5.340	73.06**	-2.398
	(1.61)	(0.83)	(-0.76)	(0.72)	(0.42)	(-1.36)	(0.77)	(1.21)	(-1.28)	(1.03)	(1.97)	(-1.09)	(1.16)	(2.17)	(-1.08)
Observations	784	784	784	394	394	394	382	382	382	382	382	382	382	382	382
Banks	98	98	98	55	55	55	53	53	53	53	53	53	53	53	53
R-squared	0.463	0.289	0.299	0.571	0.693	0.423	0.569	0.607	0.450	0.583	0.643	0.441	0.573	0.488	0.433
Adjusted R-squared	0.453	0.275	0.286	0.554	0.681	0.401	0.552	0.591	0.428	0.566	0.628	0.418	0.556	0.467	0.410
Wald tests: $\alpha_1 + \beta_1$	-0.020***	3.860***	-0.064**	-0.012**	0.233***	-0.015	-0.011**	4.377***	0.093	0,003***	1.216***	-0,073	1.400***	12.370***	0.025
$\alpha_1 + \beta_2$	0.273***	2.820***	-0.353	-0.036***	-0.006	-0.004*	-0.284	3.133***	0.188*	-0.178	0.056***	-0.015	0.010*	7.790***	0.338*
$\alpha_1 + \beta_3$	0.383***	4.960***	0.217***	0.006***	0.268***	0.008***	-0.027*	6.287***	0.414***	0.100***	0.729***	0.082**	1.681***	16.43***	0.492*

Table A4. Bank complexity and systemic risk: robustness checks

This table shows the results of the effects of bank internationalization on systemic risk over the 2005–13 period using alternative estimation methods and sample selection criteria.

Panel A reports results using four alternative estimation methods. Models (1), (2) and (3) report regression results of model: $Risk_{ijt} = (\alpha_1 + \beta_1 Crisis08\_11 + \beta_2 Post12\_13) * Foreign_{ijt} + \beta_3 Crisis08\_11 + \beta_4 Post12\_13 + \varphi X_{ijt-1} + \gamma Country_{jt-1} + \varepsilon_{ijt}$. Model (1) reports OLS regression results. Model (2) presents country-year fixed effects regression results. Model (3) reports WLS regression results. We take the inverse of the number of country observations for each country as the weight for each bank. While, Models (4) report regression results of model: $Risk_{ijt} = (\alpha_1 + \beta_1 Crisis08\_11 + \beta_2 Post12\_13) * \widehat{Foreign}_{ijt} + \beta_3 Crisis08\_11 + \beta_4 Post12\_13 + \varphi X_{ijt-1} + \gamma Country_{jt-1} + \omega_i + \varepsilon_{2ijt}$. This model reports second stage coefficient estimates from a two-stage least squares (2SLS) regression, where we use lagged regressor, asset growth and HHI assets-based as instruments for complexity proxy index in the first stage. Standard errors are reported in parentheses below their coefficient estimates and adjusted for both heteroskedasticity and within correlation clustered at the country level in columns (1a–1c), at the country-year level in columns (2a–2c), and at the country level in columns (3a–3c) and (4a–4c). Fischer test is a test of the absence of individual effects. Hansen j test (from the second stage) reports p-value of overidentification test. Kleibergen-Paap rank LM statistic (LM $\chi 2$ from the first stage) tests the null hypothesis that the excluded instruments are not correlated with the endogenous regressor. Kleibergen-Paap rk Wald F-statistic (Partial F-Stat from the first stage) testing for weak identification.

Panel B reports results of the estimation of Eq. (1) using four alternative sample selection criteria. Models (1) removes banks that operate foreign affiliates in less than six different foreign countries. Models (2) considers banks that operate strictly more than ten foreign subsidiaries. Models (3) excludes banks present in less than three different world regions. Models (4) includes banks with Herfindhal geographical complexity index strictly higher than 0.33.

Definitions of all variables are listed in Appendix Table A2. ***, **, and * indicate significance of the p-value respectively at the 1%, 5%, and 10% levels.

Panel A: Alternative estimation methods

	Model (1) OLS			Model (2) C×Y FE			Model (3) WLS			Model (4) 2SLS		
	MES (1a)	SRisk (1b)	ΔCoVaR (1c)	MES (2a)	SRisk (2b)	ΔCoVaR (2c)	MES (3a)	SRisk (3b)	ΔCoVaR (3c)	MES (4a)	SRisk (4b)	ΔCoVaR (4c)
Foreign (α_1)	-0.940***	-10.10*	-0.461**	-0.860***	-13.90**	-0.217	-0.196	-15.88***	0.506*	-1.808***	-11.86***	-1.291***
	(-2.90)	(-1.78)	(-2.57)	(-2.90)	(-2.48)	(-1.21)	(-0.44)	(-3.03)	(1.75)	(-3.39)	(-3.25)	(-2.60)
Foreign×Crisis08_11 (β_1)	1.453***	15.04***	0.386**	1.302***	18.13***	0.173	0.937***	10.65***	-0.0132	1.516***	15.29***	0.637**
	(6.12)	(4.29)	(2.04)	(4.89)	(3.36)	(0.95)	(2.65)	(3.57)	(-0.04)	(5.97)	(4.91)	(2.52)
Foreign×Post12_13 (β_2)	1.542***	17.25***	0.832***	1.433***	20.25***	0.476	0.192	13.22**	0.353	1.809***	16.81***	1.249***
	(4.91)	(4.15)	(3.46)	(3.89)	(3.19)	(1.65)	(0.39)	(2.42)	(0.98)	(5.31)	(4.65)	(4.59)
Crisis08_11	1.021***	-1.350	1.021***	-1.117	2.213	-0.577	0.981***	-1.394	1.282***	1.079***	0.412	0.967***
	(7.02)	(-1.07)	(7.02)	(-1.20)	(0.06)	(-0.88)	(2.75)	(-0.80)	(6.88)	(6.60)	(0.54)	(5.35)
Post12_13	0.950***	-5.232***	0.482***	-2.608***	-39.27	-0.888	1.133***	-4.065	0.575**	1.120***	1.183	0.285
	(5.31)	(-3.09)	(2.81)	(-5.52)	(-1.63)	(-1.56)	(3.03)	(-0.94)	(2.22)	(6.56)	(1.31)	(1.51)
Size	0.417***	9.993***	0.237***	0.478***	10.67***	0.251***	0.649***	7.784***	0.213***	-0.0967	-1.308	0.0977
	(4.82)	(4.47)	(6.56)	(6.10)	(4.61)	(5.98)	(5.05)	(4.05)	(3.13)	(-0.46)	(-0.67)	(0.56)
Leverage	-2.379	43.19	-1.512	0.384	69.67	-0.569	5.370	-44.51	-1.426	-6.571**	10.88	-4.839**
	(-1.34)	(1.08)	(-1.35)	(0.24)	(1.50)	(-0.47)	(1.48)	(-1.12)	(-0.55)	(-1.99)	(0.52)	(-2.04)
Deposit	0.0549	14.34	0.256	0.337	14.43	0.343	2.910***	-1.535	1.096*	-3.617***	-20.92*	-0.753
	(0.08)	(0.95)	(0.66)	(0.56)	(0.91)	(0.82)	(3.55)	(-0.18)	(1.72)	(-3.06)	(-1.69)	(-1.02)
Diversification	2.401**	20.46	0.430	2.785***	25.50	0.377	1.363	15.43	0.801	-0.444	-16.66*	0.286
	(2.61)	(1.05)	(0.85)	(3.51)	(1.18)	(0.66)	(0.68)	(0.79)	(0.93)	(-0.37)	(-1.77)	(0.42)
Loans	-0.772	-32.53***	-0.506	-0.860*	-32.94**	-0.474	-0.428	-44.68*	0.652	1.165	21.50	1.196**
	(-1.58)	(-2.77)	(-1.60)	(-1.70)	(-2.41)	(-1.24)	(-0.42)	(-1.69)	(1.02)	(1.13)	(1.55)	(2.01)
Efficiency	-0.156	36.26**	-0.839	0.187	39.17**	-0.341	-0.450	27.03*	-1.144	-0.481	13.08*	-1.166*
	(-0.19)	(2.05)	(-1.52)	(0.23)	(2.11)	(-0.45)	(-0.29)	(1.68)	(-1.54)	(-0.58)	(1.87)	(-1.68)
ROA	-5.071	-145.9*	21.85***	-13.55	-315.3**	22.15***	-12.34	60.51	35.57**	1.429	86.02*	11.41
	(-0.64)	(-1.72)	(2.74)	(-1.38)	(-2.05)	(3.02)	(-0.59)	(0.34)	(2.28)	(0.15)	(1.83)	(1.26)

GDP growth	-0.0655***	0.107	-0.00223	0.0261	-0.181	-0.0595	-0.131***	-0.325	-0.0216	-0.0633***	-0.0760	0.0105
	(-3.27)	(0.55)	(-0.14)	(0.22)	(-0.10)	(-1.21)	(-4.71)	(-1.08)	(-0.77)	(-2.77)	(-0.45)	(0.69)
Constant	-3.548***	-100.4***	0.0153	-3.701***	-98.38***	-1.218	-5.860***	-45.33*	-1.759*			
	(-3.62)	(-3.56)	(0.02)	(-3.55)	(-3.25)	(-1.03)	(-3.14)	(-1.81)	(-1.72)			
Bank Fixed Effects	No	No	No	No	No	No	No	No	No	Yes	Yes	Yes
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country×Year Fixed Effects	No	No	No	Yes	Yes	Yes	No	No	No	No	No	No
IV	No	No	No	No	No	No	No	No	No	Yes	Yes	Yes
Observations	784	784	784	784	784	784	784	784	784	696	696	696
Banks	98	98	98	98	98	98	98	98	98	98	98	98
R-squared	0.657	0.549	0.464	0.809	0.587	0.635	0.450	0.388	0.352	0.455	0.311	0.270
Adjusted R-squared	0.644	0.533	0.445	0.771	0.506	0.564	0.441	0.378	0.341	0.363	0.195	0.148
Fischer test (p-value)							0.000	0.000	0.000	0.000	0.000	0.000
Hansen test (p-value)										0.000	0.037	0.016
LM $\chi 2$										17.38***	17.38***	17.38***
Partial F-Stat										121.00***	121.00***	121.00***
Wald tests: $\alpha_1 + \beta_1$	0.602***	4.940*	-0.075	0.442**	4.230*	-0.044	0.741*	-5.230*	0.493**	-0.287	3.430*	-0.654**
$\alpha_1 + \beta_2$	0.513***	7.150*	0.371**	0.573*	6.350*	0.259*	-0.004	-2.660**	0.859***	0.001*	4.950**	-0.042*

Panel B: Alternative sample selection criteria

Sample if:	Model (1) Banks operate foreign affiliates in more than six countries			Model (2) Banks have more than ten foreign subsidiaries			Model (3) Banks are present in at least three world regions			Model (4) Banks with complexity index higher than 0.33		
	MES	SRisk	ΔCoVaR	MES	SRisk	ΔCoVaR	MES	SRisk	ΔCoVaR	MES	SRisk	ΔCoVaR
	(1a)	(1b)	(1c)	(2a)	(2b)	(2c)	(3a)	(3b)	(3c)	(4a)	(4b)	(4c)
Foreign (α_1)	-1.671**	-4.382	-1.084***	-0.798	-9.271	-1.004***	-1.224**	-14.89**	-1.222***	-1.190**	-14.23**	-0.584
	(-2.35)	(-0.82)	(-4.77)	(-0.89)	(-0.88)	(-3.48)	(-2.15)	(-2.05)	(-3.38)	(-2.34)	(-2.49)	(-0.84)
Foreign×Crisis08_11 (β_1)	1.749***	23.72***	0.495**	1.703***	31.20***	0.518*	1.770***	28.33***	0.411*	1.658***	25.21***	0.467**
	(6.78)	(5.33)	(2.27)	(5.79)	(5.45)	(1.95)	(6.33)	(5.19)	(1.87)	(6.31)	(5.23)	(2.25)
Foreign×Post12_13 (β_2)	2.206***	28.73***	1.116***	2.450***	40.82***	1.394***	2.657***	33.80***	0.985***	2.442***	27.84***	0.751**
	(5.69)	(5.41)	(3.55)	(5.01)	(5.81)	(4.04)	(7.06)	(5.36)	(3.33)	(7.05)	(5.30)	(2.56)
Crisis08_11	1.196***	0.230	1.075***	1.130***	-0.696	1.109***	1.180***	0.707	1.141***	1.252***	1.438	1.186***
	(7.01)	(0.20)	(6.38)	(6.20)	(-0.65)	(6.17)	(8.11)	(0.71)	(7.49)	(8.55)	(1.39)	(7.44)
Post12_13	1.263***	0.680	0.439**	1.179***	-0.417	0.469**	1.229***	1.443	0.499**	1.286***	1.983*	0.521**
	(6.61)	(0.48)	(2.01)	(5.87)	(-0.34)	(1.99)	(7.65)	(1.23)	(2.56)	(8.09)	(1.67)	(2.59)
Size	-0.231	-1.175	0.157	-0.284	-0.0947	0.214	-0.369*	-3.988*	0.0636	-0.510**	-4.539**	-0.0909
	(-0.76)	(-0.47)	(0.61)	(-0.83)	(-0.04)	(0.81)	(-1.82)	(-1.91)	(0.36)	(-2.44)	(-2.09)	(-0.50)
Leverage	-5.371	17.87	-2.747	-4.727	12.75	-0.275	-5.219	12.50	-1.666	-5.313	7.731	-0.957
	(-1.41)	(1.16)	(-1.01)	(-1.21)	(0.97)	(-0.14)	(-1.52)	(0.96)	(-0.87)	(-1.42)	(0.64)	(-0.52)
Deposit	-3.315***	-12.36	-0.796	-4.715***	-8.044	-0.715	-4.634***	-20.18*	-0.539	-3.215**	-8.786	-0.0196
	(-2.94)	(-1.03)	(-0.97)	(-4.20)	(-0.71)	(-0.78)	(-4.24)	(-1.79)	(-0.61)	(-2.56)	(-0.86)	(-0.02)
Diversification	-1.948	-19.23*	0.908	-3.606**	-22.16*	0.0326	-2.647*	-13.68	-0.528	-3.211**	-12.27	-1.137
	(-1.24)	(-1.89)	(0.87)	(-2.03)	(-1.88)	(0.03)	(-1.84)	(-1.28)	(-0.63)	(-2.20)	(-1.22)	(-1.40)
Loans	0.633	30.20**	1.140*	1.304	27.11**	0.357	1.047	38.68***	0.722	0.897	32.73**	0.634
	(0.66)	(2.09)	(1.71)	(1.22)	(2.05)	(0.52)	(1.03)	(2.64)	(1.06)	(0.89)	(2.31)	(0.93)
Efficiency	-0.385	18.56***	-1.260	0.359	14.65**	-0.716	-0.293	10.66*	-0.389	0.191	15.86**	-0.228
	(-0.35)	(3.14)	(-1.24)	(0.31)	(2.21)	(-0.66)	(-0.29)	(1.74)	(-0.43)	(0.19)	(2.48)	(-0.26)
ROA	8.806	76.36*	11.63	4.521	38.47	14.74*	0.698	5.595	16.80**	5.889	51.88	18.32**
	(0.78)	(1.72)	(1.38)	(0.40)	(1.07)	(1.88)	(0.07)	(0.15)	(2.01)	(0.59)	(1.37)	(2.25)
GDP growth	-0.0531**	0.126	-0.00382	-0.0530**	0.117	0.00663	-0.0525**	0.0355	0.00615	-0.0511**	0.0375	0.00882
	(-2.06)	(0.65)	(-0.23)	(-2.01)	(0.59)	(0.38)	(-2.03)	(0.18)	(0.37)	(-2.00)	(0.20)	(0.54)
Constant	6.685**	1.304	0.154	7.184**	-4.146	-0.248	8.310***	32.18*	1.073	9.018***	31.98**	2.229
	(2.06)	(0.06)	(0.06)	(2.01)	(-0.22)	(-0.10)	(3.93)	(1.86)	(0.72)	(4.18)	(2.00)	(1.43)
Observations	586	586	586	529	529	529	551	551	551	559	559	559
Banks	82	82	82	78	78	78	76	76	76	82	82	82
R-squared	0.485	0.454	0.269	0.478	0.544	0.278	0.491	0.497	0.264	0.490	0.452	0.274
Adjusted R-squared	0.473	0.442	0.252	0.465	0.533	0.260	0.479	0.484	0.246	0.478	0.439	0.257
Wald tests: $\alpha_1 + \beta_1$	0.078	19.338***	-0.589***	0.905	21.929***	-0.486***	0.546	13.440*	-0.811**	0.468	10.980*	-0.117*
$\alpha_1 + \beta_2$	0.535*	24.348***	0.032*	1.652*	31.549***	0.390*	1.433**	18.910**	-0.237	1.252**	13.610**	0.167*