Economic Systems 47 (2023) 101057

Contents lists available at ScienceDirect

Economic Systems

journal homepage: www.elsevier.com/locate/ecosys

# Global bank complexity and financial fragility around the world

Thi Hoang Anh Pham[a], Ngoc Thang Doan[b,*]

[a] *Research Institute for Banking, Banking Academy of Vietnam, No.12 Chua Boc, Dong Da, Hanoi, Viet Nam*
[b] *International Business Faculty, Banking Academy of Vietnam, No.12 Chua Boc, Dong Da, Hanoi, Viet Nam*

ARTICLE INFO

*JEL Classification:*
F2
G21
G28

*Keywords:*
Bank geographic complexity
Financial fragility
Financial liberalization

ABSTRACT

Using data for 123 countries from 1996 to 2020, we uncover the effect of foreign-owned banks' geographic complexity on financial fragility in the context of financial liberalization. We compute a measure of foreign-owned banks' geographic complexity for each country from data on the affiliate network of internationally active banking institutes. The financial effects of geographic complexity may help banks improve their survival by improving their solvency. After extensive testing for the sensitivity of the results, our main findings were threefold. First, a higher degree of geographic complexity of foreign-owned banks reduces the likelihood of a bank's default, and these effects become more pronounced in low- and lower-middle-income countries. Second, the effects of financial liberalization vary across income groups. Third, the joint effects of foreign-owned banks' geographic complexity and financial liberalization on financial fragility vary across forms of financial liberalization. Our findings have several policy implications: first, bank supervisors should consider the presence and structure of foreign bank ownership in their assessments; second, the government should take into account the level of economic development in choosing the proper form of financial liberalization; third, the government should promote financial freedom to strengthen the role of foreign-owned banks' geographic complexity in alleviating financial fragility.



## 1. Introduction

The complexity of global banking organizations has attracted the attention of both scholars and policymakers, especially after the recent financial crisis. However, a consensus is yet to be reached on the notion of complexity; moreover, complexity can take different forms. This could result from the scale and variety of a bank's lending portfolio (Doerr and Schaz, 2021), the scope of investment activities, or the organizational and geographic configuration of the bank (Cetorelli and Goldberg, 2014, 2016). This study concentrates on the geographic ownership of foreign banks (geographic complexity) and investigates how it facilitates banks to cope with financial liberalization.

Geographic complexity may influence bank risk in two ways. On the one hand, it can add diversification value to financial entities and, therefore, create financial stability. A higher degree of geographic complexity in the foreign bank's ownership grid helps banks reduce the negative effect of domestic economic shocks (i.e., in the parent bank's country) on their riskiness. On the other hand, geographic complexity can also lead to risk by altering how regulation affects banks. Stricter financial regulations are related to a

* Corresponding author.
*E-mail addresses:* anhpth@hvnh.edu.vn (T.H.A. Pham), ngocthangdoan@hvnh.edu.vn (N.T. Doan).

https://doi.org/10.1016/j.ecosys.2022.101057
Received 11 June 2022; Received in revised form 17 September 2022; Accepted 23 September 2022
Available online 17 October 2022
0939-3625/

higher degree of market capitalization. However, when geographic complexity is higher, the rise in systemic risk is lower following a contraction in financial regulation. This reveals that a broader geographic reach can offer banks alternative options to react to regulations, possibly affecting their resilience and risk. Therefore, banks' geographic complexity has a dual effect. On the one hand, it helps reduce the effect of domestic economic shocks and, thus, enhances banks' resilience. On the other hand, it can also impose a threat by giving banks financial regulation a more relaxed grip.

To conduct our study, we rely on a dataset of foreign banks from S&P IQ Capital Pro. This dataset contains ownership information of approximately 8085 active banking entities in 123 countries from 1996 to 2020 and reports financial statements to S&P Global. The data are unique in that they contain a large, global sample of most foreign banks in a cross-country panel. We match these macro indicators and information about the regulatory setting at the country level. This enables us to examine how banks' geographic complexity is linked to measures of the health of the bank system, risk, and their key determinants. We utilize the cross-country nature of the dataset to consider several confounding factors, consisting of country- and time-fixed effects, and achieve consistent results across different country settings. We construct a bank geographic complexity (BGC) similar to the Herfindahl-Hirschman index (HHI)-based measure of geographic representation and complexity at the country-year level. This measure conceptually reflects the presence of foreign banks in the host countries, their geographic source (number of source countries with foreign bank ownership), and the concentration of foreign banks across the host countries. We explain BGC as a measure of global geographic complexity and diversification rather than business model complexity/diversification. Complexity and diversification do not overlap. A large domestically oriented financial organization may own a highly complex business model, while a bank with a broader international operation may be simpler in terms of business model diversity. We argue that our measure of global geographic complexity covers information complementary to that reflected by the size of bank assets, the complexity of banking holding companies, and the complexity of global banking organizations and their foreign banking operations.

The papers closely related to our study investigate how the geographic spread or expansion of affiliate networks influence bank risk. Aldasoro et al. (2021) used a unique dataset of 96 global bank holding companies (BHCs) to construct geographic coverage and complexity. They indicate that a higher level of geographic complexity dampens bank risk. Martynova and Vogel (2021) rely on the German banking dataset to indicate that more complex banking organizations tend to take more risks. Our study differs from these seminal contributions in that (i) we concentrate on risk measures of the country banking system rather than the individual bank, (ii) we specifically investigate the geographic spread of foreign-owned bank linkages (as reflected by the BGC) and link this to the aggregate level of bank risk, and (iii) we use a global panel of large internationally active banks. Further, we employ the openness of the capital account and financial freedom to capture the financial liberalization that may alter the effect of geographic complexity.

The analyses in our study connect the literature on the impact of bank geographic diversification on bank risk with the literature on how global banks cope with financial liberalization. Our results elaborate on the main findings of these two streams of the literature. We contribute a vital point to the literature by indicating that global bank geographic complexity is good for the financial sector in terms of diversification benefits. Additionally, the joint impacts of bank geographic complexity and financial liberalization on financial fragility vary across types of financial liberalization. Moreover, we find that financial freedom strengthens the effects of bank geographic complexity on default risk. Our findings reveal that when a country has a high degree of independence from government control and interference in the financial sector, banks must obey market discipline to heighten the banking system's resilience. Our results are based on a large sample of global banks, indicating the importance of the geographic expansion of foreign bank ownership and a situation that intensifies the role of bank geographic complexity.

The remainder of this paper is organized as follows. Section 2 reviews the literature and develops the hypotheses. Section 3 provides the data and model specifications. Section 4 presents our empirical results. Finally, Section 5 concludes the study.

## 2. Theoretical backgrounds and hypothesis development

### 2.1. Global bank complexity

There is mounting literature on bank complexity and geographic expansion. Several authors have emphasized a sharp increase in geographic complexity in recent decades and investigated the consequences of this trend (Cetorelli and Goldberg, 2014; Claessens and Van Horen, 2014; Carmassi and Herring, 2016). On the one hand, in the theory of the firm, Coase (1937) contends that decisions within a hierarchy are driven by power concerns instead of relative prices. Lamont and Polk (2002) showed evidence that resource allocation in diversified firms is dissimilar to that of non-diversified firms in the same sector. Additionally, resource misallocation is employed to explain the action discount in diversified firms relative to a portfolio of non-diversified firms in the same sector (Scharfstein and Stein, 2000). Theories to elucidate the diversification discount include agency theories (Rajan et al., 2000) and influence cost models (Meyer et al., 1992). On the other hand, Markides and Williamson (1994) contended the advantages of diversification in the sense that the existence of friction in external capital markets helps allocate internally generated funds in diversified firms efficiently.

In the financial sector, literature on economies of scope in financial conglomerates is growing. Houston et al. (1997) indicated that bank holding companies distribute funds efficiently to bank subsidiaries confronting more favorable lending opportunities, while Laeven and Levine (2009) verified the diversification discount in financial conglomerates. They suggested that complex banking organizations tend to shift from financial intermediation transactions to fee-based transactions. While the notion of complexity and scope economies are linked in the framework of organizational structure in the banking sector, the complexity of banking organizations could cause externality distortions. They cover the moral hazard issue arising due to too-complex-to-resolve problem, which is well recognized in banking organizations, and financial stability inferences when a complex banking organization imposes systemic risk on the financial system. Concerning the too-complex-to-resolve problem, the moral hazard issue of the too-big-to-fail problem had a massive amount of literature before the occurrence of the 2008–2009 financial distress. Since the financial distress, the literature has focused on the systemic risk implications of highly complex banking bodies and the efficiency of post-crisis reforms in restraining the moral hazard problem.

Given the application of complex banking bodies in the financial system, finance scholars aim to understand their features, evolution (Cetorelli et al., 2014), and metrics to quantify global bank complexity (Cetorelli and Goldberg, 2014). Cetorelli and Goldberg (2014) proposed "organizational" complexity metrics to reflect the extent to which an organization is organized through individual affiliated bodies. Hence, organizational complexity covers an associated dimension that is particular to global bodies, specifically geographic complexity, as reflected by the spread of an organization's affiliates through separate regional areas or nations. Moreover, they propose "business" complexity, a notion capturing the form and diversity of banking activities that may be employed within the family of an institution. Organizational measures are linked to banking considerations that are naturally related to complexity, including fragmentation, international systemic risk, internal liquidity constraints, agency problems, and the too-big-to-fail moral hazard. The notion of business complexity may be related more to the diversification and fragmentation of the kind of production conducted by organizations.

### *2.2. Effect of bank geographic complexity on financial fragility*

It is widely accepted that diversification into high-risk activities could raise the overall portfolio risk. Recently, financial distress has led to revisiting the debate on the benefits of financial integration. During the crisis period, risk is more likely to spread across countries, indicating that diversification via international borders may be counterproductive. In this domain, bank risk directly affects financial and economic stability (Laeven and Levine, 2009). To reduce the potential threat of such risks, national and international authorities have concentrated on employing regulations to curb bank risk and escape future financial distress. Considerable attention has been paid to limiting bank risk within the borders of each country. However, Houston et al. (2012) contended that banks might be involved in regulatory arbitrage, bypassing stringent domestic regulations by taking more risks overseas. This implies that bank internationalization may influence the risk of individual banks, in addition to other driving forces of bank risk, such as bank capital (Mehran and Thakor, 2011), regulation and government interference (Duchin and Sosyura, 2014), competition (Martinez-Miera and Repullo, 2010), bank scale (Hakenes and Schnabel, 2011), and governance (Laeven and Levine, 2009).

On the one hand, global banks may have higher risk due to market-specific characteristics that increase the risk of foreign assets (Amihud et al., 2002). For example, local competition in host countries may increase the time needed for a new entrant to create market share and build bank-customer relationships (Chari and Gupta, 2008). Furthermore, agency problems related to complex organizational and product structures associated with foreign-owned banks may reduce their operational efficiency, thus making them more fragile (Acharya et al., 2006). On the other hand, global banks may possess lower risk as they diversify their portfolios (Amihud et al., 2002; Laeven and Levine, 2007). If asset returns are not firmly associated across countries, globally diversified banks are safer because they are less prone to local shocks (Demsetz and Strahan, 1997), as long as the risk of foreign assets is relatively low or not too high compared to that of domestic assets. Berger et al. (2017) found a positive relationship between internationalization and bank risk-taking among banks in the U.S. (Cetorelli and Goldberg, 2016), indicating that more complex foreign banks are less likely to fund shocks in the US. Aldasoro et al. (2021) investigated the association between banks' geographic complexity and risk using data from global bank holding companies. They showed that higher geographic complexity has a dual effect. On the one hand, it minimizes bank risk, as such complexity improves banks' capacity to absorb local economic shocks. On the other hand, it increases bank risk by softening the effects of financial regulation. Martynova and Vogel (2021) used German banking data to show that more complex banking organizations are more likely to take more risks.

Based on the above arguments, we propose the following hypotheses:

**H1a.** : Bank geographic complexity reduces bank risks.

**H1b.** : Bank geographic complexity increases bank risks.

## 3. Data and methodology

### *3.1. Data*

As our aim is to estimate the effect of global bank complexity on bank fragility, we must quantify both. We build a novel dataset on the complexity of internationally active banks using a list of foreign banks from the S&P IQ Capital Pro. This dataset covers the ownership information of approximately 8085 banking entities in 123 countries that were active for at least one year between 1996 and 2020 and submitted financial statements to S&P Global. For each year and bank, the dataset provides information on the country from which the bank reports and the source country of ownership, among other items. A bank is treated as foreign-owned if foreigners own 50% or more of its shares. The residence of its major owner (the country of the "parent bank") is specified as the country with the highest share among foreign shareholders.

Owing to the limitations of this dataset, we construct a measure of bank complexity in the spirit of Cetorelli and Goldberg (2014). As the banks in our data are internationally active banking entities, they have the advantage of focusing on the international aspects of banking operations. We follow Cetorelli and Goldberg (2014) and Aldasoro et al. (2021) in computing a geographic Herfindahl-Hirschman index as a proxy for global bank complexity:

$$BGC_i = \frac{R_i}{R_i - 1}\left(1 - \sum_{j=1}^{R_i}\left(\frac{FBank_{ij}}{TotalFBank_i}\right)^2\right), \quad (1)$$

where $FBank_{ij}$ is the number of foreign banks in country $i$ owned by residents in country $j$ and $R_i$ is the total number of source countries owned by banks in country $i$. $TotalFBank_i$ is the total number of banks in country $i$ owned by non-residents. A higher value in this index implies higher complexity. If all foreign banks are owned by non-residents of a single country, the index takes the lowest value of 0. If each bank has a different non-resident ownership, this index will record 1 as the highest value. Hence, the information reflected by this metric is different from, and complementary to, the information obtained from measures based on plain counts of foreign banks or source countries. As this index considers the concentration of foreign ownership in each country, it has the advantage of representing geographic complexity distinctly from the scale of banks' organizational structure.

Our measure of bank default risk relies on the z-score of the banking sector within a given country-year. The z-score is defined as the ratio of return on assets plus the capital asset ratio to the standard deviation of return on assets. Specifically, the z-score implies the number of standard deviations that a bank's return on assets must decrease below its expected value before equity is exhausted and the bank's insolvency arises. In line with the current literature and to explain increases in the index as higher bank risk, we take the natural log of the inverse of the z-score (Laeven and Levine, 2009; Berger et al., 2017). The z-score data are obtained from the database on financial development and structure.

Fig. 1 shows the means of bank risk and geographic complexity by year and country to capture the variation in bank risk and geographic complexity across time and countries. In general, geographic complexity tends to increase over time, whereas bank defaults are less likely to occur. Similarly, the distribution of bank risk and geographic complexity shows a negative association across countries. Fig. 2 displays the means of bank risk and geographic complexity across income groups. While a high level of bank fragility is associated with high complexity in LI and LMC, this trend does not hold in HIC and UMC.

### 3.2. Empirical model

In this section, we build our model, in which we estimate the relationship between global bank complexity and bank risk. We use a dynamic model based on panel data. We clean the data by dropping omitted observations and winsorizing the data to deal with outliers. Finally, we are left with 1654 observations in 123 countries between 1996 and 2020[1] (Table A1 in the appendix reports the countries covered in our analysis). As some data are unavailable for all countries and years, the panel data are unbalanced. The model is expressed as follows:

$$Risk_{it} = \beta_0 + \beta_1 BGC_{i,t-1} + \beta_2 CONTROL_{i,t-1} + \varphi_t + \omega_i + \varepsilon_{it}, \quad (2)$$

where the subscripts $i$ and $t$ represent country $i$ and year $t$, respectively. $\varphi_t$ and $\omega_i$, respectively, denote year and country fixed effects. $Risk_{it}$ is the bank default based on the natural log of the inverse of the z-score in country $i$ in year $t$. $BGC_{it}$ is the geographic complexity of foreign banks in country $i$ and year $t$. For the robustness check, we also use $TotalFBank_{it}$ and $R_{it}$ which capture organizational complexity in terms of international fragmentation. $\varepsilon_{it}$ is the standard error. We report a robust standard error to mitigate the heteroscedasticity in the data.

To mitigate omitted variable bias, we incorporate control variables, $CONTROL_{i,t}$, as recommended by existing studies on financial fragility. Similar to the specifications used by Beck et al. (2006), Klomp and De Haan (2009), and Klomp (2014), we add variables associated with the macroeconomic background, monetary policy, and level of financial development. First, we control for macroeconomic determinants by incorporating real GDP per capita (*GDPcapita*) and trade openness (*TradeOpen*) (Beck et al., 2006). Moreover, we use a measure to capture financial liberalization. Inappropriate implementation of financial liberalization tends to boost default risk, as financial institutions are in a better position to take risks in a more liberalized financial market (Kaminsky and Reinhart, 1999). By contrast, appropriate financial liberalization may mitigate banks' default risk, thanks to more chances to spread their risk. We measure financial liberalization using international capital market controls (*Capitalcontrol*) from Chinn and Ito (2006) and financial freedom (*Finfreedom*) as reported by the Heritage Foundation. While the former is an indicator that measures a country's level of capital account openness, the latter is an index measuring independence from government control and interference in the financial sector. Similarly, we incorporate the growth rate of the domestic credit offered to the private sector. A credit boom accompanied by inappropriately liberalized financial markets results in a systemic banking crisis. The growth rate of credit reflects the level of de factor liberalization, while the indicators of financial freedom represent the degree of de jure liberalization. Furthermore, we include the ratio of credit to GDP (*CredittoGDP*) as a proxy for the banking system's financial depth in a country.

Concerning the characteristics of the banking system, we control for banking sector concentration (*Concentration*). The conjecture of this variable is far from reaching a consensus. On the one hand, Nicoló et al. (2004) indicated that highly concentrated banking systems lead to higher levels of systemic risk, thanks to a competition effect. On the other hand, Beck et al. (2006) argued that banking crises are less likely to occur in more concentrated banking systems whose efficiencies are higher. Finally, we consider two variables that reflect the operational efficiency of the banking sector: liabilities-to-assets (*LTA*) and cost-income ratio (*COSTINC*). Table A2 in the Appendix shows a description of all variables, their definitions, and their sources. Table 1 reports a statistical summary of the variables used in this study.

[1] The data that support the findings of this study are available from the corresponding author upon reasonable request.

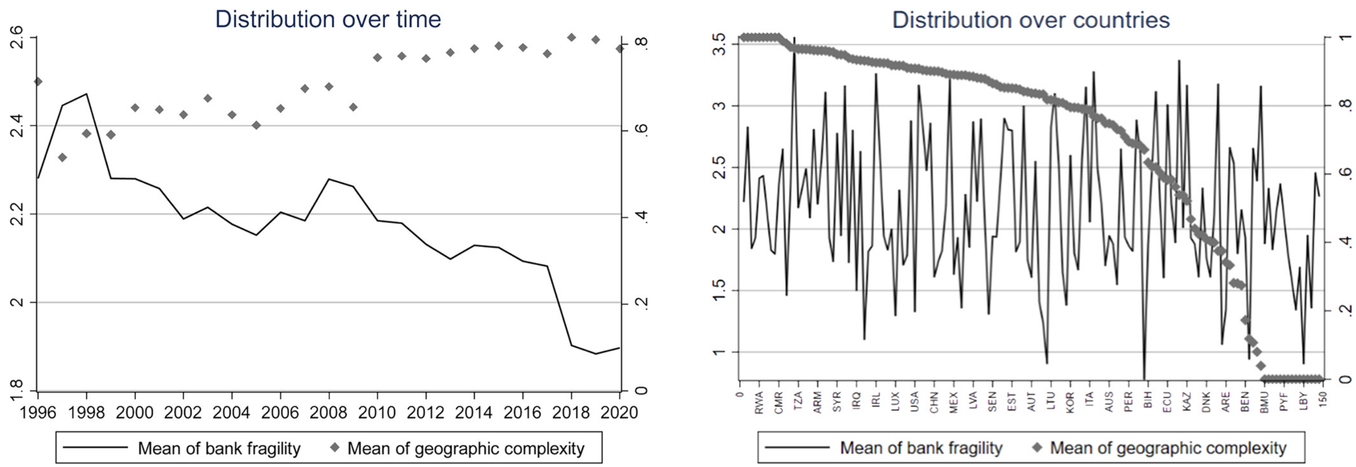


**Fig. 1.** Distribution of bank fragility (*Risk*) and geographic complexity (*BGC*) over time and countries. *Note:* The mean value of bank fragility is on the left-right scale, and the mean value of geographic complexity is on the right-hand scale.

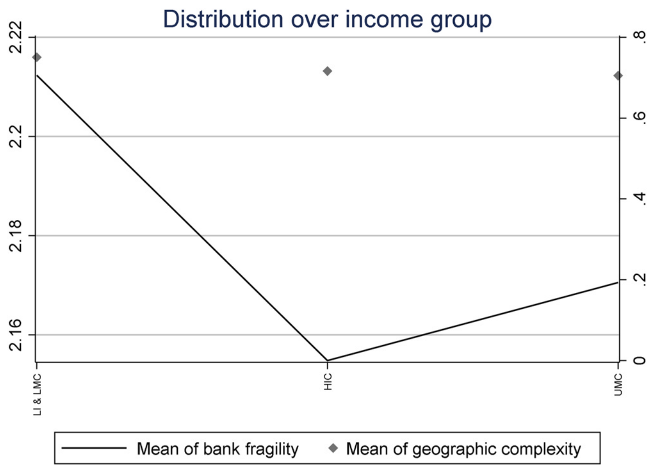


**Fig. 2.** Distribution of bank fragility (*Risk*) and geographic complexity (*BGC*) over income group. *Note:* The mean value of bank fragility is on the left-right scale, and the mean value of geographic complexity is on the right-hand scale.

**Table 1**
Statistical description.

| | obs | mean | sd | min | max |
|---|---|---|---|---|---|
| *Risk* | 1654 | 2.20 | 0.69 | 0.46 | 8.70 |
| *BGC* | 1654 | 0.73 | 0.35 | 0.00 | 1.00 |
| *TotalFBank* | 1654 | 1.38 | 0.89 | 0.00 | 4.26 |
| *R* | 1654 | 5.40 | 4.38 | 2.00 | 40.00 |
| *GDPcapita* | 1654 | 9.43 | 1.05 | 6.86 | 11.24 |
| *Tradeopen* | 1654 | 0.86 | 0.45 | 0.23 | 2.95 |
| *Finfreedom* | 1654 | 0.56 | 0.18 | 0.10 | 0.90 |
| *Concentration* | 1654 | 0.65 | 0.19 | 0.24 | 1.00 |
| *COSTINC* | 1654 | 0.57 | 0.12 | 0.26 | 0.92 |
| *LTA* | 1654 | 1.04 | 0.46 | 0.33 | 3.04 |
| *CredittoGDP* | 1654 | 0.64 | 0.97 | 0.07 | 9.33 |
| *Capitalcontrol* | 1654 | 0.63 | 0.37 | 0.00 | 1.00 |

Our final sample includes 123 countries (including 48 low- and lower-middle-income (LI and LMC) countries, 31 upper-middle-income (UMC) countries, and 44 high-income countries (HIC)) for the period 1996–2020. Table 2 shows the correlation coefficients between all the variables. Since the correlation coefficients are all less than 0.8, there may be no multicollinearity problem in our regressions (Hair et al., 2010).

Some tests were conducted for the empirical estimation approach. Due to the sample with a large N (123 countries) and short period T (1996–2020), we conducted the cross-sectional dependence (CD) tests proposed by Pesaran (2021) to check for the existence of CD. The results, reported in the second column of Table 3, reveal the existence of CD in almost all incorporated variables. Next, we apply the panel unit root test to examine the stationarity of the data in the presence of CD. As our data are unbalanced and have gaps in each individual time series, we cannot apply the Levin-Lin-Chu unit-root test developed by Levin et al. (2002) and the Im–-Pesaran–Shin unit root test developed by Im et al. (2003). We use the Fisher-type unit root test pioneered by Choi (2001), which allows unbalanced and time gap data. The results in Table 3 confirm the stationarity of the level or first difference of the variables. Therefore, a panel-corrected standard error (PCSE) model was employed to examine the association between geographic complexity and bank fragility. Applying the PCSE estimator enables us to resolve the contemporaneous correlations between subjects in the full N × N cross-sectional matrix (Beck and Katz, 1995). We follow Canh and Thanh (2020) and Schneider and Enste (2000) and use a one-year lag of explanatory variables that are stationary at the level to deal with endogeneity. As a robustness check, we use the feasible generalized least square (FGLS) model to reduce heteroscedasticity (Canh and Thanh, 2020; Liao and Cao, 2013).

## 4. Empirical results and discussion

### 4.1. Baseline results

Table 4 reports the effects of bank geographic complexity (*BGC*) on bank fragility. The results of using the PCSE estimator in columns (1) and (2) indicate that *BGC* has a negative effect on bank fragility. This implies that an increase in geographic complexity drives countries to have lower bank risk. The total number of foreign banks (*TotalFBank*) and foreign countries (*R*) also reduced bank

**Table 2**
Correlation coefficients.

| | *BGC* | *GDPcapita* | *Tradeopen* | *Finfreedom* | *Concentration* | *COSTINC* | *LTA* | *CredittoGDP* | *Capitalcontrol* |
|---|---|---|---|---|---|---|---|---|---|
| *BGC* | 1 | | | | | | | | |
| *GDPcapita* | -0.0282 | 1 | | | | | | | |
| *Tradeopen* | 0.0722** | 0.253*** | 1 | | | | | | |
| *Finfreedom* | 0.141*** | 0.489*** | 0.221*** | 1 | | | | | |
| *Concentration* | -0.185*** | 0.0676** | 0.313*** | 0.202*** | 1 | | | | |
| *COSTINC* | 0.0191 | -0.115*** | -0.217*** | 0.0114 | -0.0239 | 1 | | | |
| *LTA* | 0.00180 | 0.333*** | 0.0463 | 0.256*** | 0.100*** | -0.0255 | 1 | | |
| *CredittoGDP* | -0.0605* | 0.260*** | 0.106*** | 0.162*** | 0.0837*** | -0.0481 | 0.226*** | 1 | |
| *Capitalcontrol* | 0.0239 | 0.585*** | 0.202*** | 0.576*** | 0.169*** | 0.0219 | 0.227*** | 0.155*** | 1 |

* $p < 0.05$,
** $p < 0.01$,
*** $p < 0.001$

**Table 3**
Cross-sectional dependence tests and stationary tests.

| Variable (in level) | CD test, Pesaran (2004) | Fisher-type unit-root test | Variable (in difference) | Fisher-type unit-root test |
|---|---|---|---|---|
| *BGC* | 39.40 * ** | 725.05 * ** | | |
| *TotalFBank* | 104.30 * ** | 553.03 * ** | | |
| *R* | 87.27 * ** | 257.54 * ** | | |
| *GDPcapita* | 169.14 * ** | 423.46 * ** | | |
| *Tradeopen* | 38.67 * ** | 254.46 * | | |
| *Finfreedom* | 0.61 | 356.28 * ** | | |
| *Concentration* | 10.58 * ** | 379.72 * ** | | |
| *COSTINC* | 7.59 * ** | 507.11 * ** | | |
| *LTA* | 5.37 * ** | 476.90 * ** | | |
| *CredittoGDP* | 73.47 * ** | 325.20 * ** | | |
| *Capitalcontrol* | 1.54 | 107.24 | DCapitalcontrol | 212.57 * * |

*Note:* Regarding the CD test, the null hypothesis is that the cross-section is independent. The p-value is close to zero, implying that the data are correlated across panel groups. Regarding the Fisher-type test, the null hypothesis is “All panels contain unit root, and the alternative hypothesis is, where at least one panel is stationary.”

defaults. In other words, the tendency of commercial banks to engage in less risky activities is directly related to the increasing geographic complexity of these countries. These results support H1a. Our findings align with those of Goetz et al. (2013) and Cetorelli et al. (2017), who indicated that more complex banks can become safer as they diversify their activities, and Aldasoro et al. (2021), who pointed out that higher complexity improves banks’ capacity to resist local shocks. Our results provide empirical support for policymakers in suggesting that bank supervisors should consider the presence and structure of foreign bank ownership in their assessments.

Control variables have different effects on bank risk. The coefficient of *LTA* is positive and statistically significant at the 1% level, implying that when the banking sector operates inefficiently, it increases the possibility of default. Meanwhile, the negative and statistically significant coefficient of *Capitalcontrol* reveals that the more open the capital account, the safer the financial sector. Likewise, the estimation result also suggests that when an economy becomes more open in the financial sector, it helps the financial sector be more resilient. The FGLS estimator provides a reasonably similar estimate to that of the PCSE estimator. Other variables, including *GDPcapita*, *CredittoGDP*, *Concentration*, *COSTINC,* and *Tradeopen,* were statistically insignificant in these regressions. The adjusted R-squared value was approximately 60% in the PCSE estimation.

## *4.2. Further analysis*

### *4.2.1. The role of economic development in different income groups*

In this section, we investigate the effects of geographic complexity on bank fragility in different groups of countries. Panel A of Table 5 displays our estimate using a sample of 48 low- and lower-middle-income (LI and LMC) countries. The results using the PCSE or FGLS estimators consistently demonstrate the negative impacts of *BGC, TotalFBank,* and *R* on the *Risk* variable. This means that increasing geographic complexity in LI and LMC countries contributes to a reduction in systemic risks.

**Table 4**
The effects of geographic complexity on the bank fragility: Full sample.

| | (1) PCSE | (2) | (3) | (4) FGLS | (5) | (6) |
|---|---|---|---|---|---|---|
| VARIABLES | Risk | Risk | Risk | Risk | Risk | Risk |
| *L.BGC* | -0.27 * ** | | | -0.36 * ** | | |
| | (0.056) | | | (0.050) | | |
| *L.TotalFBank* | | -0.09 * ** | | | -0.15 * ** | |
| | | (0.028) | | | (0.020) | |
| *L.R* | | | -0.02 * ** | | | -0.03 * ** |
| | | | (0.005) | | | (0.004) |
| *D.GDPcapita* | 0.38 | 0.45 | 0.46 | -0.03 | 0.03 | 0.11 |
| | (0.536) | (0.549) | (0.567) | (0.340) | (0.339) | (0.340) |
| *D.CredittoGDP* | -0.01 | -0.01 | -0.01 | -0.00 * * | -0.00 * * | -0.01 * * |
| | (0.005) | (0.005) | (0.006) | (0.002) | (0.002) | (0.002) |
| *D.Concentration* | -0.00 | -0.00 | -0.00 | 0.00 | 0.00 | 0.00 |
| | (0.003) | (0.003) | (0.003) | (0.004) | (0.004) | (0.004) |
| *D.COSTINC* | 0.19 | 0.21 | 0.22 | 0.23 | 0.26 | 0.27 |
| | (0.254) | (0.258) | (0.259) | (0.218) | (0.217) | (0.218) |
| *L.LTA* | 0.20 * ** | 0.20 * ** | 0.20 * ** | 0.22 * ** | 0.22 * ** | 0.22 * ** |
| | (0.031) | (0.030) | (0.030) | (0.039) | (0.039) | (0.039) |
| *L.Tradeopen* | 0.00 | 0.00 | 0.01 | 0.04 | 0.04 | 0.05 |
| | (0.034) | (0.034) | (0.036) | (0.039) | (0.039) | (0.039) |
| *L.Finfreedom* | -0.47 * ** | -0.41 * ** | -0.42 * ** | -0.62 * ** | -0.59 * ** | -0.57 * ** |
| | (0.081) | (0.080) | (0.081) | (0.122) | (0.121) | (0.121) |
| *L.Capitalcontrol* | -0.11 * ** | -0.12 * ** | -0.13 * ** | -0.13 * * | -0.15 * ** | -0.17 * ** |
| | (0.036) | (0.039) | (0.040) | (0.056) | (0.056) | (0.056) |
| Constant | 2.12 * ** | 2.17 * ** | 2.19 * ** | 1.88 * ** | 1.88 * ** | 1.97 * ** |
| | (0.065) | (0.069) | (0.061) | (0.289) | (0.289) | (0.288) |
| Observations | 1574 | 1574 | 1574 | 1574 | 1574 | 1574 |
| R-squared | 0.60 | 0.56 | 0.56 | | | |
| Number of countries | 123 | 123 | 123 | 123 | 123 | 123 |
| Country FE | YES | YES | YES | YES | YES | YES |
| Year FE | YES | YES | YES | YES | YES | YES |

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

Panel B of Table 5 presents the estimated results for a sample of 31 upper-middle-income (UMC) countries. BGC, the total number of foreign banks, and source countries in a host country still play a role in mitigating the default risks in that country. In other words, the increasing tendency of countries to reduce systemic risk is associated with a higher presence of foreign-owned banks.

Panel C of Table 5 presents the results of our study using a sample of 48 high-income countries (HIC). The results show a consistently negative impact of geographic complexity on the *Risk* variable. This effect means that, in high-income countries, increasing global banking geographic complexity prevents commercial banks from engaging in risky activities. Moreover, the effects of geographic complexity on bank fragility in LI and LMC become particularly strong compared with those in UMC and HIC. This suggests that when the economy has a low level of development, it has a lower capacity to absorb economic shocks and, therefore, becomes riskier.

#### *4.2.2. The effect of financial liberalization in different income groups*

In this study, financial liberalization is reflected in the relaxation of capital control and financial freedom. The baseline model shows a negative association between capital controls and financial fragility. This result is consistent with Levine et al. (1999), who contended that countries with stricter capital controls have a higher likelihood of suffering banking distress. However, Demirgüç-Kunt and Detragiache (2000) showed that financial liberalization increases the probability of a banking crisis, and this adverse impact shrinks when a country has strong legal institutions and governance.

The mixed results suggest that we need to examine the role of financial liberalization in different economic developments. Concerning the role of financial regulation reforms, the effects of financial freedom and capital control are heterogeneous across income levels. In LI and LMC, while financial regulation reduces the systemic risk of the financial system, the higher openness of the capital account shows a mixed result. In UMC, the effect of a higher degree of financial freedom was significant. Meanwhile, the relaxation of international capital flow enhances financial stability. In HIC, the effect of financial freedom becomes statistically significant, whereas a reduction in capital account constraints improves the resilience of the financial system. These findings imply

**Table 5**
The effects of geographic complexity on the bank fragility: Sub-sample by income level.

| Panel A: LI and LMC | | | | | | |
|---|---|---|---|---|---|---|
| | (1) PCSE | (2) | (3) | (4) FGLS | (5) | (6) |
| VARIABLES | Risk | Risk | Risk | Risk | Risk | Risk |
| *L.BGC* | -0.47 * ** | | | -0.49 * ** | | |
| | (0.092) | | | (0.084) | | |
| *L.TotalFBank* | | -0.14 * ** | | | -0.15 * ** | |
| | | (0.038) | | | (0.035) | |
| *L.R* | | | -0.05 * ** | | | -0.05 * ** |
| | | | (0.011) | | | (0.009) |
| *D.GDPcapita* | -0.22 | -0.51 | -0.72 | 0.23 | -0.03 | -0.25 |
| | (0.913) | (0.845) | (0.773) | (0.874) | (0.887) | (0.873) |
| *D.CredittoGDP* | -0.03 | -0.03 | -0.03 | -0.03 | -0.02 | -0.02 |
| | (0.030) | (0.030) | (0.029) | (0.038) | (0.039) | (0.038) |
| *D.Concentration* | -0.23 | -0.34 | -0.34 | -0.36 | -0.48 | -0.47 |
| | (0.293) | (0.310) | (0.322) | (0.398) | (0.405) | (0.398) |
| *D.COSTINC* | -0.52 | -0.41 | -0.39 | -0.49 | -0.39 | -0.37 |
| | (0.379) | (0.395) | (0.403) | (0.441) | (0.448) | (0.441) |
| *L.LTA* | -0.12 | -0.10 | -0.14 * * | -0.15 | -0.14 | -0.18 * |
| | (0.079) | (0.070) | (0.065) | (0.102) | (0.103) | (0.103) |
| *L.Tradeopen* | 0.14 * * | 0.14 * * | 0.16 * * | 0.17 * | 0.16 * | 0.19 * |
| | (0.072) | (0.066) | (0.064) | (0.095) | (0.096) | (0.095) |
| *L.Finfreedom* | -1.36 * ** | -1.35 * ** | -1.29 * ** | -1.40 * ** | -1.40 * ** | -1.32 * ** |
| | (0.269) | (0.283) | (0.279) | (0.252) | (0.257) | (0.253) |
| *L.Capitalcontrol* | 0.08 | 0.11 * | 0.11 * | 0.03 | 0.05 | 0.06 |
| | (0.054) | (0.061) | (0.063) | (0.096) | (0.098) | (0.096) |
| Constant | 2.39 * ** | 2.54 * ** | 2.49 * ** | 2.35 * ** | 2.51 * ** | 2.46 * ** |
| | (0.144) | (0.151) | (0.155) | (0.174) | (0.172) | (0.170) |
| Observations | 443 | 443 | 443 | 443 | 443 | 443 |
| R-squared | 0.61 | 0.62 | 0.68 | | | |
| Number of countries | 48 | 48 | 48 | 48 | 48 | 48 |
| Country FE | YES | YES | YES | YES | YES | YES |
| Year FE | YES | YES | YES | YES | YES | YES |
| Panel B: UMC | | | | | | |
| | (1) PCSE | (2) | (3) | (4) FGLS | (5) | (6) |
| VARIABLES | Risk | Risk | Risk | Risk | Risk | Risk |
| *L.BGC* | -0.16 * * | | | -0.20 * * | | |
| | (0.081) | | | (0.094) | | |
| *L.TotalFBank* | | -0.05 * * | | | -0.12 * ** | |
| | | (0.027) | | | (0.041) | |
| *L.R* | | | -0.02 * ** | | | -0.03 * ** |
| | | | (0.006) | | | (0.009) |
| *D.GDPcapita* | 0.65 | 0.69 | 0.69 | 0.57 | 0.57 | 0.60 |
| | (0.761) | (0.775) | (0.781) | (0.411) | (0.409) | (0.407) |
| *D.CredittoGDP* | -0.04 | -0.04 | -0.04 | -0.02 | -0.03 | -0.03 |
| | (0.079) | (0.078) | (0.079) | (0.045) | (0.044) | (0.044) |
| *D.Concentration* | 0.30 | 0.29 | 0.21 | 0.42 | 0.40 | 0.28 |
| | (0.682) | (0.676) | (0.688) | (0.617) | (0.614) | (0.614) |
| *D.COSTINC* | 0.80 | 0.82 | 0.84 | 0.83 * | 0.86 * | 0.89 * |
| | (0.592) | (0.585) | (0.580) | (0.485) | (0.482) | (0.481) |
| *L.LTA* | 0.28 * ** | 0.26 * ** | 0.26 * ** | 0.28 * ** | 0.25 * ** | 0.25 * ** |
| | (0.053) | (0.055) | (0.054) | (0.072) | (0.073) | (0.072) |
| *L.Tradeopen* | 0.27 * ** | 0.26 * ** | 0.28 * ** | 0.27 * ** | 0.27 * ** | 0.30 * ** |
| | (0.084) | (0.082) | (0.086) | (0.096) | (0.095) | (0.096) |
| *L.Finfreedom* | -0.08 | -0.02 | -0.00 | -0.12 | -0.07 | -0.02 |
| | (0.172) | (0.173) | (0.179) | (0.239) | (0.233) | (0.232) |
| *L.Capitalcontrol* | -0.70 * ** | -0.69 * ** | -0.70 * ** | -0.67 * ** | -0.65 * ** | -0.66 * ** |
| | (0.111) | (0.112) | (0.111) | (0.112) | (0.112) | (0.111) |
| Constant | 1.97 * ** | 1.99 * ** | 1.95 * ** | 1.82 * ** | 1.77 * ** | 1.73 * ** |
| | (0.151) | (0.142) | (0.141) | (0.209) | (0.210) | (0.211) |
| Observations | 398 | 398 | 398 | 398 | 398 | 398 |
| R-squared | 0.68 | 0.67 | 0.68 | | | |
| Number of countries | 31 | 31 | 31 | 31 | 31 | 31 |
| Country FE | YES | YES | YES | YES | YES | YES |
| Year FE | YES | YES | YES | YES | YES | YES |
| Panel C: HIC | | | | | | |

(*continued on next page*)

**Table 5** (*continued*)

Panel A: LI and LMC

| | (1) PCSE | (2) | (3) | (4) FGLS | (5) | (6) |
|---|---|---|---|---|---|---|
| VARIABLES | Risk | Risk | Risk | Risk | Risk | Risk |
| | (1) PCSE | (2) | (3) | (4) FGLS | (5) | (6) |
| VARIABLES | Risk | Risk | Risk | Risk | Risk | Risk |
| *L.BGC* | -0.26 * ** | | | -0.35 * ** | | |
| | (0.087) | | | (0.085) | | |
| *L.TotalFBank* | | -0.08 * * | | | -0.15 * ** | |
| | | (0.036) | | | (0.034) | |
| *L.R* | | | -0.01 * ** | | | -0.02 * ** |
| | | | (0.004) | | | (0.006) |
| *D.GDPcapita* | 0.40 | 0.58 | 0.54 | -0.67 | -0.48 | -0.30 |
| | (1.001) | (1.014) | (0.999) | (0.956) | (0.953) | (0.960) |
| *D.CredittoGDP* | 0.03 | 0.03 | 0.03 | 0.01 | 0.01 | 0.01 |
| | (0.020) | (0.020) | (0.018) | (0.046) | (0.046) | (0.046) |
| *D.Concentration* | 0.23 | 0.24 | 0.24 | 0.13 | 0.14 | 0.14 |
| | (0.529) | (0.538) | (0.541) | (0.415) | (0.414) | (0.417) |
| *D.COSTINC* | 0.06 | 0.04 | 0.07 | 0.06 | 0.04 | 0.07 |
| | (0.346) | (0.353) | (0.351) | (0.324) | (0.324) | (0.326) |
| *L.LTA* | 0.16 * ** | 0.18 * ** | 0.18 * ** | 0.17 * ** | 0.22 * ** | 0.20 * ** |
| | (0.035) | (0.039) | (0.040) | (0.061) | (0.063) | (0.063) |
| *L.Tradeopen* | -0.12 * ** | -0.10 * ** | -0.09 * ** | -0.06 | -0.04 | -0.04 |
| | (0.029) | (0.030) | (0.032) | (0.053) | (0.053) | (0.054) |
| *L.Finfreedom* | -0.52 * ** | -0.48 * ** | -0.46 * ** | -0.64 * ** | -0.65 * ** | -0.58 * ** |
| | (0.130) | (0.155) | (0.159) | (0.199) | (0.198) | (0.199) |
| *L.Capitalcontrol* | -0.47 * ** | -0.53 * ** | -0.56 * ** | -0.43 * ** | -0.49 * ** | -0.55 * ** |
| | (0.075) | (0.074) | (0.079) | (0.125) | (0.123) | (0.123) |
| Constant | 2.73 * ** | 2.77 * ** | 2.84 * ** | 2.46 * ** | 2.46 * ** | 2.61 * ** |
| | (0.133) | (0.121) | (0.115) | (0.192) | (0.191) | (0.186) |
| Observations | 652 | 652 | 652 | 652 | 652 | 652 |
| R-squared | 0.66 | 0.62 | 0.59 | | | |
| Number of countries | 44 | 44 | 44 | 44 | 44 | 44 |
| Country FE | YES | YES | YES | YES | YES | YES |
| Year FE | YES | YES | YES | YES | YES | YES |

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

that, to maintain financial stability, governments should consider the stage of economic development while deciding which types of financial liberalization will be reformed.

### 4.2.3. *Joint effect of financial liberalization and bank geographic complexity*

To sum up our results, we find that bank geographic complexity has a significant negative effect on the banking sector's default. An issue that is frequently raised in the discussion of financial fragility is that the consequences of unfavorable shocks may be more severe when political institutions and policies required to assist the efficient and smooth functioning of the banking sector are not well established (Klomp, 2014). To take this into account, we determine the effect of bank geographic complexity conditional on the level of financial freedom and degree of capital control. This is done by incorporating an interaction term into the main specification and estimating the following model:

$$Risk_{it} = \beta_0 + \beta_1 BGC_{i,t-1} + \beta_2 CONTROL_{i,t-1} + \beta_3 (BGC^{*}FinLiberal)_{i,t-1} + \varphi_t + \omega_i + \varepsilon_{it}, \tag{3}$$

where $FinLiberal_{it}$ refers to our financial freedom and capital control measures, respectively. The coefficient of interest was $\beta_3$. A statistically negative sign of $\beta_3$ implies the co-movement of bank geographic complexity and financial liberalization. In this vein, high complexity and financial liberalization make the financial system more resilient. Meanwhile, the statistically positive sign of $\beta_3$ suggests that rigorous financial regulation should take place to support a high degree of bank geographic complexity.

In Table 6, we report the PCSE and FGLS estimation results on the interaction term using the various bank complexity and financial liberalization measures. The findings in Panel A show that more rigorous capital control may enhance the effect of bank complexity, particularly in the case of the number of foreign countries with banking ownership in reporting countries ($R$). One potential explanation is that an increase in $R$ makes a country more dependent on a larger set of foreign countries. Hence, strict capital control makes it more likely for a bank to survive a foreign shock. However, financial freedom intensifies the adverse effects of banks' geographic complexity on default risk. A possible reason is that when a country has a high level of independence from

**Table 6**
Conditional effect of bank geographic complexity on financial liberalization.

Panel A:

| | (1) PCSE | (2) | (3) | (4) FGLS | (5) | (6) |
|---|---|---|---|---|---|---|
| VARIABLES | Risk | Risk | Risk | Risk | Risk | Risk |
| *D.GDPcapita* | 0.42 | 0.48 | 0.47 | 0.04 | 0.09 | 0.14 |
| | (0.539) | (0.552) | (0.564) | (0.344) | (0.344) | (0.344) |
| *D.CredittoGDP* | -0.01 | -0.01 | -0.01 | -0.01 | -0.01 | -0.01 |
| | (0.026) | (0.026) | (0.026) | (0.025) | (0.025) | (0.025) |
| *D.Concentration* | 0.16 | 0.13 | 0.13 | 0.05 | 0.01 | 0.00 |
| | (0.277) | (0.282) | (0.282) | (0.265) | (0.265) | (0.266) |
| *D.COSTINC* | 0.09 | 0.09 | 0.10 | 0.12 | 0.12 | 0.14 |
| | (0.265) | (0.268) | (0.270) | (0.230) | (0.230) | (0.230) |
| *L.LTA* | 0.20 * ** | 0.20 * ** | 0.19 * ** | 0.22 * ** | 0.21 * ** | 0.20 * ** |
| | (0.022) | (0.021) | (0.019) | (0.040) | (0.041) | (0.041) |
| *L.Tradeopen* | 0.00 | 0.01 | 0.01 | 0.03 | 0.04 | 0.05 |
| | (0.033) | (0.035) | (0.036) | (0.040) | (0.040) | (0.040) |
| *L.Finfreedom* | -0.44 * ** | -0.39 * ** | -0.39 * ** | -0.58 * ** | -0.54 * ** | -0.51 * ** |
| | (0.093) | (0.096) | (0.098) | (0.124) | (0.123) | (0.124) |
| *L.Capitalcontrol* | -0.10 | -0.11 | -0.06 | -0.19 * | -0.19 * * | -0.10 |
| | (0.088) | (0.072) | (0.053) | (0.110) | (0.093) | (0.084) |
| *L.BGC* | -0.31 * ** | | | -0.34 * ** | | |
| | (0.076) | | | (0.093) | | |
| *L.BGC* L.Capitalcontrol* | 0.06 | | | 0.03 | | |
| | (0.093) | | | (0.131) | | |
| *L.TotalFBank* | | -0.11 * ** | | | -0.15 * ** | |
| | | (0.043) | | | (0.040) | |
| *L.TotalFBank* L.Capitalcontrol* | | 0.03 | | | 0.00 | |
| | | (0.038) | | | (0.054) | |
| *L.R* | | | -0.03 * ** | | | -0.04 * ** |
| | | | (0.011) | | | (0.010) |
| *L.R* L.Capitalcontrol* | | | 0.02 * * | | | 0.02 * * |
| | | | (0.009) | | | (0.012) |
| Constant | 2.09 * ** | 2.14 * ** | 2.12 * ** | 1.96 * ** | 1.97 * ** | 1.97 * ** |
| | (0.080) | (0.081) | (0.081) | (0.111) | (0.103) | (0.103) |
| Observations | 1493 | 1493 | 1493 | 1493 | 1493 | 1493 |
| R-squared | 0.69 | 0.64 | 0.65 | | | |
| Number of countries | 123 | 123 | 123 | 123 | 123 | 123 |
| Country FE | YES | YES | YES | YES | YES | YES |
| Year FE | YES | YES | YES | YES | YES | YES |

**Panel B:**

| | (1) PCSE | (2) | (3) | (4) FGLS | (5) | (6) |
|---|---|---|---|---|---|---|
| VARIABLES | Risk | Risk | Risk | Risk | Risk | Risk |
| *D.GDPcapita* | 0.43 | 0.49 | 0.48 | 0.05 | 0.10 | 0.14 |
| | (0.565) | (0.564) | (0.569) | (0.344) | (0.344) | (0.345) |
| *D.CredittoGDP* | -0.01 | -0.01 | -0.01 | -0.01 | -0.01 | -0.01 |
| | (0.027) | (0.027) | (0.027) | (0.025) | (0.025) | (0.025) |
| *D.Concentration* | 0.15 | 0.13 | 0.13 | 0.03 | 0.00 | 0.00 |
| | (0.277) | (0.283) | (0.285) | (0.265) | (0.265) | (0.266) |
| *D.COSTINC* | 0.09 | 0.09 | 0.10 | 0.12 | 0.11 | 0.14 |
| | (0.265) | (0.268) | (0.269) | (0.230) | (0.230) | (0.231) |
| *L.LTA* | 0.21 * ** | 0.21 * ** | 0.20 * ** | 0.22 * ** | 0.22 * ** | 0.21 * ** |
| | (0.023) | (0.022) | (0.020) | (0.040) | (0.041) | (0.041) |
| *L.Tradeopen* | -0.01 | 0.00 | 0.01 | 0.03 | 0.04 | 0.05 |
| | (0.033) | (0.035) | (0.036) | (0.040) | (0.040) | (0.040) |
| *L.Finfreedom* | -0.71 * ** | -0.46 * ** | -0.31 * * | -1.01 * ** | -0.72 * ** | -0.40 * * |
| | (0.217) | (0.132) | (0.126) | (0.255) | (0.197) | (0.169) |
| *L.Capitalcontrol* | -0.14 * ** | -0.15 * ** | -0.16 * ** | -0.16 * ** | -0.19 * ** | -0.20 * ** |
| | (0.039) | (0.041) | (0.042) | (0.058) | (0.058) | (0.058) |
| *L.BGC* | -0.09 | | | -0.06 | | |
| | (0.109) | | | (0.161) | | |
| *L.BGC*L.Finfreedom* | -0.36 * * | | | -0.57 * | | |
| | (0.222) | | | (0.295) | | |
| *L.TotalFBank* | | -0.07 * | | | -0.08 | |

(*continued on next page*)

**Table 6** (*continued*)

Panel A:

| | (1) PCSE | (2) | (3) | (4) FGLS | (5) | (6) |
|---|---|---|---|---|---|---|
| VARIABLES | Risk | Risk | Risk | Risk | Risk | Risk |
| | | (0.035) | | | (0.061) | |
| *L.TotalFBank* LFinfreedom* | | 0.04 | | | 0.12 | |
| | | (0.053) | | | (0.105) | |
| *L.R* | | | -0.03 * ** | | | -0.04 * ** |
| | | | (0.011) | | | (0.014) |
| *L.R*L.Finfreedom* | | | 0.02 * * | | | 0.02 * * |
| | | | (0.010) | | | (0.020) |
| Constant | 2.25 * ** | 2.20 * ** | 2.14 * ** | 2.16 * ** | 2.06 * ** | 1.97 * ** |
| | (0.105) | (0.075) | (0.080) | (0.145) | (0.120) | (0.115) |
| Observations | 1493 | 1493 | 1493 | 1493 | 1493 | 1493 |
| R-squared | 0.65 | 0.64 | 0.64 | | | |
| Number of countries | 123 | 123 | 123 | 123 | 123 | 123 |
| Country FE | YES | YES | YES | YES | YES | YES |
| Year FE | YES | YES | YES | YES | YES | YES |

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

**Table 7**
Mechanism analysis.

| VARIABLES | (1) BGC $\widetilde{Risk}$ | (2) TotalFbank $\widetilde{Risk}$ | (3) R $\widetilde{Risk}$ |
|---|---|---|---|
| Income diversification | -0.25 * ** | -0.10 * ** | -0.02 * ** |
| | (0.064) | (0.029) | (0.004) |
| Asset diversification | -0.31 * ** | -0.09 * ** | -0.02 * * |
| | (0.055) | (0.030) | (0.005) |
| Asset capability | -0.29 * ** | -0.11 * ** | -0.02 * ** |
| | (0.054) | (0.030) | (0.005) |
| All channels jointly | -0.28 | -0.11 | -0.02 |
| | (0.059) | (0.027) | (0.004) |

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

government control and interference in the financial sector, banks have to cope with market discipline, thereby enhancing the banking system's resilience.

### *4.3. Mechanism*

In this section, we study the channels that transmit the impact of BGC on bank fragility. Three effect channels have been documented in the literature: Portfolio diversification and capacity improvement. After choosing a set of mediators, we follow Acharya et al. (2016) and Doan and Ha (2022) to calculate the average controlled direct effect (ACDE), which aligns with the impact of BGC on bank fragility when the set of mediators is kept unchanged. The ACDE is constructed using a three-step estimation process. In the first step, the effects of the mediators on the dependent variable *Risk* are estimated.

$$Risk_{it} = \beta_0 + \beta_1 BGC_{i,t-1} + \beta_2 M_{i,t-1} + \beta_3 CONTROL_{i,t-1} + \varphi_t + \omega_i + \varepsilon_{it,} \tag{4}$$

where $M$ is the vector of mediators. In the second step, we drop the mediator value from the observed outcome, $\widetilde{Risk}_{it} = Risk_{it} - \hat{\beta}_2 M_{i,t-1}$. In the third step, ACDE is estimated by regressing

$$\widetilde{Risk}_{it} = \beta_0 + \beta_1 BGC_{i,t-1} + \beta_2 CONTROL_{i,t-1} + \varphi_t + \omega_i + \varepsilon_{it} \tag{5}$$

Coefficient $\hat{\beta}_1$ is the effect of the BGC when considering the mediator variable $M$. If this coefficient is statistically insignificant, it means that BGC alters bank fragility through mediator $M$.

In the first channel, based on the work of Acharya et al. (2006), Sang (2017), Sang and Linh (2019), and Shim (2019), we used the

**Table 8**
IV estimation result.

| VARIABLES | (1) GMM | (2) GMM | (3) GMM |
|---|---|---|---|
| *BGC* | -0.32 * * | | |
| | (0.12) | | |
| *TotalFBank* | | -0.14 * * | |
| | | (0.04) | |
| *R* | | | -0.00 |
| | | | (0.00) |
| *L.Risk* | 0.56 * ** | 0.58 * ** | 0.63 * ** |
| | (0.12) | (0.07) | (0.05) |
| *GDPcapita* | 0.01 | 0.01 | 0.00 |
| | (0.06) | (0.02) | (0.02) |
| *CredittoGDP* | -0.01 | -0.01 | -0.01 |
| | (0.02) | (0.01) | (0.01) |
| *Concentration* | 0.03 | -0.03 | 0.06 |
| | (0.48) | (0.14) | (0.11) |
| *COSTINC* | 0.69 | 0.69 * ** | 0.60 * ** |
| | (0.72) | (0.21) | (0.20) |
| *LTA* | 0.09 | 0.09 | 0.08 * |
| | (0.22) | (0.06) | (0.05) |
| *Tradeopen* | 0.04 | 0.04 | 0.03 |
| | (0.14) | (0.06) | (0.05) |
| *Finfreedom* | -0.12 | -0.11 | -0.11 |
| | (0.35) | (0.16) | (0.13) |
| *Capitalcontrol* | -0.11 | -0.10 | -0.09 |
| | (0.26) | (0.08) | (0.07) |
| Constant | 0.46 | 0.48 * | 0.39 * * |
| | (1.13) | (0.25) | (0.19) |
| Observations | 1493 | 1493 | 1493 |
| F-test (p-value) | 0.000 | 0.000 | 0.000 |
| Arellano–Bond AR (1) p-value | 0.073 | 0.061 | 0.059 |
| Arellano–Bond AR (2) p-value | 0.282 | 0.279 | 0.289 |
| Hansen test (p-value) | 0.994 | 0.983 | 0.981 |

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

income diversification (*Diver_Income*) and asset diversification (*Diver_Assets*) as proxies for portfolio diversification. Income diversification reflects the extent of operating income, which comprises interest and non-interest income. Asset diversification captures the extent of assets made up of customer loans, cash and cash equivalents, securities, intangible assets, and other earning assets. An increase in *Diver_Income* and *Diver_Assets* indicates an improvement in a bank's portfolio diversification. Next, the ratio of bank assets to GDP is used to capture asset capability (*asset capacity*). A higher value for *Assetcapacity* indicates an improvement in capability.

Table 7 shows the estimation results from Eq. (5), focusing on coefficient $\hat{\beta}_1$. When working alone, both portfolio diversification and asset capacity adequately interpret the impact of bank complexity on bank fragility because the coefficients are statistically insignificant. More importantly, we failed to reject the null hypothesis H0: $\beta_1 = 0$ in all model specifications. This means that the joint set of the three mediators is the channel used to transfer the impact of bank complexity on bank risk.

### 4.4. Endogeneity problem

In the regressions so far, we assume that geographic complexity is exogenous. However, the criteria for constructing banking geographic complexity are more endogenous. For example, as stated above, the total number of foreign banks may be positively linked to the income level and depth of the banking sector. If we cannot explicitly control for these determinants, our estimation results may be biased. To solve the potential endogeneity problem, we apply Arellano and Bond's (1991) generalized method of moments (GMM) estimator. In this method, the endogeneity problem is addressed by computing an estimated instrumental variable for the first-difference equation using the second- and higher-order lags of the endogenous and regression variables and the first difference of the exogenous variables as instruments.

However, this method also has several limitations. The first drawback is that differencing the equation eliminates long-run cross-country information appearing in the variable levels. Next, if the explanatory variables persist over time, their lagged levels are not good instruments for their differences. The additional assumptions allow us to build an alternative GMM estimator that bypasses these issues. Specifically, there are more moment conditions when we assume that the independent variables are uncorrelated with sole effects (Arellano and Bover, 1995). In this situation, the lagged differences of these variables and of the regression variable may also be valid instruments for the first-stage equation. Based on this, the estimation includes the set of moment conditions available for the first-differenced equations, with the additional moment conditions inferred for the levels equation (Blundell and Bond, 1998). Finally, if the model's over-identification is satisfied, the validity of the assumptions underlying both the difference and the system estimators can be examined via Sargan tests of orthogonality between the instruments and the errors and via tests of second- or higher-order residual autocorrelation.

The results in Table 8 point to the same direction as those in Table 4, except for the regression on the number of foreign counties (*R*). We still find that *BGC* and *TotalFBank* have a significantly negative impact on default risk. Moving to the bottom part of Table 8, the Hansen test shows no evidence of a misspecification. Additionally, the Arellano–Bond serial correlation tests indicate that there exists first-order autocorrelation of the residuals but no second-order autocorrelation of the residuals, which aligns with the assumptions of the selection of instruments.

## 5. Conclusion

This study is one of the first to examine the effect of bank geographic complexity on the default risk faced by commercial banks. We employ a panel model that includes approximately 123 countries from 1996 to 2020. Our measure of default risk was based on the natural logarithm of the inverse z-score. We construct a bank geographic complexity (BGC), such as the Herfindahl-Hirschman index (HHI)-based measure of geographic representation and complexity, at the country-year level.

After extensive robustness checks of the results, our main findings reveal that geographic complexity increases the probability of a bank's default. The results of this study clearly show that geographic complexity of banks may boost the solvency of the commercial banking sector. To maintain stability, policymakers should consider the presence and structure of foreign bank ownership in their assessments.

Additionally, it seems that the effect of banks' geographic complexity depends on the degree of economic development of a given country and the level of financial liberalization. First, the adverse impact of banks' geographic complexity on financial fragility becomes more evident for LI and LMC. Second, the role of financial liberalization is heterogeneous across income groups. This suggests that policymakers should consider the level of economic development to select the right form of financial liberalization. Third, to reinforce the role of banks' geographic complexity in mitigating bank fragility, the government should foster financial freedom.

## Funding source declaration

This research is funded by Vietnam Banking Academy Grant ID: NCM_02/2020.

## Appendix

(See here Appendix Tables A1,A2).

**Table A1**
List of countries.

| No. | Reporter | Percent | No. | Reporter | Percent | No. | Reporter | Percent |
|---|---|---|---|---|---|---|---|---|
| 1 | AGO | 0.49 | 42 | GAB | 0.49 | 83 | NER | 0.49 |
| 2 | ALB | 0.85 | 43 | GBR | 1.34 | 84 | NGA | 0.85 |
| 3 | ARE | 1.03 | 44 | GEO | 0.85 | 85 | NIC | 0.49 |
| 4 | ARG | 1.28 | 45 | GHA | 1.03 | 86 | NLD | 1.22 |
| 5 | ARM | 0.73 | 46 | GMB | 0.24 | 87 | NOR | 1.34 |
| 6 | AUS | 0.79 | 47 | GRC | 0.97 | 88 | NPL | 0.49 |
| 7 | AUT | 1.09 | 48 | GTM | 0.55 | 89 | NZL | 0.67 |
| 8 | AZE | 0.73 | 49 | HND | 0.49 | 90 | OMN | 0.79 |
| 9 | BDI | 0.24 | 50 | HRV | 1.15 | 91 | PAK | 0.67 |
| 10 | BEL | 1.09 | 51 | HUN | 1.28 | 92 | PAN | 0.79 |
| 11 | BEN | 0.73 | 52 | IDN | 1.28 | 93 | PER | 1.15 |
| 12 | BFA | 0.55 | 53 | IND | 0.79 | 94 | PHL | 1.09 |
| 13 | BGD | 0.49 | 54 | IRL | 1.28 | 95 | POL | 1.34 |
| 14 | BGR | 1.09 | 55 | ITA | 1.34 | 96 | PRT | 1.22 |
| 15 | BHR | 0.97 | 56 | JAM | 0.85 | 97 | PRY | 0.49 |
| 16 | BIH | 1.03 | 57 | JOR | 1.15 | 98 | QAT | 0.18 |
| 17 | BLR | 1.03 | 58 | JPN | 0.97 | 99 | RUS | 1.22 |
| 18 | BOL | 0.36 | 59 | KAZ | 1.15 | 100 | RWA | 0.49 |
| 19 | BRA | 1.34 | 60 | KEN | 0.97 | 101 | SEN | 1.03 |
| 20 | BRB | 0.36 | 61 | KGZ | 0.49 | 102 | SGP | 0.49 |
| 21 | BWA | 0.97 | 62 | KHM | 0.49 | 103 | SLE | 0.18 |
| 22 | CAN | 0.79 | 63 | KOR | 1.09 | 104 | SVK | 1.15 |
| 23 | CHE | 1.28 | 64 | KWT | 0.91 | 105 | SVN | 1.09 |
| 24 | CHL | 0.73 | 65 | LBN | 0.49 | 106 | SWE | 1.28 |
| 25 | CHN | 0.67 | 66 | LBY | 0.3 | 107 | SYC | 0.12 |
| 26 | CMR | 0.67 | 67 | LKA | 0.79 | 108 | SYR | 0.12 |
| 27 | COL | 1.15 | 68 | LSO | 0.36 | 109 | TGO | 0.61 |
| 28 | CPV | 0.49 | 69 | LTU | 1.22 | 110 | THA | 1.34 |
| 29 | CRI | 0.85 | 70 | LVA | 1.09 | 111 | TJK | 0.18 |
| 30 | CYP | 0.3 | 71 | MAR | 1.15 | 112 | TUN | 0.97 |
| 31 | DEU | 0.79 | 72 | MDA | 1.03 | 113 | TZA | 0.49 |
| 32 | DJI | 0.18 | 73 | MDG | 0.49 | 114 | UGA | 0.79 |
| 33 | DNK | 1.34 | 74 | MEX | 1.34 | 115 | UKR | 1.15 |
| 34 | DOM | 0.49 | 75 | MLI | 0.61 | 116 | URY | 0.55 |
| 35 | DZA | 0.67 | 76 | MLT | 1.15 | 117 | USA | 1.34 |
| 36 | ECU | 0.55 | 77 | MNG | 0.85 | 118 | UZB | 0.3 |
| 37 | EGY | 1.15 | 78 | MOZ | 0.67 | 119 | VEN | 0.85 |
| 38 | ESP | 1.03 | 79 | MUS | 0.85 | 120 | VNM | 0.24 |
| 39 | EST | 1.15 | 80 | MWI | 0.79 | 121 | ZAF | 0.49 |
| 40 | FIN | 1.03 | 81 | MYS | 0.55 | 122 | ZMB | 0.97 |
| 41 | FRA | 0.55 | 82 | NAM | 0.79 | 123 | ZWE | 0.55 |

**Table A2**
Definition of variables, measurements and sources.

| Variable | Definition | Measure | Source |
|---|---|---|---|
| *GBC* | Geographic complexity | $BGC_i = \frac{R_i}{R_i - 1}\left(1 - \sum_{j=1}^{R_i}\left(\frac{FBank_{ij}}{TotalFBank_i}\right)^2\right)$ | S&P Capital IQ Pro |
| *TotalFBank* | Organizational complexity | Total number of banks in a country that are owned by non-residents | S&P Capital IQ Pro |
| *R* | Organizational complexity | Total number of source countries that own banks in a reporting country | S&P Capital IQ Pro |
| *Risk* | Default risk | Natural log of the inverse of the z-score | |
| *GDPcapita* | GDP per capita | Natural log of the real GDP per capita (constant 2010 US dollars) | WDI |
| *Tradeopen* | Trade openness | Trade (% of GDP) | WDI |
| *Finfreedom* | Financial freedom | Financial freedom index | Heritage Foundation |
| *Concentration* | Banking sector concentration | Share of assets of a country's three largest banks | DFDS |
| *COSTINC* | Ratio of costs to income | Cost/income | DFDS |
| *LTA* | Ratio of liabilities to assets | Liabilities/assets | DFDS |
| *CredittoGDP* | Financial depth | Credit (% of GDP) | DFDS |
| *Capitalcontrol* | Openness of capital account | Chinn–Ito index (KAOPEN) | Chinn and Ito (2006) |

Note: Database on Financial Development and Structure (DFDS)

## References


Acharya, A., Blackwell, M., Sen, M., 2016. Explaining causal findings without bias: Detecting and assessing direct effects. Am. Polit. Sci. Rev. 110 (3), 512–529.
Acharya, V.V., Hasan, I., Saunders, A., 2006. Should banks be diversified? evidence from individual bank loan portfolios. J. Bus. 79 (3), 1355–1412.
Aldasoro, I., Hardy, B., Jager, M., 2021. The Janus face of bank geographic complexity. J. Bank. Financ., 106040. https://doi.org/10.1016/j.jbankfin.2020.106040
Amihud, Y., DeLong, G.L., Saunders, A., 2002. The effects of cross-border bank mergers on bank risk and value. J. Int. Money Financ. 21 (6), 857–877.
Arellano, M., Bond, S., 1991. Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. Rev. Econ. Stud. 58 (2), 277–297.
Arellano, M., Bover, O., 1995. Another look at the instrumental variable estimation of error-components models. J. Econ. 68 (1), 29–51. https://doi.org/10.1016/0304-4076(94)01642-D
Beck, N., Katz, J.N., 1995. What to do (and not to do) with time-series cross-section data. Am. Political Sci. Rev. 89 (3), 634–647. https://doi.org/10.2307/2082979
Beck, T., Demirgüç-Kunt, A., Levine, R., 2006. Bank concentration, competition, and crises: first results. J. Bank. Financ. 30 (5), 1581–1603.
Berger, A.N., El Ghoul, S., Guedhami, O., Roman, R.A., 2017. Internationalization and bank risk. Manag. Sci. 63 (7), 2283–2301.
Blundell, R., Bond, S., 1998. Initial conditions and moment restrictions in dynamic panel data models. J. Econ. 87 (1), 115–143. https://doi.org/10.1016/S0304-4076(98)00009-8
Canh, N.P., Thanh, S.D., 2020. Financial development and the shadow economy: a multi-dimensional analysis. Econ. Anal. Policy 67, 37–54. https://doi.org/10.1016/j.eap.2020.05.002
Carmassi, J., Herring, R., 2016. The corporate complexity of global systemically important banks. J. Financ. Serv. Res. 49 (2), 175–201.
Cetorelli, N., Goldberg, L.S., 2014. Measures of global bank complexity. FRBNY Econ. Policy Rev. 20 (2), 107–126.
Cetorelli, N., Goldberg, L.S., 2016. Organizational complexity and balance sheet management in global banks. National Bureau of Economic Research,.
Cetorelli, N., McAndrews, J., Traina, J., 2014. Evolution in bank complexity. Forthcoming Version of Evolution in Bank Complexity. Econ. Policy Rev. 20 (2).
Cetorelli, N., Jacobides, M.G., Stern, S., 2017. Transformation of Corporate Scope in U.S. Banks: Patterns and Performance Implications (SSRN Scholarly Paper ID 2977857). Social Science Research Network. 〈https://papers.ssrn.com/abstract=2977857〉.
Chari, A., Gupta, N., 2008. Incumbents and protectionism: the political economy of foreign entry liberalization. J. Financ. Econ. 88 (3), 633–656.
Chinn, M.D., Ito, H., 2006. What matters for financial development? Capital controls, institutions, and interactions. J. Dev. Econ. 81 (1), 163–192.
Choi, I., 2001. Unit root tests for panel data. J. Int. Money Financ. 20 (2), 249–272.
Claessens, S., Van Horen, N., 2014. Foreign banks: trends and impact. J. Money, Credit Bank. 46 (s1), 295–326.
Coase, R.H., 1937. The nature of the firm. Economica 4 (16), 386–405.
Demirgüç-Kunt, A., Detragiache, E., 2000. Monitoring banking sector fragility: a multivariate logit approach. World Bank Econ. Rev. 14 (2), 287–307.
Demsetz, R.S., Strahan, P.E., 1997. Diversification, size, and risk at bank holding companies. J. Money, Credit, Bank. 300–313.
Doan, N.T., Ha, L.T., 2022. Trade credit and global value chain: evidence from cross-country firm-level data. Int. Econ. 171, 110–129.
Doerr, S., Schaz, P., 2021. Geographic diversification and bank lending during crises. J. Financ. Econ. 140 (3), 768–788.
Duchin, R., Sosyura, D., 2014. Safer ratios, riskier portfolios: Banks' response to government aid. J. Financ. Econ. 113 (1), 1–28.
Goetz, M.R., Laeven, L., Levine, R., 2013. Identifying the valuation effects and agency costs of corporate diversification: evidence from the geographic diversification of U.S. Banks. Rev. Financ. Stud. 26 (7), 1787–1823. https://doi.org/10.1093/rfs/hht021
Hair, J.F., Anderson, R.E., Babin, B.J., Black, W.C., 2010. Multivariate Data Analysis: A Global Perspective. 7 Pearson, Upper Saddle River, NJ.
Hakenes, H., Schnabel, I., 2011. Bank size and risk-taking under Basel II. J. Bank. Financ. 35 (6), 1436–1449.
Houston, J., James, C., Marcus, D., 1997. Capital market frictions and the role of internal capital markets in banking. J. Financ. Econ. 46 (2), 135–164.
Houston, J.F., Lin, C., Ma, Y., 2012. Regulatory arbitrage and international bank flows. J. Financ. 67 (5), 1845–1895.
Im, K.S., Pesaran, M.H., Shin, Y., 2003. Testing for unit roots in heterogeneous panels. J. Econ. 115 (1), 53–74. https://doi.org/10.1016/S0304-4076(03)00092-7
Kaminsky, G.L., Reinhart, C.M., 1999. The twin crises: the causes of banking and balance-of-payments problems. Am. Econ. Rev. 89 (3), 473–500.
Klomp, J., 2014. Financial fragility and natural disasters: an empirical analysis. J. Financ. Stab. 13, 180–192.
Klomp, J., De Haan, J., 2009. Central bank independence and financial instability. J. Financ. Stab. 5 (4), 321–338.
Laeven, L., Levine, R., 2007. Is there a diversification discount in financial conglomerates? J. Financ. Econ. 85 (2), 331–367.
Laeven, L., Levine, R., 2009. Bank governance, regulation and risk taking. J. Financ. Econ. 93 (2), 259–275.
Lamont, O.A., Polk, C., 2002. Does diversification destroy value? Evidence from the industry shocks. J. Financ. Econ. 63 (1), 51–77.
Levin, A., Lin, C.-F., James Chu, C.-S., 2002. Unit root tests in panel data: asymptotic and finite-sample properties. J. Econ. 108 (1), 1–24. https://doi.org/10.1016/S0304-4076(01)00098-7
Levine, R., Caprio, G., Barth, J., 1999. Financial Regulation and Performance: Cross-Country Evidence. The World Bankhttps://doi.org/10.1596/1813-9450-2037
Liao, H., Cao, H.-S., 2013. How does carbon dioxide emission change with the economic development? Statistical experiences from 132 countries. Glob. Environ. Change 23 (5), 1073–1082. https://doi.org/10.1016/j.gloenvcha.2013.06.006
Markides, C.C., Williamson, P.J., 1994. Related diversification, core competences and corporate performance. Strateg. Manag. J. 15 (S2), 149–165.
Martinez-Miera, D., Repullo, R., 2010. Does competition reduce the risk of bank failure? Rev. Financ. Stud. 23 (10), 3638–3664.
Martynova, N., Vogel, U., 2021. Banks' complexity-risk nexus and the role of regulation. J. Bank. Financ., 106120. https://doi.org/10.1016/j.jbankfin.2021.106120

Mehran, H., Thakor, A., 2011. Bank capital and value in the cross-section. Rev. Financ. Stud. 24 (4), 1019–1067.
Meyer, M., Milgrom, P., Roberts, J., 1992. Organizational prospects, influence costs, and ownership changes. J. Econ. Manag. Strategy 1 (1), 9–35.
Nicoló, G.D., Bartholomew, P., Zaman, J., & Zephirin, M. (2004). Bank consolidation, internationalization, and conglomeration: Trends and implications for financial risk. Financial Markets, Institutions & Instruments, 13(4), 173–217.
Pesaran, M.H., 2021. General diagnostic tests for cross-sectional dependence in panels. Empir. Econ. 60, 13–50.
Rajan, R., Servaes, H., Zingales, L., 2000. The cost of diversity: the diversification discount and inefficient investment. J. Financ. 55 (1), 35–80.
Sang, M.N., 2017. Income diversification and bank efficiency in Vietnam. J. Econ. Dev. 19 (3), 52–67.
Sang, N.M., & Linh, T.T. T. (2019). Revenue diversification and total assets in commercial banks: evidence from selected Asean countries. OSF Preprints. August, Journal of Economics and Development, 20(3), 20–30.
Scharfstein, D.S., Stein, J.C., 2000. The dark side of internal capital markets: divisional rent-seeking and inefficient investment. J. Financ. 55 (6), 2537–2564.
Schneider, F., Enste, D.H., 2000. Shadow economies: size, causes, and consequences. J. Econ. Lit. 38 (1), 77–114. https://doi.org/10.1257/jel.38.1.77
Shim, J., 2019. Loan portfolio diversification, market structure and bank stability. J. Bank. Financ. 104, 103–115.