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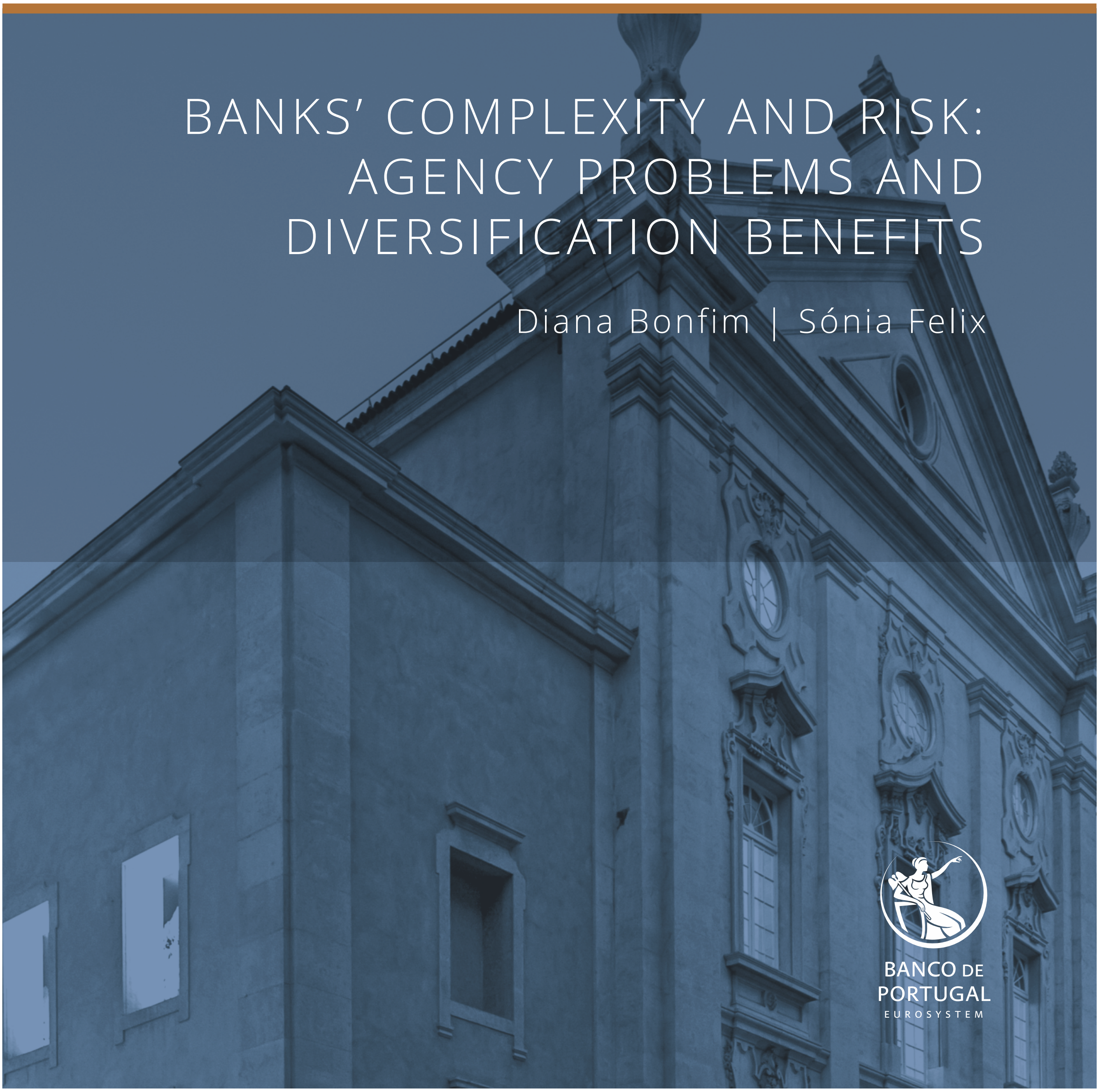
Diana Bonfim | Sónia Felix



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Banks' complexity and risk: agency problems and diversification benefits

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Abstract
Bank complexity is often associated with risk, due to moral hazard and agency problems. At the same time, complexity may be linked to diversification and scale economies, thus leading to less risk. In this paper, we provide empirical evidence on the relationship between bank complexity and risk-taking. We find a positive relationship between geographical complexity and bank risk. Banks that operate in more countries, both through banks and non-banks, have riskier balance sheets and more non-performing loans. Further, banks that operate in Africa have higher risk levels due to larger volatility of returns. The link between structural complexity and bank risk is weaker, but generally negative. Our results suggest that moral hazard and agency problems may be more acute when banks operate in many geographies and in emerging market economies. In contrast, the results are consistent with diversification and scale benefits arising from operating in more business areas.

JEL: F23, G21, G23

Keywords: bank complexity, risk-taking, diversification.

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1. Introduction

Bank complexity is perceived today as something negative for financial stability. If a bank is too big, too opaque or too complex, monitoring it becomes much more challenging. One of the lessons of the global financial crisis was that the costs of living with the pervasive incentives facing too-big-to-fail banks could be too-big-to-fund using taxpayers' money. There were immediate calls to make sure that these large (and complex) institutions would internalize the costs they might impose on society through this too-big-to-fail problem. If banks become reckless in their decisions due to the belief that they will be bailed out in case of a bad outcome, then regulation should make sure that something breaks this costly moral hazard problem. Regulation has thus moved in the direction of providing incentives for banks to become smaller, more transparent, and simpler. This should allow supervisors to better perform their jobs, as well as for depositors and other investors to be more aware of the risks that they are exposed to.

Despite the regulatory changes, the link between banks' complexity and the risks they assume is not entirely clear. On the one hand, complexity may indeed have a dark side and be associated with risk-taking behaviors. More complex banks are more opaque and more difficult to manage and monitor, thus creating moral hazard and agency problems (Morgan 2002; Dam and Koetter 2012; Duchin and Sosyura 2014; Beck *et al.* 2017). Banks might also take too much risk because they believe that they are too big to fail (Acharya *et al.* 2016; Cetorelli and Traina 2018) or because of strategic complementarities (Farhi and Tirole 2012). On the other hand, complexity may be necessary to achieve a certain operating scale and thus be part of a bank's business model without entailing more risk-taking (Cetorelli *et al.* 2014; Cetorelli and Goldberg 2016). Complexity can be a different name for diversification, which has well established benefits in finance (Markowitz 1952; Laeven and Levine 2007; Buch *et al.* 2012; Berger *et al.* 2016).

Given the ambiguous predictions and findings in the literature, in this paper we empirically analyze the relationship between complexity and risk in banks. We consider two different concepts of bank complexity: geographical and structural. The former refers to the complexity that might arise from the fact that a banking group operates across many jurisdictions. The latter refers to the business structure of the banking group, taking into account its internal organization through affiliates and business types.

Using supervisory data on the activity and organization of Portuguese banking groups, we estimate the relationship between these two dimensions of bank complexity and bank risk. We consider several indicators of risk, to take on board different aspects of risk in the banking business.

We find that banks that are more exposed to geographical complexity have more risk. This positive relationship works through two channels. First, the number of countries in which a bank operates, both through bank and non-bank activities, is positively related with the riskiness of banks' assets. Second, activities in emerging markets increase banks' risk through income volatility. This result is anchored on the fact that the geographical exposure of Portuguese banks is based on two pillars: part of the cross-border activity refers to activity in other European countries, while another important part refers to activity in Africa, notably in former Portuguese colonies. The moral hazard and agency problems that explain a positive relationship between complexity and risk may assume a different magnitude when banks operate in countries that are very similar in terms of the legal, economic, governance, regulatory and supervisory framework, or when they operate in countries in which many of these dimensions may differ significantly. La Porta *et al.* (2000), Levine *et al.* (2000), Beck *et al.* (2006), and Correa and Goldberg (2019) discuss the importance of these differences in the activity of banks. Beck *et al.* (2011), Demirgüç-Kunt and Klapper (2012), Beck and Cull (2013), and Beck (2015) discuss in detail how banks operate in Africa and which challenges they face.

When it comes to structural complexity, the results are quite different. We find a negative relationship between structural complexity and bank risk. This is consistent with positive effects stemming from diversification and economies of scale.

That said, the results obtained for structural complexity are generally weaker than those obtained for geographical complexity. Risk seems to stem more from the fact that banks are exposed to multiple geographies than from complexity measures associated with their organizational structure and the reach of their activities in terms of business sectors.

One important concern underlying these results is that it is challenging to establish a causal relationship between complexity and risk. To mitigate endogeneity concerns arising from reverse causality and omitted variables, we explore one recent change in bank regulation that might affect banks' complexity, without necessarily directly affecting banks' risk. Systemically important institutions in each European country have to hold additional capital buffers, through the Other Systemically Important Institutions capital buffer (O-SII buffer). This buffer is calibrated by taking into account banks' size, their importance for the economy, their interconnection and, crucially, their complexity. As such, a bank that is subject to this buffer may have incentives to decrease its complexity (Carmassi and Herring 2016). We explore this exogenous change in regulation using an instrumental variables approach. The results differ in several aspects when we use this approach, but the most important conclusions remain valid. We confirm a positive and robust relationship between geographical complexity and banks' risk and we obtain (weaker) evidence of a negative relationship between structural complexity and risk.

Our paper contributes to the literature on banks' complexity and risk. This literature offers conflicting theoretical and empirical evidence on the relationship between these two variables. Our analysis helps to understand whether more complexity goes hand in hand with more risk, coming from agency problems and moral hazard (Farhi and Tirole 2012; Dam and Koetter 2012; Duchin and Sosyura 2014; Acharya *et al.* 2016; Chernobai *et al.* 2020; Beck *et al.* 2017), or if complexity is associated with diversification benefits, enhanced performance and risk resilience

(Markowitz 1952; Laeven and Levine 2007; Buch *et al.* 2012; Cetorelli *et al.* 2014; Cetorelli and Goldberg 2016; Berger *et al.* 2016).

Our results reconcile these two apparently contradictory hypothesis, showing that bank complexity can be associated both with more and less risk. Operating across many regions, notably in emerging market economies, is more likely to create moral hazard and agency problems, thus leading to more risk. Having a complex business structure and operating across different business types can allow for more diversification and scale benefits, thus leading to lower risk levels.

2. Data

Our empirical analysis is based on quarterly bank-level data obtained from supervisory reports, for the period between 2014 and 2018. These reports include data on 17 banking holding companies (BHC). Standalone banks are excluded from the analysis, given that most of the complexity indicators would not have a meaningful interpretation.

The first building block of our analysis are the complexity measures. Bank complexity is in itself a complex concept and we will rely on a broad set of indicators to rank banks according to their complexity (Cetorelli *et al.* 2014; Goldberg and Meehl 2019). Most of the measures are constructed using end-of-year data on the activities of banking groups. The second pillar is the construction of bank-level risk-taking indicators, also using supervisory data. Finally, to study the relationship between complexity and risk, we need to control for relevant bank characteristics. Below we describe in detail each of the data blocks.

2.1. Measuring bank complexity

We consider two broad concepts of bank complexity: geographical complexity and structural complexity.

Geographical complexity describes how affiliate entities are spanned across regions or countries. Arguably, operating across a larger set of geographies adds complexity to the management of the banking groups. That said, this wider reach also promotes diversification. The relationship between geographical complexity and risk can thus be positive or negative.

To measure geographical complexity we start by considering the number of countries in which a banking group operates. On average banks have activities in 5 different countries, but there is significant variation, as some banks operate only in Portugal, while other are present in 16 countries (Table 1). These banks do not hold vastly complex structures in their foreign operations, as the number of foreign affiliates is only slightly larger: banks have, on average, 8.5 affiliates abroad. Not all these foreign operations are related to banking. The average number of foreign affiliates is 4, which means that when a banking group operates in another country, it typically does so only through one bank. The remaining affiliates may also be financial institutions, but they are not deposit-taking institutions.

The cross-border activity of Portuguese banks hinges on two pillars. Part of their operations refers to activity in other European countries, while another important part refers to activity in Africa, notably in former Portuguese colonies. In terms of complexity, these two universes may be quite different. While in Europe most of the regulatory and supervisory framework is common (or very similar), in African emerging economies there are important differences not only in these frameworks, but also on the design and effectiveness of the legal system or on corporate governance (La Porta *et al.* 2000; Levine *et al.* 2000; Beck *et al.* 2006, 2011; Correa and Goldberg 2019). Furthermore, the risks that banks are exposed to might also be different in these two geographies. In order to examine how banks' exposures to emerging markets may shape the relationship between complexity and risk, we add to the set of geographical complexity the number of affiliates each banking group has in Africa. We find that, on average, each banking group has one affiliate in Africa. However, there is a lot of heterogeneity in this variable. Only 40% of the banking groups actually have operations in Africa through affiliates.

The second concept of complexity that we explore is not related to geography, but rather to business complexity. In this dimension, we consider a set of indicators that capture the structural complexity of a banking group by looking into how the group is organized through affiliates and business types. The simplest indicator that we consider is the number of affiliates of each banking group. This number ranges from 1 to 91 affiliates in each group. The median number of affiliates in each group is 16.

Another dimension of structural complexity derives from the number of activities carried out within each banking group. Bank holding companies can operate in non-banking financial activities, such as insurance, mutual funds or advisory services, as well as on non-financial activities. Some banking groups in our sample have operations in a broad set of sectors, such as tourism, real estate or health care. One of the indicators we use to capture this complexity is the share of non-financial business types, defined as the percentage of the group's non-financial activities.

On average, only 45% of the types of business carried out by the banking groups in our sample refer to the financial sector. Once more, there is considerable heterogeneity. Some groups are highly focused on financial activities, with a share of non-financial business types of 33%. Other groups are highly diversified and non-financial activities account for 91% of their operations.

We also consider the number of business activities within each banking group. On average, each group engages in 3.5 activities, but this number varies from 1 to 11. Finally, we also compute the Herfindahl-Hirschman Index (HHI) for business types, which equals 0 when a group operates only in one business type. On average, the HHI stands at 0.66.

Taken together, these indicators show that Portuguese banks operate in several geographies and engage in diversified activities, though there is significant dispersion across banks.

When we consider the evolution of complexity indicators during the sample period, we see that most of the indicators showed a downward trend from 2014 to 2018 (Figures 1 and 2). That said, the decrease was concentrated in the first two years of our analysis. This reflects the adjustment of the Portuguese banking sector in the aftermath of the euro area sovereign debt crisis. Regulatory and supervisory changes, such as the implementation of systemic buffers or the creation of the Single Supervisory Mechanism (SSM), might have provided incentives for a decrease in complexity. The only exception to this broad-based decrease in complexity comes from the HHI for business types, which increased throughout most of the sample period.

To better characterize the heterogeneity within the banking sector, in Table 2 we compare the complexity indicators for the 6 largest banking groups with the smaller banking groups. These 6 largest banking groups are classified as systemically important institutions in Portugal, being subject to the O-SII buffer foreseen in the European regulation. This buffer is calibrated using a systemic risk score that depends on each bank's size, importance for the economy, interconnection, potential contagion, and complexity. The complexity metrics used to calibrate the O-SII buffer are the notional value of OTC derivatives, cross-jurisdictional liabilities and cross-jurisdictional claims. Even though these metrics differ from the ones used in our analysis, we would expect them to be significantly correlated.

The statistics reported in Table 2 confirm this. The 6 largest banks in Portugal operate in more countries, and have more foreign affiliates. Most of them have activities in Africa, while most of the smaller banks do not. They also rank higher in terms of structural complexity: they have more affiliates and operate in more types of business activities.

2.2. Measuring bank risk

Risk is part of a bank's business and there are many ways to measure it. Some indicators focus on specific risk dimensions, such as credit risk. Others are more encompassing, but sometimes not focused only on risk. Given the challenges in measuring risk, we consider four different indicators, which we summarize in Table 3.

The first indicator is a measure of financial risk designed to capture the banks' risk of default, by taking into account the volatility of returns and the bank's leverage (ln z_score). It is computed as the logarithm of the inverse of the average return on assets in a given period plus the equity to assets ratio of the bank, divided by the standard deviation of the return on assets (in the last eight quarters). The higher the z-score, the higher the risk. According to this indicator, risk increased slightly in 2015, in the aftermath of the bail-in of one of the largest Portuguese banks (Beck *et al.* 2020). After that year, the z-score for Portuguese banks showed a sustained decrease, although with substantial heterogeneity across banks. Nonetheless, this trend in risk reduction seems to have been halted in 2018.

We can also capture risk by using granular information on the banks' exposures. To do that, we consider the logarithm of the average default probability of the loans granted to firms by each bank, using the output of an in-house firm-level credit scoring model (Antunes *et al.* 2016). The average default probability of firms in the portfolio of the banks between 2014 and 2018 is 7%. This relatively high number reflects the protracted recovery of the Portuguese economy in the aftermath of the euro area sovereign debt crisis. Further, while the z-score started to decrease only in 2016, the default probability of banks' corporate portfolios decreased markedly already in 2015. Again, there is considerable dispersion in the average default probability in each banks' corporate loan book, reflecting a diversified exposure in terms of risk profiles.

Another way to capture banks' risk-taking is to consider the evolution of non-performing loans (NPL). We consider a flow indicator (New NPL / Assets), which captures the flow of impairments and provisions recorded in each year, as a percentage of total assets. The variation within the sample is substantial. On average, new non-performing loans in each year represent 0.52% of banks' assets, but this ratio ranges from -1.43 to 2.66%. The flow of non-performing loans has been steadily declining since 2014, reflecting a consistent effort to improve the quality of banks' assets in the aftermath of the financial assistance program to the Portuguese economy (Bonfim *et al.* 2020).

Finally, a broad way to capture the risks taken by a financial institution is to consider the ratio between risk-weighted assets and total assets (RWA / Assets). A bank with high risk-weighted assets to total assets has high risk weights attached to its assets. While this could mean that the bank has more prudent risk management policies, the fact that only three banks in Portugal use internal credit risk models to estimate regulatory capital requirements suggests instead that higher risk weights reflect higher risk-taking levels. The sample average ratio is 0.61, but it ranges from 0.4 to 0.94, confirming that there is substantial variety in risk profiles in the Portuguese banking sector. This indicator also decreased towards less risk during the period analyzed.

If we jointly consider the evolution of complexity and risk indicators, we observe that both have been declining in the last years, for most of the indicators considered. Still, these aggregate time trends might hide important cross-sectional variation. When we compute pairwise correlations between the complexity and risk indicators, the positive relationship is generally confirmed.

2.3. Bank characteristics

The apparent positive unconditional correlation between risk and complexity indicators might be hiding the role of other bank characteristics that also influence bank risk and bank complexity. It is thus crucial to control for potentially relevant bank characteristics in a multivariate setting.

In Table 4 we report the summary statistics for a set of bank characteristics. Bank size, captured by the logarithm of total assets (ln Assets), is often associated with risk-taking, as larger banks might be perceived as too-big-to-fail (Demirgüç-Kunt and Huizinga 2013). The implicit belief of a bailout might lead to excessive risk (Gropp *et al.* 2011).

We also control for the ratio between loans and assets. This indicator captures banks' specialization in lending, thus reflecting the banks' business model. Banks with a larger fraction of total assets linked to loans to customers have a more traditional intermediation profile, which is often associated with less risk. There is substantial variation in our sample, with a minimum of 1.8% and a maximum of 96%, showing that there are different business models. On average, slightly more than half of the banks' total assets refer to bank loans.

Bank profitability might also be a relevant control variable. In the sample, banks' return on assets (ROA) is on average 0.76%, showing a gradual improvement during the sample period. Many banks still recorded losses during part of the sample period, mainly due to the recognition of impairments in their loan books in the aftermath of the euro area sovereign debt crisis.

We also control for bank efficiency, captured by the cost-to-income ratio. On average this ratio stood at 60.5, showing a persistent improvement since 2016. This improvement reflects both the growth in income mentioned above and the adoption of cost-cutting measures, such as massive branch closures (Bonfim *et al.* 2019).

Finally, we also control for the effects of bank capital on risk. Better capitalized banks are expected to take less risks, as shareholders have more skin in the game (Berger and Bouwman 2013; Peek and Rosengren 2005; Blattner *et al.* 2019). Banks' Tier 1 ratio was on average 16.1% and showed a significant improvement during the period analyzed.

3. Complexity and risk-taking

3.1. Empirical strategy

Our main goal is to understand whether complexity is associated with more or less bank risk. On the one hand, more complex banks are less transparent and so may be more prone to take risk. On the other hand, more complex banks are also more diversified, which may be linked to less risk.

To explore the direct link between complexity and risk-taking of Portuguese banks, we estimate the following model:

$$Risk_{it} = \beta_0 + \beta_1 Complexity_{i,t-1} + \delta X_{i,t-1} + \gamma_t + \varepsilon_{it} \tag{1}$$

where *i* denotes an individual bank and *t* denotes time. The term $Risk$ will capture banks' risk-taking and $Complexity$ is the set of bank complexity indicators, which enter the model one at a time. In these regressions we will control for bank-specific time-varying characteristics captured by the vector $X_{i,t-1}$ and time fixed effects γ_t.[1] The independent variables are lagged by one period. The term ε_{it} is an error term with the conventional statistical properties. This specification allows us to contribute to the debate on the link between risk and complexity. As discussed above, the evidence available in the literature is mixed regarding the expected sign of β_1. Complexity may be a synonym for diversification, thus implying less risk, or for opacity, having an opposite effect. With this specification we can better understand the (non-causal) relationship between these two dimensions.

3.2. Main results

3.2.1. Geographical complexity and risk. In Table 5 we report the results for the estimation of Equation (1) for the relationship between geographical complexity and the most encompassing risk indicator in our analysis, the logarithm of banks' z-scores. The z-score is the inverse of the average return on assets in a given period plus the equity to assets ratio of the bank, divided by the standard deviation of the return on assets in the last 8 quarters. This means that a higher z-score is associated with more risk through the combination of more leverage and more volatility of returns (Boyd *et al.* 1993). Both dimensions are by themselves important signs of bank fragility. Their combination renders banks especially vulnerable, as a high leveraged bank coping with volatile returns will find it much harder to withstand negative shocks.

We estimate the relationship between banks' z-score and each one of the five geographical complexity indicators: Number of countries, Number of foreign affiliates, Number of foreign bank affiliates, Number of affiliates in Africa, Dummy variable for affiliates in Africa. None of the first three dimensions shows a statistically significant relationship with banks' z-scores. Banking groups operating in more countries, with more foreign bank and non-bank affiliates do not have significantly different z-scores from banks that have less geographical complexity.

However, we find a significant positive relationship between the indicators that capture geographical complexity through exposure to emerging market economies (namely to Africa). Banks that have more affiliates in Africa show higher z-scores. The relationship is stronger when we consider only the effect of having or not exposure to Africa through local affiliates.

The higher risk associated with operations in Africa captured by the z-score might be related to the higher volatility of returns in these economies. The most significant part of the exposure refers to Angola, an oil-exporting economy. This means that banks' operations in this country are affected by fluctuations in oil prices and exchange rates, leading to larger volatility in their returns (IMF 2016).

1. We do not consider bank fixed effects in the estimated models because of the short time span of the dataset.

In Table 6, we report the results of geographical complexity on the average default probability in banks' corporate loan portfolio (ln PD). This indicator captures a very different dimension of bank's risk. While the z-score considers the capital structure and volatility of returns, this indicator zooms in on one of the main sources of bank losses: corporate loans. Using an in-house credit scoring model with granular loan and firm information (Antunes *et al.* 2016), we compute the average default probability in each bank's corporate loan book.

The results are very different when we use this indicator. Now we find that the first three geographical complexity measures (Number of countries, Number of foreign affiliates, Number of foreign bank affiliates) are positively related with the risk banks take in their corporate loan book. It is important to note that the default probabilities are computed only for domestic firms. This means that banks that have stronger activity abroad, both through banks and through other activities, are exposed to more corporate risk domestically. One possible explanation for this result might be related to higher risk tolerance for the banks that choose to expand abroad. That said, the results do not point to any link between activities in Africa and risk in banks' domestic corporate loan book.

The results for the third risk indicator, new NPLs over total assets, are broadly consistent with those obtained with the average default probabilities (Table 7). Banks that operate in more countries, both through banking and non-banking activities, show higher increases in NPLs. Once more, this relationship does not hold for activities in Africa.

The consistency between the results obtained with average default probabilities and new NPLs is not unexpected. Most of the loan losses recorded in the Portuguese banking sector during the euro area sovereign debt crisis were in the corporate loan book (Marques *et al.* 2020). Banks with a portfolio of riskier borrowers are thus expected to also be those with more NPLs.

Finally, we examine the relationship between geographical complexity and the risk-weighted assets ratio (Table 8). This indicator offers an encompassing view of the riskiness of the entire portfolio of bank assets. The higher the risk weights assigned to banks' assets, the higher the risk in the balance sheet. The results show that there is also a positive relationships between geographical complexity and this risk indicator. However, this relationships occurs only through the number of countries and the number of foreign affiliates. The number of foreign bank affiliates does not seem have a significant relationship with risk as measured by the risk-weighted ratio, suggesting that the link exists mainly through non-bank activities abroad which might, in some cases, have higher risk weights attached. Finally, operations in Africa do not have a statistically significant relationship with the risk weighted assets ratio.

In sum, we find a significant positive relationship between geographical complexity and banks' risk. This relationship has two main dimensions. First, banks more exposed to Africa show higher risk as captured by z-scores. This possibly reflects the volatility in returns generated by these exposures. Second, the number of countries in which a bank operates, including both bank and non-bank activities, is positively related with the riskiness of banks' assets, captured by corporate default probabilities, non-performing loans and risk-weights.

3.2.2. Structural complexity and risk. Geographical and structural complexity refer to different dimensions of complexity. While some banks have complex internal structures and also operate in a wide set of regions, other banks, often smaller, have very simple structures and operate dominantly in the domestic market. That said, most banks are somewhere in the middle of these extremes, ranking high in one of the dimensions but not in the other. For this reason, we repeat the analysis of the previous sub-section, but now looking into four indicators of structural complexity: number of affiliates, share of non-financial business types, number of business types, and HHI for business types.

In Table 9 we report the results for the estimation of Equation (1) using structural complexity indicators for the first bank risk indicator, the z-score. We find a negative significant relationship between the number of affiliates a bank has and the z-score. Banks with more complex internal structures reflected in a larger number of affiliates show lower levels of risk. This result contrasts with the positive relationship between risk and geographical complexity. One possible explanation for this result might be that banks with more affiliates are more diversified, which allows them to mitigate the volatility of their income stream (Baele *et al.* 2007; Goddard *et al.* 2008).

The negative relationship between structural complexity and risk, captured by the z-score, works through the number of affiliates, but not through the other three indicators that capture complexity through the composition of activities carried out by these affiliates. Having a larger share of non-financial activities, a larger number of business types or a higher HHI in business types is not positively nor negatively related with our broader measure of risk, the z-score.

In Tables 10, 11, and 12, we report the relationship of the four structural complexity indicators with the remaining three bank risk indicators: the average default probability of the corporate loan book, new NPLs over total assets and the risk-weighted assets ratio. We cannot find any statistically significant relationship between structural complexity and banks' risk-taking in any of these estimations.

While for geographical complexity we could document a consistently positive relationship between complexity and risk, with structural complexity we find a negative relationship between the number of affiliates and risk measured by the z-score, but not for any other complexity or risk indicator. This suggests that the link between structural complexity and risk is weaker than for geographical complexity.

3.3. Complexity, risk and regulation: an instrumental variables approach

The results presented so far do not allow us to establish a causal relationship between complexity and risk. The link between these two dimensions may be endogenous for a number of different reasons, including reverse causality and omitted variables. For instance, banker managers' (time-varying) risk tolerance may shape decisions both on the level of geographical and structural complexity and on the riskiness of assets held.

To help us in getting closer to a causal analysis, we explore one recent change in bank regulation: the announcement of the Other Systemically Important Institutions capital buffer (O-SII buffer).

The systemic risk buffer was one of the solutions put forth by the Basel Committee in the aftermath of the global financial crisis to mitigate banks' contribution to systemic risk due to their size and complexity. Global banks that are considered systemic have to hold additional capital buffers, thus contributing to a better alignment of incentives. At the European level, the Capital Requirements Directive allows national macroprudential authorities to impose capital buffers on banks that are systemically relevant in each jurisdiction (Budrys *et al.* 2018). Banco de Portugal adopted this framework in 2015, initially front-loading some of the implementation foreseen in international regulation. Six of the largest banking groups have been classified as O-SII, based on a set of criteria related to each bank's size, its importance for the economy, its interconnection and potential connection and, finally, its complexity.[2] These six banks can be subject to additional capital requirements, ranging from 0 to 2% of the total risk exposure amount.[3] If this capital buffer is a binding constraint for the banks' desired or optimal capital level, banks may choose to react in three different ways: i) they may increase their Core Tier 1 capital (CET1) to meet the new requirements; ii) they may reduce risk-weighted assets (RWA); or iii) they may decrease their contribution to systemic risk, thus reducing their O-SII buffer in the future. While the first two adjustment mechanisms are similar to those seen after the implementation of any capital requirement, the last one is specific to this buffer. Indeed, the third adjustment mechanism is deeply intertwined with complexity, as this is one of the ingredients in the calibration of the O-SII score. According to the guidelines of the European Banking Authority (EBA), the score is computed using four categories of indicators: size, importance, complexity and interconnectedness. Each one of these categories has a weight of 25% on the computation of the score, which can then be fine-tuned using supervisory judgment. Complexity is captured by the (notional) value of OTC derivatives, cross-jurisdictional claims and cross-jurisdictional liabilities. Though these metrics differ from the complexity indicators used in this paper, we expect them to be significantly correlated.

Given that these buffers create an exogenous incentive for banks to decrease their complexity levels, we explore this regulatory shock in an instrumental variables setting. We examine how bank complexity affects banks' risk taking behaviors by exploring an exogenous shock coming from a regulatory tool that targets the complexity of banks, thus exploring the idea that regulation might have an

2. Methodological details on the calibration of O-SII buffers can be found in https://www.bportugal.pt/sites/default/files/anexos/doc_osii_en_0.pdf.

3. In Table 2 we report the complexity indicators for banks that are classified as O-SIIs and for the other banks in the sample.

important role in shaping the link between complexity and risk in banking (Laeven and Levine 2009; DeYoung *et al.* 2013; Brandao-Marques *et al.* 2018).

We re-estimate Equation 1 in a two-stage least square framework, where the O-SII buffer is an instrumental variable for banks' complexity. The first stage equation can be written as follows:

$$Complexity_{it} = \beta_0 + \beta_1 O - SII_{i,t-1} + \delta X_{i,t-1} + \gamma_t + \varepsilon_{it} \tag{2}$$

This empirical specification allows us to explore the intensity of the treatment, given that the buffer is calibrated individually for each banking group, depending on its contribution to systemic risk. As such, this empirical strategy allows to explore the time-series and cross-sectional variation in the calibration of systemic risk buffers for Portuguese banks.

3.3.1. Results. In Tables 13 to 20 we repeat the estimations reported in Tables 5 to 12 using the instrumental variables approach. Part of the results are consistent, but there are also some noteworthy differences.

In Table 13 we report the results of the effects of geographical complexity on banks' z-score. When we use an instrumental variables approach to mitigate endogeneity concerns, the results still support a positive relationship between geographical complexity and bank's risk captured by the z-score. However, while in the OLS approach the results were statistically significant only for the exposures to Africa, with this estimation strategy we continue to obtain a positive relationship between presence in Africa and risk (though only for the number of affiliates in Africa) but we also find a (marginally) statistically significant relationship for the number of countries in which a bank operates, as well as for the number of foreign affiliates. The results for the first-stage of the estimation confirm that the O-SII buffer is a valid instrument, except for the binary variable that refers to exposures in Africa.

When we consider the effects of geographical complexity on the average corporate default probability of banks, the statistically significant positive effects we obtained in the OLS specification are no longer valid (Table 14). This positive relationship was possibly affected by omitted variables which simultaneously influence banks' complexity and risk, such as bank manager's risk preferences.

In contrast, the effects of geographical complexity on new non-performing loans become stronger with the instrumental variables approach (Table 15). Banks that operate in more countries, both through bank and non-bank affiliates, have larger NPL flows (the coefficients are more precisely estimated). Further, the effect of the number of affiliates in Africa becomes statistically significant in the instrumental variables approach.

Finally, the effect of geographical complexity on banks' risk as measured by the risk weighted ratio is not significant in the instrumental variables estimation (Table 16), suggesting that this result was possibly affected by endogeneity problems.

In sum, when we explore the role of the announcement of the O-SII buffer as an instrument that exogenously affects complexity, the results do not remain entirely unchanged. That said, the most important conclusion of our analysis remains valid. There is a positive relationship between geographical complexity and banks' risk.

The next step is to estimate the instrumental variables approach for the effect of business complexity on the four risk variables: z-score (Table 17), average corporate default probability (Table 18), new NPLs (Table 19), and the risk weighted asset ratio (Table 20). In the OLS estimation, the relationship between structural complexity and risk was very weak. We could only find a negative relationship between the number of affiliates and risk measured by the z-score. The results are broadly the same with the instrumental variables approach. There is a marginally statistically significant coefficient on the effects of the share of non-financial business types on banks' z-score. Banks with a larger share of non-financial activities have more risk. None of the other complexity-risk combinations yields statistically significant results. Further, the results for the first step are also generally not-statistically significant. Even though the announcement of the O-SII buffer was associated with changes in geographical complexity, it did not lead to changes in structural complexity.

3.3.2. Additional results. In the results presented in Tables 13 to 20, the instrumental variable used in the first step refers to the announced O-SII buffer for each institution, which can vary from 0 to 2%. In unreported estimations, we also considered as an instrument a binary version of this variable, taking the value one for all the banking groups classified as O-SII from 2015 onwards.

The results confirm a positive relationship between geographical complexity and bank risk, but only in one case: the effect of having or not activities in Africa on banks' z-score. The weaker results for the binary version of the instrumental variable are essentially linked to its weaker performance in the first stage of the estimations.

However, for structural complexity the results are stronger with this binary instrument, which performs better in the first stage estimation of complexity. Although the majority of complexity-risk links remains not statistically significant, there is a significant negative effect of the share of non-financial business types and of the number of business types on banks' z-score. There is also a negative effect of the share of non-financial business types on new NPLs.

The period analyzed in the paper corresponds to the first years of the Single Supervisory Mechanism (SSM). In 2014, the ECB became responsible for the direct supervision of "significant institutions" in the euro area. The set of Portuguese institutions that became directly supervised by the ECB in 2014 greatly overlaps, albeit not entirely, with the set of institutions subject to O-SII buffers. When we consider as an instrumental variable a dummy that captures whether or not a banking group is supervised directly by the ECB, the results are generally consistent with those previously obtained, though more imprecisely estimated.

4. Concluding remarks

The existing literature on the relationship between bank complexity and risk offers ambiguous predictions. On the one hand, bank complexity can be linked to moral hazard and agency problems. This means that more complex banks are expected to have higher levels of risk. On the other hand, being more complex might allow banks to benefit from diversification and from scale economies. This implies that more complex banks can have lower levels of risk.

In this paper, we examine a set of complexity and risk indicators to shed more light on these conflicting predictions. We discuss two types of complexity: geographical and structural. The link between these two concepts of complexity and risk has opposite signs. We find a positive relationship between geographical complexity and bank risk. Banks that operate in more countries, both through banks and non-banks, have higher risk in their balance sheets. Their credit portfolios have, on average, higher default probabilities, they have more new non-performing loans, and they have higher risk-weights per unit of exposure. In contrast, we find a (weak) negative relationship between structural complexity and bank risk. Banks that have more affiliates show higher levels of risk as captured by the z-score. That said, for most structural complexity indicators, we do not find a statistical significant relationship with risk.

Geographical complexity may be captured by the number of countries and affiliates that a banking group has abroad, but considering what type of countries this exposure refers to might also be relevant. We explore the heterogeneous exposure of Portuguese banks to Africa to understand how is complexity, as captured through exposure to an emerging market economy, related to risk. We find that banks that operate in Africa indeed have higher levels of risk, as captured by the z-score. This reflects the larger volatility of returns arising from these exposures. However, exposure to Africa is not related to other risk indicators that capture the overall risk in banks' balance sheets.

Taken together, our results validate two apparently contradictory hypotheses. Bank complexity can be associated with both more and less risk. Geographical complexity is more likely to create moral hazard and agency problems, thus leading to more risk, notably when banks operate in many geographies and in volatile emerging markets. In turn, structural complexity can allow for more diversification and scale benefits, thus leading to lower risk levels.

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Tables and Figures

	Count	Mean	St. dev.	Min.	Q1	Q2	Q3	Max.
Geographical complexity								
Number of countries	64	5.27	4.11	1	1	4	8.5	16
Number of foreign affiliates	64	8.50	9.21	0	0	6	13	32
Number of foreign bank affiliates	64	4.03	4.08	0	0	3	6	17
Number of affiliates in Africa	64	1.09	1.80	0	0	0	2	8
Dummy variable for affiliates in Africa	64	0.42	0.50	0	0	0	1	1
Structural complexity								
Number of affiliates	64	26.16	26.92	1	4.5	16	43.5	91
Share of non-financial business types	45	0.55	0.15	0.33	0.50	0.50	0.60	0.91
Number of business types	64	3.53	2.32	1	2	3	4	11
HHI business types	56	0.66	0.26	0.14	0.44	0.74	0.88	1.00

Table 1. Summary statistics on complexity indicators

Notes: The sample period goes from 2014 to 2018. Count refers to the number of observations and Q1, Q2, and Q3 refer to the first, second, and third quartiles of the sample distribution of each complexity indicator, respectively. The number of countries counts the countries in which each banking group operates. The number of foreign affiliates considers all branches and subsidiaries abroad, while the number of foreign bank affiliates considers only foreign branches and subsidiaries registered as banks. The number of affiliates (in Africa) counts all affiliates (in Africa). The share of non-financial business types captures the percentage of the group's non-financial activities. The HHI for business types refers to the Herfindahl-Hirschman Index for business types and equals 0 when a group only operates in one business type.

	Largest 6 banks (mean) (1)	Other banks (mean) (2)	Difference (3)	*t*-statistic (4)
Geographical complexity				
Number of countries	7.93	2.91	-5.02***	-6.12
Number of foreign affiliates	13.73	3.88	-9.85***	-5.03
Number of foreign bank affiliates	6.57	1.79	-4.77***	-5.72
Number of affiliates in Africa	2.17	0.15	-2.02***	-5.40
Dummy variable for affiliates in Africa	0.73	0.15	-0.59***	-5.79
Structural complexity				
Number of affiliates	39.53	14.35	25.18***	-4.20
Share of non-financial business types	0.58	0.50	-0.08	-1.83
Number of business types	4.43	2.74	-1.70**	-3.12
HHI business types	0.58	0.74	0.16*	2.36

Table 2. Summary statistics on complexity indicators: largest 6 banks vs. other institutions

Notes: The sample period goes from 2014 to 2018. The largest 6 banks (G6) refer to the sub-sample of systemically important institutions. Column (1) reports means for this group of banks and column (2) reports the means for the other banks. Column (3) reports the differences between these two sub-samples and column (4) reports the t-statistic under the null hypothesis of no difference of means between the two sub-samples. The number of countries counts the countries in which each banking group operates. The number of foreign affiliates considers all branches and subsidiaries abroad, while the number of foreign bank affiliates considers only foreign branches and subsidiaries registered as banks. The number of affiliates (in Africa) counts all affiliates (in Africa). The share of non-financial business types captures the percentage of the group's non-financial activities. The HHI for business types refers to the Herfindahl-Hirschman Index for business types and equals 0 when a group only operates in one business type.***, **, and * stand for statistical significance at 1%, 5%, and 10%, respectively.

	Count	Mean	St. dev.	Min.	Q1	Q2	Q3	Max.
ln z-score	55	-2.74	0.85	-4.7	-3.36	-2.86	-2.15	-0.51
ln PD	64	-2.73	0.44	-3.41	-3	-2.78	-2.5	-0.46
New NPL / Assets	64	0.52	0.75	-1.43	0.05	0.31	0.91	2.66
RWA / Assets	60	0.61	0.14	0.4	0.51	0.6	0.67	0.94

Table 3. Summary statistics on risk-taking indicators

Notes: The sample period goes from 2014 to 2018. Count refers to the number of observations and Q1, Q2, and Q3 refer to the first, second, and third quartiles of the risk measures distribution, respectively. The ln z-score is computed as the logarithm of the inverse of the average return on assets in a given period plus the equity to assets ratio of the bank, divided by the standard deviation of the return on assets in the last 8 quarters. Ln PD is computed as the logarithm of the average default probability of loans granted to firms by each bank, using the output of a firm-level credit scoring model (Antunes et al., 2016). New NPL / Assets is the flow of non-performing loans over total assets; and RWA / Assets is the ratio between risk-weighted assets and total assets.

	Count	Mean	St. dev.	Min.	Q1	Q2	Q3	Max.
ln Assets	64	9.07	1.89	5.23	7.49	9.65	10.77	11.52
Loans / assets	64	50.60	25.53	1.77	32.25	58.91	65.39	95.50
ROA	64	0.76	1.86	-4.75	-0.15	0.65	1.76	7.03
Cost-to-income	64	60.48	26.75	21.13	43.21	55.56	69.30	165.25
Tier 1 ratio	54	16.07	11.02	0.01	10.87	13.57	20.27	60.67

Table 4. Summary statistics on bank characteristics

Notes: The sample period goes from 2014 to 2018. Count refers to the number of observations and Q1, Q2, and Q3 refer to the first, second, and third quartiles of the risk measures distribution, respectively. ROA refers to return on assets.

	Geographical complexity indicator				
	Number of countries	Number of foreign foreign affiliates	Number of foreign bank affiliates	Number of affiliates in Africa	Dummy variable for affiliates in Africa
	(1)	(2)	(3)	(4)	(5)
Geographical complexity	0.0082	-0.0046	-0.0145	0.1652*	1.1136***
	(0.0721)	(0.0407)	(0.0628)	(0.0888)	(0.1793)
ln Assets	0.3055	0.3438*	0.3606*	0.1630	0.0394
	(0.1883)	(0.1872)	(0.1697)	(0.1417)	(0.0816)
Loans / assets	0.0052	0.0043	0.0033	0.0070	0.0027
	(0.0054)	(0.0063)	(0.0057)	(0.0061)	(0.0036)
ROA	0.1181	0.1087	0.1153	0.1764	0.1254
	(0.1878)	(0.1884)	(0.1649)	(0.1559)	(0.0957)
Cost-to-income	0.0152*	0.0143	0.0143	0.0143*	0.0127*
	(0.0078)	(0.0100)	(0.0081)	(0.0072)	(0.0068)
Tier 1 ratio	0.0511*	0.0519*	0.0489**	0.0384*	0.0073
	(0.0241)	(0.0269)	(0.0168)	(0.0193)	(0.0084)
N	33	33	33	33	33
adj. R^2	0.173	0.173	0.176	0.333	0.590

Table 5. Geographical complexity and risk: z-score

The table reports the estimation of Equation 1. The dependent variable is the logarithm of the z-score calculated over eight quarters (ln Z-score). The ln z-score is computed as the logarithm of the inverse of the average return on assets in a given period plus the equity to assets ratio of the bank, divided by the standard deviation of the return on assets in the last 8 quarters. Columns (1) to (5) correspond to the different measures of the independent variable on geographical complexity (Number of countries, Number of foreign affiliates, Number of foreign bank affiliates, Number of affiliates in Africa, Dummy variable for affiliates in Africa). The number of countries counts the countries in which each banking group operates. The number of foreign affiliates considers all branches and subsidiaries abroad, while the number of foreign bank affiliates considers only foreign branches and subsidiaries registered as banks. The number of affiliates (in Africa) counts all affiliates (in Africa). All the independent variables are lagged by one quarter. The sample period goes from 2014 to 2018. All specifications include time fixed effects. Ordinary Least Squares estimates with robust standard errors clustered at the bank level in parentheses. ***, **, and * stand for statistical significance at 1%, 5%, and 10%, respectively.

	Geographical complexity indicator				
	Number of countries (1)	Number of foreign foreign affiliates (2)	Number of foreign bank affiliates (3)	Number of affiliates in Africa (4)	Dummy variable for affiliates in Africa (5)
Geographical complexity	0.0546**	0.0220**	0.0293**	0.0385	0.0058
	(0.0184)	(0.0081)	(0.0102)	(0.0262)	(0.1609)
ln Assets	-0.1114**	-0.0896	-0.0814	-0.0631	-0.0407
	(0.0462)	(0.0511)	(0.0470)	(0.0560)	(0.0598)
Loans / assets	-0.0096*	-0.0102	-0.0098	-0.0121	-0.0115
	(0.0051)	(0.0061)	(0.0063)	(0.0072)	(0.0069)
ROA	-0.1469***	-0.1425***	-0.1671***	-0.1631***	-0.1722***
	(0.0309)	(0.0437)	(0.0513)	(0.0527)	(0.0528)
Cost-to-income	-0.0053**	-0.0052	-0.0060	-0.0057	-0.0063
	(0.0022)	(0.0031)	(0.0034)	(0.0035)	(0.0035)
Tier 1 ratio	-0.0129	-0.0125	-0.0092	-0.0151	-0.0128
	(0.0126)	(0.0150)	(0.0159)	(0.0160)	(0.0142)
N	39	39	39	39	39
adj. R^2	0.310	0.252	0.207	0.178	0.158

Table 6. Geographical complexity and risk: default probability on corporate loan book

Notes: The table reports the estimation of Equation 1. The dependent variable is the logarithm of the probability of default of the firms in the bank's portfolio (ln PD). Columns (1) to (5) correspond to the different measures of the independent variable on geographical complexity (Number of countries, Number of foreign affiliates, Number of foreign bank affiliates, Number of affiliates in Africa, Dummy variable for affiliates in Africa). The number of countries counts the countries in which each banking group operates. The number of foreign affiliates considers all branches and subsidiaries abroad, while the number of foreign bank affiliates considers only foreign branches and subsidiaries registered as banks. The number of affiliates (in Africa) counts all affiliates (in Africa). All the independent variables are lagged by one quarter. The sample period goes from 2014 to 2018. All specifications include time fixed effects. Ordinary Least Squares estimates with robust standard errors clustered at the bank level in parentheses. ***, **, and * stand for statistical significance at 1%, 5%, and 10%, respectively.

	Geographical complexity indicator				
	Number of countries (1)	Number of foreign foreign affiliates (2)	Number of foreign bank affiliates (3)	Number of affiliates in Africa (4)	Dummy variable for affiliates in Africa (5)
Geographical complexity	0.0527**	0.0344**	0.0525*	0.0391	0.2572
	(0.0219)	(0.0157)	(0.0285)	(0.0442)	(0.1968)
ln Assets	0.0383	0.0292	0.0325	0.0837	0.0563
	(0.0629)	(0.0591)	(0.0563)	(0.0767)	(0.0720)
Loans / assets	0.0006	0.0009	0.0017	-0.0018	-0.0027
	(0.0063)	(0.0053)	(0.0070)	(0.0070)	(0.0066)
ROA	-0.1385	-0.1166	-0.1540	-0.1537	-0.1702*
	(0.1072)	(0.1135)	(0.0962)	(0.0887)	(0.0877)
Cost-to-income	-0.0028	-0.0020	-0.0033	-0.0032	-0.0033
	(0.0077)	(0.0072)	(0.0068)	(0.0073)	(0.0075)
Tier 1 ratio	0.0120	0.0125	0.0184	0.0098	0.0044
	(0.0139)	(0.0125)	(0.0188)	(0.0176)	(0.0168)
N	39	39	39	39	39
adj. R^2	0.236	0.284	0.244	0.170	0.186

Table 7. Geographical complexity and risk: new NPL / assets

Notes: The table reports the estimation of Equation 1. The dependent variable is the new NPL to total assets ratio. Columns (1) to (5) correspond to the different measures of the independent variable on geographical complexity (Number of countries, Number of foreign affiliates, Number of foreign bank affiliates, Number of affiliates in Africa, Dummy variable for affiliates in Africa). The number of countries counts the countries in which each banking group operates. The number of foreign affiliates considers all branches and subsidiaries abroad, while the number of foreign bank affiliates considers only foreign branches and subsidiaries registered as banks. The number of affiliates (in Africa) counts all affiliates (in Africa). All the independent variables are lagged by one quarter. The sample period goes from 2014 to 2018. All specifications include time fixed effects. Ordinary Least Squares estimates with robust standard errors clustered at the bank level in parentheses. ***, **, and * stand for statistical significance at 1%, 5%, and 10%, respectively.

	Geographical complexity indicator				
	Number of countries (1)	Number of foreign foreign affiliates (2)	Number of foreign bank affiliates (3)	Number of affiliates in Africa (4)	Dummy variable for affiliates in Africa (5)
Geographical complexity	0.0214***	0.0063**	0.0074	0.0205	0.0667
	(0.0069)	(0.0028)	(0.0060)	(0.0120)	(0.0705)
ln Assets	-0.0806***	-0.0668**	-0.0630*	-0.0650**	-0.0657***
	(0.0179)	(0.0260)	(0.0296)	(0.0222)	(0.0202)
Loans / assets	-0.0008	-0.0012	-0.0011	-0.0019	-0.0019
	(0.0013)	(0.0017)	(0.0017)	(0.0019)	(0.0019)
ROA	-0.0416*	-0.0429	-0.0502	-0.0466	-0.0533*
	(0.0210)	(0.0261)	(0.0290)	(0.0281)	(0.0260)
Cost-to-income	-0.0021	-0.0022	-0.0024	-0.0022	-0.0024
	(0.0014)	(0.0018)	(0.0019)	(0.0019)	(0.0018)
Tier 1 ratio	-0.0007	-0.0005	0.0003	-0.0019	-0.0026
	(0.0032)	(0.0044)	(0.0046)	(0.0040)	(0.0034)
N	39	39	39	39	39
adj. R^2	0.502	0.302	0.242	0.277	0.246

Table 8. Geographical complexity and risk: risk-weighted assets to total assets

Notes: The table reports the estimation of Equation 1. The dependent variable is the ratio of risk-weighted assets to total assets. Columns (1) to (5) correspond to the different measures of the independent variable on geographical complexity (Number of countries, Number of foreign affiliates, Number of foreign bank affiliates, Number of affiliates in Africa, Dummy variable for affiliates in Africa). The number of countries counts the countries in which each banking group operates. The number of foreign affiliates considers all branches and subsidiaries abroad, while the number of foreign bank affiliates considers only foreign branches and subsidiaries registered as banks. The number of affiliates (in Africa) counts all affiliates (in Africa). All the independent variables are lagged by one quarter. The sample period goes from 2014 to 2018. All specifications include time fixed effects. Ordinary Least Squares estimates with robust standard errors clustered at the bank level in parentheses. ***, **, and * stand for statistical significance at 1%, 5%, and 10%, respectively.

	Business complexity indicator			
	Number of affiliates	Share of non-financial business types	Number of business types	HHI business types
	(1)	(2)	(3)	(4)
Business complexity	-0.0139***	-2.3905	-0.1660	0.3179
	(0.0041)	(2.1681)	(0.1115)	(0.5250)
ln Assets	0.4328***	0.5013*	0.4554**	0.3456**
	(0.1008)	(0.2579)	(0.1466)	(0.1308)
Loans / assets	0.0073	-0.0326	0.0029	0.0037
	(0.0069)	(0.0204)	(0.0080)	(0.0086)
ROA	0.0147	-0.0860	0.1136	0.1125
	(0.1531)	(0.1668)	(0.1577)	(0.1886)
Cost-to-income	0.0090	0.0193***	0.0156*	0.0134
	(0.0070)	(0.0053)	(0.0078)	(0.0084)
Tier 1 ratio	0.0693***	0.0290	0.0632***	0.0463
	(0.0189)	(0.0210)	(0.0166)	(0.0279)
N	33	26	33	32
adj. R^2	0.320	0.251	0.274	0.174

Table 9. Business complexity and risk: z-score

Notes: The table reports the estimation of Equation 1. The dependent variable is the logarithm of the z-score calculated over eight quarters (ln Z-score). The ln z-score is computed as the logarithm of the inverse of the average return on assets in a given period plus the equity to assets ratio of the bank, divided by the standard deviation of the return on assets in the last 8 quarters. Columns (1) to (4) correspond to the different measures of the independent variable on business complexity (Number of affiliates, Share of non-financial business types, Number of business types, HHI business types). The share of non-financial business types captures the percentage of the group's non-financial activities. The HHI for business types refers to the Herfindahl-Hirschman Index for business types and equals 0 when a group only operates in one business type. All the independent variables are lagged by one quarter. The sample period goes from 2014 to 2018. All specifications include time fixed effects. Ordinary Least Squares estimates with robust standard errors clustered at the bank level in parentheses. ***, **, and * stand for statistical significance at 1%, 5%, and 10%, respectively.

	Business complexity indicator			
	Number of affiliates	Share of non-financial business types	Number of business types	HHI business types
	(1)	(2)	(3)	(4)
Business complexity	0.0031	0.3684	0.0200	0.4160
	(0.0032)	(0.7027)	(0.0472)	(0.2934)
ln Assets	-0.0571	0.0270	-0.0530	0.0110
	(0.0573)	(0.1056)	(0.0636)	(0.0677)
Loans / assets	-0.0121	0.0002	-0.0115	-0.0152
	(0.0073)	(0.0063)	(0.0070)	(0.0088)
ROA	-0.1529***	-0.0850*	-0.1735***	-0.2040***
	(0.0484)	(0.0390)	(0.0526)	(0.0533)
Cost-to-income	-0.0051	0.0014	-0.0062	-0.0071**
	(0.0034)	(0.0022)	(0.0036)	(0.0031)
Tier 1 ratio	-0.0155	0.0052	-0.0138	-0.0180
	(0.0179)	(0.0074)	(0.0173)	(0.0166)
N	39	29	39	35
adj. R^2	0.173	0.630	0.161	0.146

Table 10. Risk and business complexity: logarithm of the probability of default of the firms in the bank's portfolio

Notes: The table reports the estimation of Equation 1. The dependent variable is the logarithm of the probability of default of the firms in the bank's portfolio (ln PD). Columns (1) to (4) correspond to the different measures of the independent variable on business complexity (Number of affiliates, Share of non-financial business types, Number of business types, HHI business types). The share of non-financial business types captures the percentage of the group's non-financial activities. The HHI for business types refers to the Herfindahl-Hirschman Index for business types and equals 0 when a group only operates in one business type. All the independent variables are lagged by one quarter. The sample period goes from 2014 to 2018. All specifications include time fixed effects. Ordinary Least Squares estimates with robust standard errors clustered at the bank level in parentheses. ***, **, and * stand for statistical significance at 1%, 5%, and 10%, respectively.

	Business complexity indicator			
	Number of affiliates	Share of non-financial business types	Number of business types	HHI business types
	(1)	(2)	(3)	(4)
Business complexity	0.0013	0.6727	-0.0721	-0.1681
	(0.0059)	(1.3867)	(0.0477)	(0.5414)
ln Assets	0.1003	0.3681*	0.1563**	0.0653
	(0.0658)	(0.1742)	(0.0709)	(0.1076)
Loans / assets	-0.0015	-0.0174	-0.0011	0.0013
	(0.0069)	(0.0114)	(0.0066)	(0.0092)
ROA	-0.1547	-0.1194	-0.1576*	-0.1730*
	(0.0975)	(0.1261)	(0.0830)	(0.0838)
Cost-to-income	-0.0032	0.0021	-0.0042	-0.0028
	(0.0077)	(0.0082)	(0.0069)	(0.0060)
Tier 1 ratio	0.0110	0.0150	0.0163	0.0186
	(0.0181)	(0.0171)	(0.0170)	(0.0196)
N	39	29	39	35
adj. R^2	0.160	0.299	0.180	0.186

Table 11. Business complexity and risk: new NPL / assets

Notes: The table reports the estimation of Equation 1. The dependent variable is the new NPL to total assets ratio. Columns (1) to (4) correspond to the different measures of the independent variable on business complexity (Number of affiliates, Share of non-financial business types, Number of business types, HHI business types). The share of non-financial business types captures the percentage of the group's non-financial activities. The HHI for business types refers to the Herfindahl-Hirschman Index for business types and equals 0 when a group only operates in one business type. All the independent variables are lagged by one quarter. The sample period goes from 2014 to 2018. All specifications include time fixed effects. Ordinary Least Squares estimates with robust standard errors clustered at the bank level in parentheses. ***, **, and * stand for statistical significance at 1%, 5%, and 10%, respectively.

	Business complexity indicator			
	Number of affiliates	Share of non-financial business types	Number of business types	HHI business types
	(1)	(2)	(3)	(4)
Business complexity	0.0001	-0.2522	-0.0046	0.1705
	(0.0011)	(0.1850)	(0.0164)	(0.1200)
ln Assets	-0.0532*	0.0568*	-0.0492	-0.0266
	(0.0272)	(0.0285)	(0.0278)	(0.0220)
Loans / assets	-0.0016	-0.0015	-0.0015	-0.0034
	(0.0020)	(0.0016)	(0.0020)	(0.0020)
ROA	-0.0505*	-0.0164	-0.0511*	-0.0653**
	(0.0243)	(0.0142)	(0.0286)	(0.0234)
Cost-to-income	-0.0025	0.0010	-0.0025	-0.0029*
	(0.0017)	(0.0009)	(0.0019)	(0.0015)
Tier 1 ratio	-0.0007	0.0044	-0.0003	-0.0028
	(0.0048)	(0.0036)	(0.0048)	(0.0042)
N	39	29	39	35
adj. R^2	0.202	0.310	0.204	0.285

Table 12. Business complexity and risk: risk weighted assets to total assets ratio

Notes: The table reports the estimation of Equation 1. The dependent variable is the ratio of risk-weighted assets to total assets. Columns (1) to (4) correspond to the different measures of the independent variable on business complexity (Number of affiliates, Share of non-financial business types, Number of business types, HHI business types). The share of non-financial business types captures the percentage of the group's non-financial activities. The HHI for business types refers to the Herfindahl-Hirschman Index for business types and equals 0 when a group only operates in one business type. All the independent variables are lagged by one quarter. The sample period goes from 2014 to 2018. All specifications include time fixed effects. Ordinary Least Squares estimates with robust standard errors clustered at the bank level in parentheses. ***, **, and * stand for statistical significance at 1%, 5%, and 10%, respectively.

	Geographical complexity indicator				
	Number of countries (1)	Number of foreign foreign affiliates (2)	Number of foreign bank affiliates (3)	Number of affiliates in Africa (4)	Dummy variable for affiliates in Africa (5)
Geographical complexity	0.1051*	0.0610*	0.1007	0.2061**	1.7462
	(0.0561)	(0.0357)	(0.0639)	(0.1007)	(1.1552)
Loans / assets	0.0124	0.0082	0.0138**	0.0076	0.0017
	(0.0087)	(0.0082)	(0.0069)	(0.0055)	(0.0048)
ROA	0.1723	0.1786	0.1011	0.1920	0.1322
	(0.1872)	(0.1997)	(0.1810)	(0.1247)	(0.0860)
Cost-to-income	0.0177**	0.0242*	0.0197*	0.0141**	0.0114
	(0.0088)	(0.0124)	(0.0101)	(0.0059)	(0.0076)
Tier 1 ratio	0.0479**	0.0444**	0.0682***	0.0352**	-0.0177
	(0.0186)	(0.0208)	(0.0125)	(0.0170)	(0.0509)
ln Assets	0.0895	0.0569	0.0685	0.1232	-0.1221
	(0.1743)	(0.2053)	(0.2050)	(0.1505)	(0.3038)
First-stage F-stat.	14.2489***	15.7643***	11.3370***	29.7177***	0.6539
N	33	33	33	33	33

Table 13. Geographical complexity and risk: z-score

Notes: The table reports the estimation of Equation 1, when using a two-stages least square estimation where the first-stage is estimated using Equation (2). The dependent variable is the logarithm of the z-score calculated over eight quarters (ln Z-score). The ln z-score is computed as the logarithm of the inverse of the average return on assets in a given period plus the equity to assets ratio of the bank, divided by the standard deviation of the return on assets in the last 8 quarters. Columns (1) to (5) correspond to the different measures of the independent variable on geographical complexity (Number of locations, Number of foreign affiliates, Number of foreign bank affiliates, Number of affiliates in Africa, Dummy variable for affiliates in Africa). The number of countries counts the countries in which each banking group operates. The number of foreign affiliates considers all branches and subsidiaries abroad, while the number of foreign bank affiliates considers only foreign branches and subsidiaries registered as banks. The number of affiliates (in Africa) counts all affiliates (in Africa). All the independent variables are lagged by one quarter. The sample period goes from 2014 to 2018. All specifications include time fixed effects. Two-stage least squares estimates with robust standard errors clustered at the bank level in parentheses. ***, **, and * stand for statistical significance at 1%, 5%, and 10%, respectively.

	Geographical complexity indicator				
	Number of countries (1)	Number of foreign foreign affiliates (2)	Number of foreign bank affiliates (3)	Number of affiliates in Africa (4)	Dummy variable for affiliates in Africa (5)
Geographical complexity	0.0231	0.0108	0.0237	0.0480	0.3140
	(0.0287)	(0.0144)	(0.0295)	(0.0607)	(0.4991)
Loans / assets	-0.0106**	-0.0108**	-0.0101*	-0.0123**	-0.0133*
	(0.0051)	(0.0055)	(0.0056)	(0.0061)	(0.0074)
ROA	-0.1614***	-0.1575***	-0.1681***	-0.1609***	-0.1811***
	(0.0349)	(0.0414)	(0.0414)	(0.0480)	(0.0506)
Cost-to-income	-0.0059**	-0.0057**	-0.0061**	-0.0056*	-0.0057
	(0.0023)	(0.0027)	(0.0028)	(0.0030)	(0.0036)
Tier 1 ratio	-0.0128	-0.0126	-0.0099	-0.0157	-0.0222
	(0.0123)	(0.0132)	(0.0154)	(0.0129)	(0.0187)
ln Assets	-0.0699	-0.0641	-0.0734	-0.0690	-0.1022
	(0.0554)	(0.0533)	(0.0625)	(0.0565)	(0.1032)
First-stage F-stat	7.7410**	11.8872***	4.5571*	8.1762**	1.4662
N	39	39	39	39	39

Table 14. Geographical complexity and risk: default probability on corporate loan book

Notes: The table reports the estimation of Equation 1, when using a two-stages least square estimation where the first-stage is estimated using Equation (2). The dependent variable is the logarithm of the probability of default of the firms in the bank's portfolio (ln PD). Columns (1) to (5) correspond to the different measures of the independent variable on geographical complexity (Number of locations, Number of foreign affiliates, Number of foreign bank affiliates, Number of affiliates in Africa, Dummy variable for affiliates in Africa). The number of countries counts the countries in which each banking group operates. The number of foreign affiliates considers all branches and subsidiaries abroad, while the number of foreign bank affiliates considers only foreign branches and subsidiaries registered as banks. The number of affiliates (in Africa) counts all affiliates (in Africa). All the independent variables are lagged by one quarter. The sample period goes from 2014 to 2018. All specifications include time fixed effects. Two-stage least squares estimates with robust standard errors clustered at the bank level in parentheses. ***, **, and * stand for statistical significance at 1%, 5%, and 10%, respectively.

	Geographical complexity indicator				
	Number of countries (1)	Number of foreign foreign affiliates (2)	Number of foreign bank affiliates (3)	Number of affiliates in Africa (4)	Dummy variable for affiliates in Africa (5)
Geographical complexity	0.2293***	0.1072***	0.2356***	0.4774***	3.1209
	(0.0714)	(0.0391)	(0.0800)	(0.1081)	(2.2441)
Loans / assets	0.0067	0.0052	0.0118	-0.0094	-0.0194
	(0.0091)	(0.0072)	(0.0079)	(0.0081)	(0.0188)
ROA	-0.0572	-0.0186	-0.1234	-0.0518	-0.2529
	(0.1826)	(0.1819)	(0.1678)	(0.1541)	(0.2591)
Cost-to-income	0.0004	0.0017	-0.0018	0.0029	0.0017
	(0.0108)	(0.0094)	(0.0092)	(0.0096)	(0.0182)
Tier 1 ratio	0.0112	0.0132	0.0400*	-0.0176	-0.0823
	(0.0195)	(0.0160)	(0.0233)	(0.0207)	(0.0837)
ln Assets	-0.1946	-0.1373	-0.2296**	-0.1853**	-0.5159
	(0.1230)	(0.0910)	(0.1162)	(0.0916)	(0.4636)
First-stage F-stat	7.7410**	11.8872***	4.5571*	8.1762**	1.4662
N	39	39	39	39	39

Table 15. Geographical complexity and risk: new NPL / assets

Notes: The table reports the estimation of Equation 1, when using a two-stages least square estimation where the first-stage is estimated using Equation (2). The dependent variable is the new NPL to total assets ratio. Columns (1) to (5) correspond to the different measures of the independent variable on geographical complexity (Number of locations, Number of foreign affiliates, Number of foreign bank affiliates, Number of affiliates in Africa, Dummy variable for affiliates in Africa). The number of countries counts the countries in which each banking group operates. The number of foreign affiliates considers all branches and subsidiaries abroad, while the number of foreign bank affiliates considers only foreign branches and subsidiaries registered as banks. The number of affiliates (in Africa) counts all affiliates (in Africa). All the independent variables are lagged by one quarter. The sample period goes from 2014 to 2018. All specifications include time fixed effects. Two-stage least squares estimates with robust standard errors clustered at the bank level in parentheses. ***, **, and * stand for statistical significance at 1%, 5%, and 10%, respectively.

	Geographical complexity indicator				
	Number of countries (1)	Number of foreign foreign affiliates (2)	Number of foreign bank affiliates (3)	Number of affiliates in Africa (4)	Dummy variable for affiliates in Africa (5)
Geographical complexity	0.0089	0.0042	0.0092	0.0185	0.1212
	(0.0112)	(0.0057)	(0.0120)	(0.0249)	(0.1687)
Loans / assets	-0.0012	-0.0013	-0.0010	-0.0019	-0.0023
	(0.0015)	(0.0016)	(0.0018)	(0.0016)	(0.0018)
ROA	-0.0473**	-0.0458*	-0.0499*	-0.0471*	-0.0549***
	(0.0221)	(0.0259)	(0.0256)	(0.0254)	(0.0206)
Cost-to-income	-0.0023	-0.0023	-0.0024	-0.0022	-0.0023
	(0.0014)	(0.0017)	(0.0017)	(0.0017)	(0.0016)
Tier 1 ratio	-0.0006	-0.0006	0.0005	-0.0018	-0.0043
	(0.0033)	(0.0038)	(0.0049)	(0.0033)	(0.0051)
ln Assets	-0.0641***	-0.0619***	-0.0655***	-0.0638***	-0.0766**
	(0.0217)	(0.0220)	(0.0249)	(0.0225)	(0.0329)
First-stage F-stat	7.7410**	11.8872***	4.5571*	8.1762**	1.4662
N	39	39	39	39	39

Table 16. Geographical complexity and risk: risk-weighted assets to total assets

Notes: The table reports the estimation of Equation 1, when using a two-stages least square estimation where the first-stage is estimated using Equation (2). The dependent variable is the ratio of risk-weighted assets to total assets. Columns (1) to (5) correspond to the different measures of the independent variable on geographical complexity (Number of countries, Number of foreign affiliates, Number of foreign bank affiliates, Number of affiliates in Africa, Dummy variable for affiliates in Africa). The number of countries counts the countries in which each banking group operates. The number of foreign affiliates considers all branches and subsidiaries abroad, while the number of foreign bank affiliates considers only foreign branches and subsidiaries registered as banks. The number of affiliates (in Africa) counts all affiliates (in Africa). All the independent variables are lagged by one quarter. The sample period goes from 2014 to 2018. All specifications include time fixed effects. Two-stage least squares estimates with robust standard errors clustered at the bank level in parentheses. ***, **, and * stand for statistical significance at 1%, 5%, and 10%, respectively.

	Business complexity indicator			
	Number of affiliates (1)	Share of non-financial business types (2)	Number of business types (3)	HHI business types (4)
Business complexity	-1.0623	-6.7087*	1.6958	7.8397
	(21.7628)	(3.7034)	(6.8611)	(11.9839)
Loans / assets	0.2151	-0.0373*	0.0217	-0.0160
	(4.1602)	(0.0195)	(0.0566)	(0.0413)
ROA	-7.4390	-0.2577	0.1132	-0.3563
	(152.1972)	(0.2879)	(0.5112)	(0.5629)
Cost-to-income	-0.4422	0.0155*	0.0082	-0.0159
	(9.2865)	(0.0084)	(0.0450)	(0.0389)
Tier 1 ratio	1.4222	0.0390***	-0.0696	-0.0723
	(27.8413)	(0.0122)	(0.5457)	(0.1976)
ln Assets	8.6595	0.7086**	-1.0207	0.4969
	(174.1964)	(0.2884)	(5.2992)	(0.5554)
First-stage F-stat	0.0015	3.2543	0.0503	0.2420
N	33	26	32	33

Table 17. Business complexity and risk: z-score

Notes: The table reports the estimation of Equation 1, when using a two-stages least square estimation where the first-stage is estimated using Equation (2). The dependent variable is the logarithm of the z-score calculated over eight quarters (ln Z-score). The ln z-score is computed as the logarithm of the inverse of the average return on assets in a given period plus the equity to assets ratio of the bank, divided by the standard deviation of the return on assets in the last 8 quarters. Columns (1) to (4) correspond to the different measures of the independent variable on business complexity (Number of affiliates, Share of non-financial business types, Number of business types, HHI business types). The share of non-financial business types captures the percentage of the group's non-financial activities. The HHI for business types refers to the Herfindahl-Hirschman Index for business types and equals 0 when a group only operates in one business type. All the independent variables are lagged by one quarter. The sample period goes from 2014 to 2018. All specifications include time fixed effects. Two-stage least squares estimates with robust standard errors clustered at the bank level in parentheses. ***, **, and * stand for statistical significance at 1%, 5%, and 10%, respectively.

	Business complexity indicator			
	Number of affiliates	Share of non-financial business types	Number of business types	HHI business types
	(1)	(2)	(3)	(4)
Business complexity	0.0222	-3.1813	0.2461	0.6549
	(0.0516)	(2.1923)	(0.5832)	(1.6773)
Loans / assets	-0.0163	-0.0042	-0.0116*	-0.0160
	(0.0146)	(0.0076)	(0.0061)	(0.0106)
ROA	-0.0350	-0.2072**	-0.1896**	-0.2224*
	(0.3597)	(0.0931)	(0.0871)	(0.1319)
Cost-to-income	0.0021	-0.0026	-0.0048	-0.0075*
	(0.0219)	(0.0047)	(0.0048)	(0.0045)
Tier 1 ratio	-0.0334	0.0077	-0.0264	-0.0209
	(0.0555)	(0.0093)	(0.0395)	(0.0254)
ln Assets	-0.1657	0.1933	-0.2051	0.0161
	(0.2849)	(0.2038)	(0.4137)	(0.0704)
First-stage F-stat	0.1605	1.5815	0.1576	0.6968
N	39	29	39	35

Table 18. Business complexity and risk: default probability on corporate loan book

Notes: The table reports the estimation of Equation 1, when using a two-stages least square estimation where the first-stage is estimated using Equation (2). The dependent variable is the logarithm of the probability of default of the firms in the bank's portfolio (ln PD). Columns (1) to (4) correspond to the different measures of the independent variable on business complexity (Number of affiliates, Share of non-financial business types, Number of business types, HHI business types). The share of non-financial business types captures the percentage of the group's non-financial activities. The HHI for business types refers to the Herfindahl-Hirschman Index for business types and equals 0 when a group only operates in one business type. All the independent variables are lagged by one quarter. The sample period goes from 2014 to 2018. All specifications include time fixed effects. Two-stage least squares estimates with robust standard errors clustered at the bank level in parentheses. ***, **, and * stand for statistical significance at 1%, 5%, and 10%, respectively.

	Business complexity indicator			
	Number of affiliates	Share of non-financial business types	Number of business types	HHI business types
	(1)	(2)	(3)	(4)
Business complexity	0.2209	-13.6915	2.4464	8.5468
	(0.4641)	(11.8372)	(5.1716)	(9.3397)
Loans / assets	-0.0499	-0.0351	-0.0029	-0.0285
	(0.1226)	(0.0309)	(0.0252)	(0.0345)
ROA	1.1996	-0.6139	-0.3369	-0.8444
	(3.4002)	(0.3842)	(0.6344)	(0.6279)
Cost-to-income	0.0796	-0.0138	0.0112	-0.0196
	(0.2030)	(0.0161)	(0.0469)	(0.0241)
Tier 1 ratio	-0.1943	0.0252	-0.1247	-0.0892
	(0.4921)	(0.0339)	(0.3288)	(0.1182)
ln Assets	-1.1470	1.0410	-1.5387	0.2496
	(2.3855)	(0.9535)	(3.4642)	(0.4821)
First-stage F-stat	0.1605	1.5815	0.1576	0.6968
N	39	29	39	35

Table 19. Business complexity and risk: new NPL / assets

Notes: The table reports the estimation of Equation 1, when using a two-stages least square estimation where the first-stage is estimated using Equation (2). The dependent variable is the new NPL to total assets ratio. Columns (1) to (4) correspond to the different measures of the independent variable on business complexity (Number of affiliates, Share of non-financial business types, Number of business types, HHI business types). The share of non-financial business types captures the percentage of the group's non-financial activities. The HHI for business types refers to the Herfindahl-Hirschman Index for business types and equals 0 when a group only operates in one business type. All the independent variables are lagged by one quarter. The sample period goes from 2014 to 2018. All specifications include time fixed effects. Two-stage least squares estimates with robust standard errors clustered at the bank level in parentheses. ***, **, and * stand for statistical significance at 1%, 5%, and 10%, respectively.

	Business complexity indicator			
	Number of affiliates	Share of non-financial business types	Number of business types	HHI business types
	(1)	(2)	(3)	(4)
Business complexity	0.0086	-0.9431	0.0950	0.1506
	(0.0264)	(0.7375)	(0.2839)	(0.5580)
Loans / assets	-0.0034	-0.0023	-0.0016	-0.0033
	(0.0067)	(0.0019)	(0.0018)	(0.0025)
ROA	0.0015	-0.0402	-0.0582	-0.0638
	(0.1843)	(0.0344)	(0.0409)	(0.0460)
Cost-to-income	0.0007	0.0002	-0.0028*	-0.0019
	(0.0113)	(0.0015)	(0.0028)	(0.0017)
Tier 1 ratio	-0.0086	0.0048	-0.0059	-0.0026
	(0.0277)	(0.0038)	(0.0186)	(0.0067)
ln Assets	-0.1011	0.0892**	-0.1163	-0.0270
	(0.1428)	(0.0397)	(0.1983)	(0.0203)
First-stage F-stat	0.1605	1.5815	0.1576	0.6968
N	39	29	35	39

Table 20. Business complexity and risk: risk-weighted assets to total assets

Notes: The table reports the estimation of Equation 1, when using a two-stages least square estimation where the first-stage is estimated using Equation (2). The dependent variable is the ratio of risk-weighted assets to total assets. Columns (1) to (4) correspond to the different measures of the independent variable on business complexity (Number of affiliates, Share of non-financial business types, Number of business types, HHI business types). The share of non-financial business types captures the percentage of the group's non-financial activities. The HHI for business types refers to the Herfindahl-Hirschman Index for business types and equals 0 when a group only operates in one business type. All the independent variables are lagged by one quarter. The sample period goes from 2014 to 2018. All specifications include time fixed effects. Two-stage least squares estimates with robust standard errors clustered at the bank level in parentheses. ***, **, and * stand for statistical significance at 1%, 5%, and 10%, respectively.

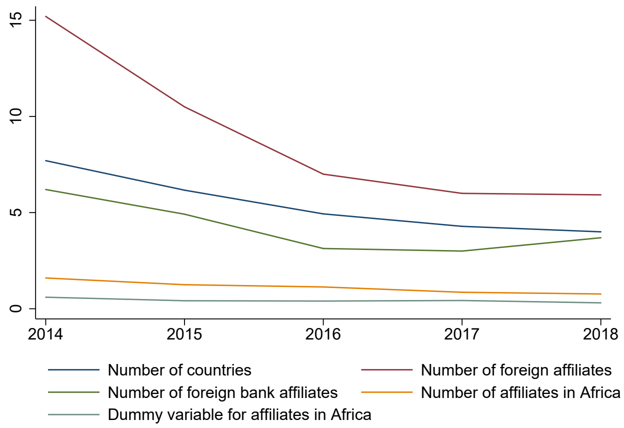

Figure 1: Geographical complexity indicators

Notes: The number of countries counts the countries in which each banking group operates. The number of foreign affiliates considers all branches and subsidiaries abroad, while the number of foreign bank affiliates considers only foreign branches and subsidiaries registered as banks. The number of affiliates (in Africa) counts all affiliates (in Africa).

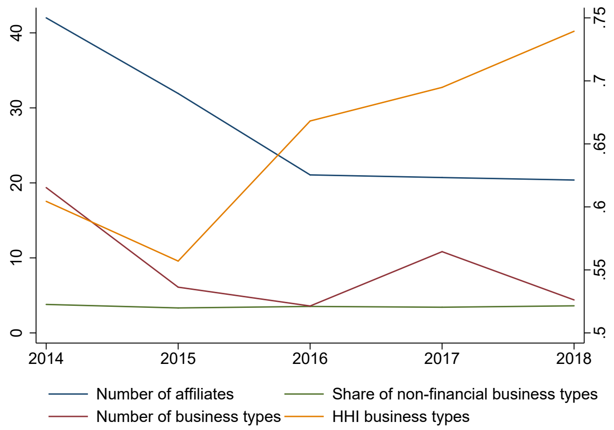

Figure 2: Structural complexity indicators

Notes: The share of non-financial business types captures the percentage of the group's non-financial activities. The HHI for business types refers to the Herfindahl-Hirschman Index for business types and equals 0 when a group only operates in one business type (left-hand scale).

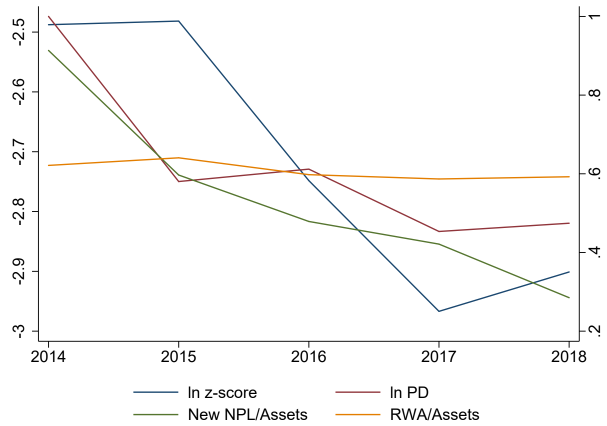

Figure 3: Risk-taking indicators

Notes: The ln z-score is computed as the logarithm of the inverse of the average return on assets in a given period plus the equity to assets ratio of the bank, divided by the standard deviation of the return on assets in the last 8 quarters. Ln PD is computed as the logarithm of the average default probability of loans granted to firms by each bank, using the output of a firm-level credit scoring model (Antunes et al., 2016). New NPL / Assets is the flow of non-performing loans over total assets (right-hand scale). RWA / Assets is the ratio between risk-weighted assets and total assets (right-hand scale).

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