

Heterogeneity of business models and banking sector resilience

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Abstract

This paper studies the relationship between the heterogeneity of business models and the banking sector's resilience, in light of the interplay between diversification, market power, and resilience. Our goal is to tackle the open puzzle related to the effects of diversification-induced homogeneity of banks' business models on the banking sector's stability. Using a sample of 1,268 banks from 33 countries (Europe, Asia, America), for the period between 2005 and 2021, we estimate a 3SLS model that accounts for the interplay between revenue diversification, heterogeneity, market power and resilience. We apply principal components and clustering analysis to identify the banks' business models and compute an ecology-based measure of heterogeneity per country. We find that revenue diversification reduces bank heterogeneity, suggesting that banks pursue uniform diversification strategies. We also uncover a positive relationship between bank heterogeneity and market power, suggesting low rivalry among different business models. Importantly, our results indicate that bank heterogeneity positively impacts resilience and is economically significant. Namely, we estimate a 4.5% increase in the Z-score due to a one (within) standard deviation increase in business model heterogeneity. We discuss several implications of our results for micro- and macro-prudential supervision and regulation, and identify potential avenues for future research.

JEL classification: G20; G21; G28; G32.

Keywords: banking; business models; heterogeneity; resilience; supervision and regulation.

1. Introduction

The 2007-08 financial crisis ignited interest among academia and policymakers regarding the structure and resilience of the financial system [1]. One key question is related to the effects of diversification-induced homogeneity of banks on the sector's resilience [2, 3].

Effectively, while it is generally accepted that banks may be able to reduce risk 'locally' by combining assets from different risk classes, some authors have argued that diversification also induces greater homogeneity in the risk exposures, increasing risk 'systemically' [4, 5, 6]. For instance, Dissem [7] finds that the level and speed of contagion are greater among banks with significant portfolio overlap. Moreover, the degree to which a banking sector includes banks exposed to similar risks is bound to influence individual market power, ultimately impacting the sector's resilience. Adjacent to the notion that not all banks are the same concerning their business strategy and risk exposures, has been explored by a recent strand of the literature focused on studying banks' business models [8, 9, 10, 11, 12, 13], defined as the "pattern of assets and liabilities adopted by one or several banks that differs from the pattern adopted by other banks, each with different combinations of expected return and risk" [14 p.248].

Such a backdrop leads us to ask the following research questions: Does diversification reduce the heterogeneity of banking business models? Does the heterogeneity of business models impact market power? Does heterogeneity boost resilience?

This paper tackles these questions by estimating a 3SLS fixed-effects model that accounts for the complex relationships between revenue diversification, heterogeneity of business models, market power, and resilience, using a sample of 1,268 banks from 33 countries across Europe, Asia and America, between 2005 and 2021. We identify the business models of each bank by applying clustering analysis [12] and develop an ecology-based measure of the heterogeneity of business

models at the country-level (Shannon heterogeneity) [15]. We use standard measures drawn from the literature regarding revenue diversification, market power, and resilience: the Herfindahl-Hirschman Index of operating revenues, the Lerner Index, and the Z-score. Finally, driven by the intuition that the type of financial system may induce essential differences in how heterogeneity influences resilience, we check whether our baseline results differ for bank- and market-oriented financial systems. Finally, we compute a set of robustness checks.

Our results may be summarized in the following way. First, we find that revenue diversification significantly reduces business model heterogeneity, in tune with the view that banks tend to pursue uniform diversification strategies [5] that, as a whole, yield a more homogenous banking sector [2]. Second, we uncover a positive relationship between business model heterogeneity and market power. This result suggests that banks with different business models compete for different market segments [16]. Third, the results indicate that business model heterogeneity positively and significantly impacts resilience. This finding suggests that less homogeneous banking systems are less likely to face systemic distress [17]. Specifically, we estimate a 4.5% increase in the Z-score of banks as a consequence of a one standard deviation increase in business model heterogeneity. Fourth, we find that revenue diversification negatively affects the distance to distress. Importantly, this result suggests the relevance of decoupling the simultaneous effect of diversification on homogeneity and bank resilience – as, otherwise, the true impact of heterogeneity on resilience might not be uncovered.

Lastly, regarding the sensitivity of the baseline results to the type of financial system, we find that the positive relationship between business model heterogeneity and resilience only holds for market-based systems. This may be interpreted as evidence of the stabilizing effects of heterogeneity on market-based systems, which tend to be more prone to bank contagion via short-term wholesale markets [18].

This paper makes two main contributions. First, it links the homogeneity of the banking sector to its (lack of) resilience [2, 4, 5, 19, 20, 21, 22]. Particularly, to the best of our knowledge, the only works to have documented this relationship have been done by Baum *et al.* [20] and by Pisicoli [21] – wherein our work is closer to the former, given that the latter focuses on credit risk as the dependent variable. While our results are similar, given that the authors find that institutional heterogeneity positively impacts resilience, our paper differs from Baum *et al.* [20] in various meaningful ways; (i) our paper incorporates the identification of business models and underlying balance sheet risks, while the authors rely on the classification between commercial, cooperative and savings banks provided by Bankscope; (ii) our paper uses a 3SLS framework to capture the endogenous relationships between diversification, heterogeneity, market power and resilience, while the authors do not account for such endogeneity; (iii) to ensure we have sufficient heterogeneity, we explore the banking sectors of 33 countries operating in Europe, Asia, and America, while the authors focus exclusively on European countries; and (iv) we study a more recent sample period, i.e., from 2005 to 2021 (vs 1998-2014).

Second, we contribute to the literature relating the type of financial system to banking sector resilience [23, 24]. Namely, our results regarding the differences in heterogeneity-resilience between bank- and market-oriented financial systems are novel and could bear interesting implications for bank regulation. Our findings suggest that the lack of a significant relationship between bank heterogeneity and resilience for bank-oriented systems may be linked to difficulties supervising a heterogeneous set of banks [25].

The remaining paper is structured as follows. **Section 2** provides an overview of the literature. **Section 3** presents the methodologies. **Section 4** presents the data and identifies banking business models. The results and discussion are shown in **Section 5**, and robustness checks in **Section 6**, before concluding in **Section 7**.

2. Literature review

While a number of advancements have been made in the study of the ‘financial structure and systemic resilience’ nexus since the aftermath of the 2007-08 financial crisis [1, 2, 3, 4, 5, 6, 7], the idea that some financial structures are designed in a way that reduces (or amplifies) the risk of joint bank failures can be traced to earlier studies, for instance by Acharya [26] and Allen & Gale [27, 28]. In this section, we organize our literature review around two well-covered channels in the literature, via which heterogeneity may be expected to impact resilience: diversification and market power.

[Figure 1]

The 'diversification-resilience' channel comprises an indirect effect ('A'), whereby diversification is expected to influence heterogeneity ('A1') which, in turn, should impact resilience ('A2'); and a direct effect ('B'). Regarding 'A1', a strand of the literature has suggested that as banks diversify into new business lines, they tend to become more alike and reduce the overall heterogeneity of the banking sector [2, 5, 19]. According to Wagner [2], such a phenomenon can be explained by deregulation (which has allowed banks, particularly in the US, to widen the scope of activities) and financial innovation (for instance, via the growth of the derivatives markets, which increased risk-sharing among financial institutions). Beale *et al.* [5] suggest that the formation of bank conglomerates has stemmed from regulators' narrow focus on individual (rather than systemic) risk. We expect to find a negative effect of diversification on the heterogeneity of banking business models.

For 'A2' the theoretical literature suggests that an increased bank-level homogeneity may boost the likelihood of joint bank failures [4, 5, 6]. According to these works, a banking system comprising banks sharing the same risks is more likely to face contagion whenever a systemic event occurs,

such as a large drop in asset market prices or a sudden liquidity shortage. This rationale leads us to expect a positive relationship between the heterogeneity of business models and resilience. More recently, Goldstein *et al.* [22] have developed a bank-run theoretical model that shows how the systemic effects of costly liquidations and fire-sale spillovers can be amplified by each other. On the empirical-side, two works have explored this relationship: Baum *et al.* [20] analyses the relationship between institutional diversity of the banking system and stability (proxied by the Z-score), for 22 EU countries, between 1998 and 2014. The authors use the Bank Focus specialization code to identify different types of banks and compute country-level measures of diversity. In general, the findings suggest that more diverse banking sectors are more stable; Pisicoli [21], on the other hand, studies the relationship between the diversity of banks and the level of non-performing loans (NPL) recorded in the Italian banking sector, from 2006 to 2020. Namely, the author computes several measures of diversity (ownership, competition, geography, and funding strategy) at the province level and relates them to the level of NPLs recorded. The author finds that diversity is negatively related to NPLs, particularly during periods of financial distress.

For 'B', the literature offers mixed predictions. On the one hand, banks that successfully tap into alternative revenue streams may, on average, record more stable results than their non-diversified peers if the revenue streams do not show a perfect positive correlation. In such a case, a banking sector's resilience would increase as banks diversify their asset portfolios [29]. This intuition is backed by a recent study performed by Gelman *et al.* [30], which analyses the relationship between banks' level of asset diversification and resilience for US banks between 1997 to 2017. The authors compute two measures of diversification: asset diversification, using small business lending data, and geographic diversification (number of states where the bank operates); and two measures of resilience: lending and idiosyncratic risk. In general, the authors find evidence suggesting that asset diversification reduces idiosyncratic risk and stabilizes revenue streams. On the other hand,

seemingly uncorrelated assets may become highly correlated under systemic distress [31]. Also, moving outside the core business lines to diversify may increase bank riskiness due to increased moral hazard [32] and lack of expertise and experience [33]. This argument has found recent support in a study developed by Blickle *et al.* [34], which uses loan-level data from large US banks, between 2012 and 2021. In general, the authors find that such banks tend to specialize in specific industries, and such industry-specific knowledge allows them to attract high-quality borrowers, with lower default risk, especially in times of instability. Moreover, such mixed predictions are backed by a lack of consensus in the empirical literature [33, 34, 35, 36].

As for the 'market power-resilience' channel, **Figure 1** shows a single indirect effect (C), wherein heterogeneity is expected to influence market power ('C1') which, in turn, is foreseen to impact resilience ('C2'). To frame 'C1', we draw on Strategic Groups Theory (SGT) [16], which puts forward three factors to explain the impact of industry composition on market power: (i) the number and size distribution of strategic groups¹, i.e., a larger number of strategic groups and/or greater homogeneity of relative size, reduces market power; (ii) the extent to which strategies differ between strategic groups ('strategic distance'), i.e., a longer strategic distance between groups, reduces market power (reducing the feasibility of tacit collusion); and (iii) whether different strategic groups compete for the same market segments ('market interdependence'), i.e., greater market interdependence reduces market power. The expected sign of the relationship depends critically on the composition of business models that emerge from our clustering analysis stage.

Regarding 'C2', the literature offers mixed perspectives. On the one hand, market power is expected to contribute to the systemic 'buffer' against adverse shocks (via higher profits), as well to the

¹ According to Porter [16], 'strategic groups' represent set of firms operating in a given market that have made similar decisions regarding certain long-term strategic dimensions (e.g., distribution channel, value chain integration, geographical reach).

overall bank charter value [29], mitigating the incentives for owners and managers to take on excessive risk, hence decreasing the likelihood of a systemic banking crisis [27]. On the other hand, market power may lead to reduced resilience, given that banks in a monopolistic position will tend to increase interest rates charged to borrowers, which in turn is likely to increase the bankruptcy risk of borrowers and, under moral hazard, generate incentives for them to adopt risky business strategies [37]. This notion finds support in the recent paper by Altunbas *et al.* [38], who studied the relationship between market power and bank systemic risk during the 2007-2008 financial crisis, for the largest listed banks in 15 countries. Their results show that (i) banks with higher market power before the crisis recorded greater realized systemic risk during the crisis and (ii) that securitization amplified the impact of market power on systemic risk, while capitalization mitigated it. Alternatively, Silva-Buston [2019] studies the mechanism underlying the ‘competition-systemic risk’ nexus for a sample of listed European banks in the 2000-2007 period, by distinguishing the two sources of commonality included in systemic risk: excess systemic risk and diversification. The author does not find a significant relationship between competition and the diversification component; suggesting that diversification is not the mechanism driving this relationship, but rather excess systemic risk. In sum, the existing empirical literature focused on the ‘market power-resilience’ nexus does not offer a clear answer regarding the relationship sign and may be better described as mixed.

3. Methodology

3.1. Identification of banking business model heterogeneity

The first step to measuring the heterogeneity of banking business models consists in identifying business models at the bank-level. Following² Marques & Alves [12], we start by running principal components analysis on a selection of business model variables related to the assets and funding structures, diversification, size, and capital. The business model variables are described in **Table 1** ('Business model features'). This step ensures that clustering is performed in an orthogonal space [40]. Second, we run clustering analysis using three methods: Fuzzy C-Means, Self-Organizing Maps, Partitioning Around Medoids; and combine the classification outputs of each algorithm into a single classification, using a majority consensus rule. Using an ensemble of clustering methods (rather than one single method) is expected to increase the accuracy of the assignment of banks to business models relative to their *true*, unobserved classification [41]. We rely on internal selection criteria to determine the optimal number of clusters: Silhouette Width, the Calinski-Harabasz Index, Davies-Bouldin Index, Dunn Index. Finally, business models are identified using the full period mean values of each bank's input variables, resulting in each bank's allocation to a unique business model over the entire sample period. Such an approach aligns with the notion of a business model as a stable and long-term concept [9]. To ensure the comparability of results with other studies focused on banking business models, which are mainly addressed at European banks [9, 10, 11, 14, 42], we perform clustering at the regional level, by running the clustering procedures separately for banks operating in Europe, Asia, and America.

Next, we follow Baum *et al.* [20] and draw on ecology literature to compute the country-level heterogeneity of banking business models. We use the notion of Shannon heterogeneity to measure the level of banking business model heterogeneity for each country-year ($SHE_{i,t}$) [15]:

² Notably, the literature on business model classification has developed significantly in recent years, wherein two techniques stand out: dimensionality reduction [9, 11] and clustering analysis [10, 14, 42, 43]. The methodology we follow in this paper can best be described as a combination of dimensionality reduction and clustering analysis. For a detail description of the method, see Marques & Alves [12].

$$SHE_{i,t} = - \sum_{j=1}^J p_{i,t}^j \times \ln p_{i,t}^j \quad (1)$$

wherein $p_{i,t}^j$ is the market share of assets held by all banks with headquarters in country i , in year t , operating under business model j (with $j = 1, \dots, J$). The higher the value of the Shannon heterogeneity, the more evenly distributed the total assets across business models. Alternative heterogeneity measures (e.g., Simpson heterogeneity) are used as a robustness check [15].

3.2. Impact of business model heterogeneity on resilience

A key takeaway from our literature review is that the relationship between heterogeneity and resilience seems intertwined with diversification and market power. This means that key variables of interest should be considered on the left and right sides of the estimated equations. Such an empirical setting sets up well for estimating a three-stage simultaneous equation model (3SLS), which allows us to model endogeneity while ensuring a superior use of information compared to 2SLS [44]. Also, one typically includes unit-level dummies in the regression to control for unobserved time-invariant confounders per unit. However, in our case, following this procedure would lead to model overfitting [45], as our baseline specification would not meet the commonly used threshold of $n/p > 10$ (wherein n is the number of observations and p is the number of estimated coefficients). To address this concern, we demean all the variables in the model, which equates to estimating a fixed-effects model, without the need to include dummies per unit of analysis [46]. For these reasons, we jointly estimate the following system of equations (wherein the endogenous variables are identified in **bold**; note that the definitions of all variables are provided in **Table 1**):

$$\left\{ \begin{array}{l} (SHE_{i,t} - \overline{SHE}_i) = \alpha_1(DIV_{i,t} - \overline{DIV}_i) + \alpha_2(ARI_{i,t} - \overline{ARI}_i) + \alpha_3(STK_{i,t} - \overline{STK}_i) + Y_t + (\varepsilon_{i,t} - \bar{\varepsilon}_i) \quad (2) \\ (LI_{i,t} - \overline{LI}_i) = \beta_1(SHE_{i,t} - \overline{SHE}_i) + \beta_2(ERI_{i,t} - \overline{ERI}_i) + \beta_3(CON_{i,t} - \overline{CON}_i) + \beta_4(BCL_{i,t} - \overline{BCL}_i) + Y_t + (\varepsilon_{i,t} - \bar{\varepsilon}_i) \quad (3) \\ (ZSC_{i,t} - \overline{ZSC}_i) = \gamma_1(SHE_{i,t} - \overline{SHE}_i) + \gamma_2(DIV_{i,t} - \overline{DIV}_i) + \gamma_3(LI_{i,t} - \overline{LI}_i) + \gamma_4(SIZ_{i,t} - \overline{SIZ}_i) + \gamma_5(BCL_{i,t} - \overline{BCL}_i) + \gamma_6(NPL_{i,t} - \overline{NPL}_i) + PC + Y_t + (\varepsilon_{i,t} - \bar{\varepsilon}_i) \quad (4) \end{array} \right.$$

Regarding equation (2), our main relationship of interest is between revenue diversification (DIV), computed as the Herfindahl-Hirschman Index of operating revenues, and heterogeneity, proxied by Shannon heterogeneity (SHE). Despite DIV not being defined as an explained variable in any other equations, we set it as endogenous because it is likely to be influenced by several variables included in the system (e.g., scope of activities, size). In addition to DIV, equation (2) includes two exogenous regressors: activity restriction index (ARI), which depicts the level of restrictions imposed on the ability of banks to perform activities related to securities, insurance, and real estate [47] and the share of total assets held by stakeholder banks (STK), which have often been considered drivers of heterogeneity in the banking sector [42], given their propensity to stick to a traditional way of doing business, avoiding the diversification herd [4].

As for equation (3), we are mainly focused on the relationship between SHE and market power, which is proxied by the Lerner Index (LI). Literature on market power is quite profuse; hence we include three exogenous variables in the regression: entry restriction index (ERI), which evaluates the number of entry requirements imposed by a country's bank supervisory agencies [47], and proxies for the height of barriers faced by new entrants; the concentration of assets in the five largest banks of each country (CON); and the business cycle, computed as the annual growth of GDP (BCL).

[Table 1]

Finally, equation (4) models the level of resilience in the banking system, proxied by the median Z-score in each country-year (ZSC). The main relationships of interest in this equation are threefold: (i) SHE and ZSC, (ii) DIV and ZSC, and (iii) LI and ZSC. Three exogenous variables are included: the total size of banking assets in proportion to GDP (SIZ), which reflects the degree to which the country is 'overbanked' [48]; the business cycle (BCL); and the ratio of non-performing loans to gross loans to customers (NPL) and a set of dummies that account for past financial crises (PC), which may reflect the persistent nature of bank risk culture [49] and/or a learning effect [50]. Equations (2), (3), and (4) include year (Y_t) fixed effects. Importantly, we perform and report the Sargan-Hansen test of the validity of instruments.

4. Data

4.1. Sample selection

Our sample selection process comprises two steps. First, we identify the bank-level sample using the Bankscope/Orbis dataset and implement a set of criteria followed in similar studies [9], namely: (a) consolidation code (C1, C2, U1); (b) specialization code (commercial bank, savings bank, cooperative bank, real estate and mortgage bank, investment bank, specialized governmental credit institutions); (c) more than 5 billion euros in total assets at least one year in the sample period (2005-2021) [12, 13]; (d) average customer deposits to total funding and gross loans to customers to total assets greater than 5%; and (e) at least three observations in the sample period, with no gaps. Applying these criteria, we avoid the duplication of entities in our sample and only deal with institutions with some level of bank activity and relatively high-quality data reporting.

Next, given the focus of our study on the heterogeneity of business models, we require countries to have (a) at least ten banks in one year during the sample period; and (b) no missing data in the

World Bank's Global Financial Database regarding the variables of interest. Moreover, to ensure additional confidence regarding our heterogeneity measures, we place critical importance on the stability of our sample by (c) only using country-year observations for which the number of banks is at least 2/3 of the maximum number of banks recorded for each country during the entire sample period. This leads us to remove a set of years for some countries while avoiding *gaps* in the sample, yielding an unbalanced panel of 496 country-year observations distributed across 33 countries³. The underlying bank-level sample comprises 1,268 banks and 17,474 bank-year observations.

4.2. Banking business models

Our results suggest the existence of four banking business models⁴, which is consistent with extant literature [10, 12, 13, 42]. **Table 2** shows the popularity and composition of each business model:

- **BM1** is the most popular model in the number of banks (45.0%) but represents the lowest share of total assets (15.0%), which speaks to the relatively small size of such banks (total assets: 7.1, log); in terms of composition, BM1 couples high values of gross loans to customers (61.8%) and customer deposits (77.9%), and records the lowest revenue diversification (39.3, HHI), which is in line with a traditional, retail oriented banking model; hence, BM1 is labelled as *retail focused*;
- **BM2** represents the second most popular business model (23.3%); the assets are concentrated in gross loans to customers (69.7%), but the funding is relatively diversified, mainly due to the significant exposures to wholesale funding (18.5%); BM2 banks also

³ The final list of countries includes 17 from Europe (Austria, Belgium, Czech Republic, France, Germany, Ireland, Italy, Luxembourg, Netherlands, Norway, Poland, Portugal, Russia, Spain, Switzerland, Turkey, United Kingdom), 11 from Asia (Australia, China, Hong Kong, India, Indonesia, Japan, Korea, Malaysia, Philippines, Thailand, Vietnam) and 5 from America (Brazil, Chile, Colombia, Mexico, United States).

⁴ The auxiliary results that support the findings of an optimal partition of four clusters (e.g., Calinski-Harabasz Index) are available in the supplementary materials.

tend to be relatively large (7.3, log); as such, BM2 is termed *retail diversified funding*;

- **BM3** is the most popular business model in terms of total assets (34.1%); BM3 records a diversified asset structure composed of relatively high values of interbank lending (18.2%) and low values of gross loans to the customer (44.2%) when compared to the other business models; on the other hand, it relies mostly on traditional customer deposits for its funding (54.1%); given its composition, BM3 is denoted as *retail diversified assets*; and
- **BM4** is the least popular business model (8.5%), but represents the second largest share of total assets (33.5%), which is mainly driven by its strong presence among market-based systems (45.8%); BM4 exhibits diversified asset and funding structures, as evidenced by the relatively high values of trading assets (10.7%) and wholesale funding (15.4%), and the low values of gross loans to customers (38.9%) and customer deposits (33.3%); these banks also tend to exhibit high values of derivatives (14.2%), revenue diversification (54.8, HHI) and size (7.9, log); such description may be seen as resembling the notion of global diversified banks, which leads us to label BM4 as *large diversified*.

[Table 2]

4.3. Summary statistics

Table 3 provides an overview of the descriptive statistics for three samples: all financial systems (Panel A), market-based systems (Panel B), and bank-based systems (Panel C). Countries with a market (bank) based system are below (above) the cross-section median value of the financial system index (82.7%). In Panel A, column 'Mean', we report the results of a Tuckey HSD test to compare means between market and bank-based systems.

[Table 3]

The mean values of the key variables of interest (resilience, heterogeneity, revenue diversification) are significantly different between market and bank-based systems. Namely, market-based systems are more resilient and less diverse than bank-based systems. This is in line with extant literature documenting that financial crises tend to be more severe in bank-based systems [51]. Moreover, most of our control variables exhibit significant differences between both systems. Particularly, market-based systems tend to have lower restrictions on the scope of activities, are more concentrated, have lower entry requirements (barriers), and are less populated by stakeholder banks than bank-based systems.

5. Results and discussion

5.1. *Impact of business model heterogeneity on resilience*

The output of the 3SLS baseline regressions is presented in **Table 4**. First, we note that the null hypothesis of the exogeneity of instruments (Sargan-Hansen test) is not rejected for any of the specifications. Regarding the estimated coefficients, column (1a) shows a negative impact of revenue diversification on heterogeneity, reflecting our literature-based expectation that banks tend to pursue *uniform* diversification strategies [5] that, as a whole, yield a more homogenous sector [17]. Moreover, we uncover a positive effect of the share of assets held by stakeholder banks on heterogeneity, in tune with the notion that cooperative and savings banks have a particular way of doing business [42], and hence are less likely to herd around uniform diversification strategies.

[Table 4]

As for the impact of heterogeneity on market power – column (1b) –, the estimated coefficient is positive and significant. Effectively, under the ‘Strategic Groups Theory’ [16], one may attribute such result to the relatively small number of business models ($J=4$), the relatively small strategic

distance (which facilitates tacit collusion) and/or the low market interdependence (which reduces rivalry for the same customers). Moreover, we find that a higher 'Entry Requirements Index' significantly increases market power, which indicates that imposing restrictions on the entry of new banks effectively limits bank competition.

Regarding the determinants of resilience, presented in column (1c), we document a positive impact of business model heterogeneity on the Z-score. This result supports the argument that less homogeneous banking systems are less likely to face systemic distress [5, 17]. Also, the magnitude of the effect is economically significant, as we estimate a 4.5% increase in the country-level Z-score due to a one-within standard deviation of business model heterogeneity ($e^{\gamma_1 \times \text{Within SD of SHE}} = e^{0.554 \times 0.0794} = 1.045$). Moreover, the results suggest that revenue diversification negatively affects the distance to distress, in line with the notion that moving outside the core business lines to diversify may increase bank riskiness due to increased moral hazard [32] and lack of expertise and experience [33]. In sum, by decoupling the simultaneous effect of diversification on homogeneity and bank resilience, our approach allows us to uncover heterogeneity's (significant) impact on resilience – which constitutes a novel and significant contribution to literature.

Finally, an apparent inconsistency in the results catches our attention. Namely, while **Table 3** shows that market-based countries tend to be significantly more resilient than bank-based countries, despite being less diverse, our 3SLS estimates (**Table 4**) suggest the opposite sign: a positive association between heterogeneity and resilience. We try to reconcile both results in the following section.

5.2. Type of financial system, heterogeneity, and resilience

In this section, we examine whether the relationship between heterogeneity and resilience differs per type of financial system, i.e., systems-oriented towards bank financing and relationship-

contracts, enforced mainly via bank regulation and supervision ('bank-based system') [23] or those with a stronger orientation towards stock and bond market financing, characterized by the prevalence of arms-length contracts and monitoring via market discipline [24].

In **Figure 2**, we explore the bivariate relationship between heterogeneity and resilience per type of financial system. Regarding market-based systems, the graph suggests the presence of a positive correlation between heterogeneity and resilience (0.18). For instance, we may see that the UK (ISO:GBR) simultaneously records a lower heterogeneity and Z-score than the US. On the other hand, a less clear correlation is found for bank-based systems. For instance, while Italy, Germany, and Russia have a similar (high) business model heterogeneity level, their distance to distress varies significantly. Consistently, untabulated results show that only in market-based systems the most resilient banking sectors (top quartile) also tend to exhibit more heterogeneity.

[Figure 2]

Furthermore, two additional analyses are performed: 3SLS regressions using the sub-samples of market and bank-based countries (**Table 5**) and rolling regressions using the financial system as the mediating variable (**Figure 3**). Regarding the sub-sample regressions, Panel A shows that business model heterogeneity is positive in market-based countries and significantly impacts resilience (one within standard deviation increase in heterogeneity yields a 8.8% increase in Z-score, $e^{1.133 \times 0.0742} = 1.088$). In contrast, no significant effect is detected in the bank-based sample (Panel B). The rolling regressions corroborate this result. Notably, **Figure 3** shows that the coefficient of heterogeneity on resilience is only positive and significant when the regressions include mostly market-based observations (left side of the graph).

[Table 5]

One way to interpret such findings is to consider the interplay between heterogeneity and the

monitoring mechanisms that prevails in each type of financial system: the regulation and supervision in bank-based systems, and market monitoring in market-based systems. Effectively, the lack of a significant relationship between heterogeneity and resilience in bank-based systems may reflect the fact that heterogeneity poses a number of challenges to bank regulation and supervision, rendering it less effective. For instance, Beck *et al.* [25] argue that monitoring a few banks in a homogeneous banking system is substantially easier. Moreover, new business models may bear hidden risks which are not immediately visible to supervisors. This seems to have been the case, for instance, regarding the fall of The Royal Bank of Scotland, following a change in its business model from a retail-funded model to a short-term wholesale funded model [52]. Regarding market-based systems, the positive effect of heterogeneity on resilience suggests that investors are able to segregate their beliefs concerning different business models, effectively lowering the potential for contagion. In particular, it seems plausible that, within market-based systems, the higher degree and speed of adjustment with which market participants react to inefficient noisy public signals [18] may be mitigated if banks are seen to operate sufficiently different business models [53].

[Figure 3]

6. Robustness checks

6.1. Estimation methods

The first concern with our baseline regression is related to heteroscedasticity. Effectively, when performing the Breusch-Pagan LM test on our baseline regression, we reject the null hypothesis of no overall system heteroscedasticity. Moreover, our baseline 3SLS estimates are reported using uncorrected standard deviations due to software limitations. To mitigate this issue, we re-estimate

our baseline system of equations using the ‘Seemingly Unrelated Regressions’ (SURE) approach, which allows the computation of Huber-White robust standard errors [54]. We implement SURE by applying the conditional mixed-process regression approach Roodman [55] envisioned. The results reported in **Table 6**, column (1), suggest that the effect of heterogeneity on resilience remains positive and statistically significant. Moreover, untabulated results show that the correlation of the error terms of the three estimated equations is not statistically different from zero, which suggests the absence of overidentification issues.

[Table 6]

Another potential issue in our baseline regression is related to autocorrelation. In particular, we reject the null hypothesis of no overall system autocorrelation in our baseline specification when performing the Harvey LM test. To mitigate this concern, we apply dynamic Generalized Method of Moments (GMM) (i.e., the lag-dependent variable is included as an explanatory variable) with robust standard errors, *ala* Arellano & Bover [56]. The results in column (2) show that the coefficient of heterogeneity on resilience remains positive and statistically significant using the dynamic GMM method, although at lower levels than the baseline results, and we do not reject the null hypothesis of instruments' exogeneity, as given by the Hansen test results.

6.2. Alternative proxies and disturbances to sample composition

An additional concern regarding our results is whether they are robust to changes to the proxy used to measure the resilience of banking sectors. To this effect, we change our baseline specification to include as a dependent variable (i) the natural log of V-lab's Systemic Risk, measured as "the expected capital shortfall of a financial firm in a systemic crisis where the broad market index falls by more than 40% in a six-month period" [57]; (ii) the natural log of capital ratio (i.e., total equity

to total assets); and (iii) the ratio of non-performing loans to total gross loans, both (ii) and (iii) obtained via the World Bank's Global Financial Development Database. As reported in columns (4) and (5) of **Table 6**, business model heterogeneity is expected to significantly reduce systemic risk and increase capital, which aligns with our baseline results. As for loan riskiness, the effect of heterogeneity is negative and statistically significant. For brevity reasons, we refrain from exploring the other potential profit channels (e.g., efficiency, interest income, non-interest income), but flag this as a possible avenue for future research. Finally, we explore the association between business model heterogeneity and the probability of a systemic banking crisis occurring, as surveyed by Laeven & Valencia [58], using a logit model with year-fixed effects. As expected, the heterogeneity coefficient is negative and significant, which indicates that more diverse banking systems are less likely to face systemic banking crises.

Next, we test whether replacing our measure of business model heterogeneity (Shannon heterogeneity) with other measures taken from ecology literature significantly changes the nature of our baseline results [15]. In particular, we test (i) Simpson's formulation of heterogeneity, which is computed as the inverse of the Herfindahl-Hirschman Index using the total assets' market shares of each business model per country; and (ii) Shannon evenness, measured as the Shannon heterogeneity divided by the natural log of the number of business models identified in each country. The results in columns (8) and (9) show a positive and significant impact of the alternative measures of heterogeneity on resilience, which may indicate the robustness of the 'heterogeneity-resilience' nexus to potential measurement errors.

We also check whether the impact of heterogeneity on resilience depends on the quality of governance. Namely, some studies suggest that country-level quality of governance may have a role in banking sector resilience, although not always positive [59]. For instance, Houston *et al.* [59] find that strong creditor rights tend to be associated with greater risk-taking by banks. In

contrast, information-sharing and transparency initiatives tend to potentiate the profitability and resilience of banks. We follow the literature [60] and build an index of governance quality by computing the first principal component of six variables obtained from the World Bank's Governance Indicators (see list of variables in the notes in **Table 6**). To assess the impact of the quality of governance on our baseline results, we include the governance quality index as an interaction term with heterogeneity. The results presented in column (10) show that our main findings remain unchanged and that heterogeneity does not seem to depend significantly on the level of governance quality.

Moreover, we analyse whether iteratively removing the two largest banking sectors in total assets (US and China) from our sample modifies the baseline results. As observed in columns (11) and (12), the impact of heterogeneity on resilience remains positive and significant after removing the US and China, respectively, which suggests that our results may be generally deemed robust to disturbances to the sample composition.

Our final inquiry is related to the period sample. Namely, to test whether our results are sensitive to the period sample, we re-run the baseline regressions using three rolling sub-samples of 12 years: 2005-16, 2008-19, and 2010-21. The results provided in columns (12) to (14) show that the main coefficient of interest remains positive and statistically significant in all regressions.

7. Conclusions and policy implications

The 2007-08 financial crisis raised the awareness of policymakers and academics about the effects of diversification-induced homogeneity of banks on the resilience of the banking sector as a whole [1, 2]. However, despite the emergence of several theoretical studies discussing this topic, the empirical works are surprisingly scant.

This paper attempts to bridge this knowledge gap by analyzing the banking sectors of 33 countries, in Europe, Asia, and America, between 2005 and 2021. Innovatively, the paper draws on the concept of the banking business model to assert the heterogeneity of banking sectors, and models the complex relationship between revenue diversification, business model heterogeneity, market power, and resilience using a 3SLS approach.

Revenue diversification reduces business model heterogeneity, yielding a more homogenous banking sector [2]. Moreover, our results suggest that heterogeneity increases market power, supporting that banks with different business models target non-related market segments [16]. Importantly, we document that business model heterogeneity bears a positive and significant impact on resilience, in line with the intuition that less homogeneous banking systems are less likely to face systemic distress [17]. Finally, the positive impact of business model heterogeneity on resilience occurs only for market-based systems, which we interpret as an indication of the stabilizing effects of heterogeneity on financial systems that are more prone to bank contagion, for instance, via the short-term wholesale markets [18].

The findings in this paper bear relevant implications for micro and macro-prudential policies. The absence of a significant positive effect of revenue diversification on resilience and the positive effect of heterogeneity indicates that heterogeneity is an important element to consider in the bank regulatory framework. Namely, on the micro-prudential side, our results suggest that it may be beneficial for supervisors of low-heterogeneity banking sectors to be warranted with the discretion to lower the diversification benefits that impact the calculation of Pillar 2 capital requirements; on the macro-prudential side, our findings indicate the potential benefits of monitoring the composition of the banking sectors in terms of business models, and considering the effects of a "push for cross-border consolidation" [61] in the heterogeneity of the banking sector. Finally, the lack of a significant relationship between heterogeneity and resilience in bank-oriented systems

suggests that bank supervisors may face considerable challenges in monitoring a heterogeneous set of banks, which could be mitigated, for instance, with a reinforcement of the skills of supervisors in high-heterogeneity countries.

Finally, we identify two potential avenues for research drawn from our study. First, our study suggests the presence of significant differences in bank heterogeneity among countries, even within a given region. How is such bank heterogeneity currently incorporated into bank regulation and supervision? As a case in point, Flood *et al.* [62] argue that bank heterogeneity is currently not being adequately explored in the design of macroprudential stress test scenarios, which can have significant implications for bank stability. Second, the fact that our study suggests that bank heterogeneity is particularly relevant in market-based systems may be used as a starting point to understand the recent bank runs in the US (triggered by the fall of Silicon Valley Bank), where the market's perception on the similarity of bank business models has been seen one of the triggers of the subsequent turmoil in the banking sector. In this context, one question that emerges is whether imposing more bank disclosure on the risks faced by each bank, would have helped reduce contagion, by allowing stakeholders to monitor their bank's activity, *ex-ante*, as suggested by Goldstein *et al.* [22], or whether such data is not actionable in a bank run context.

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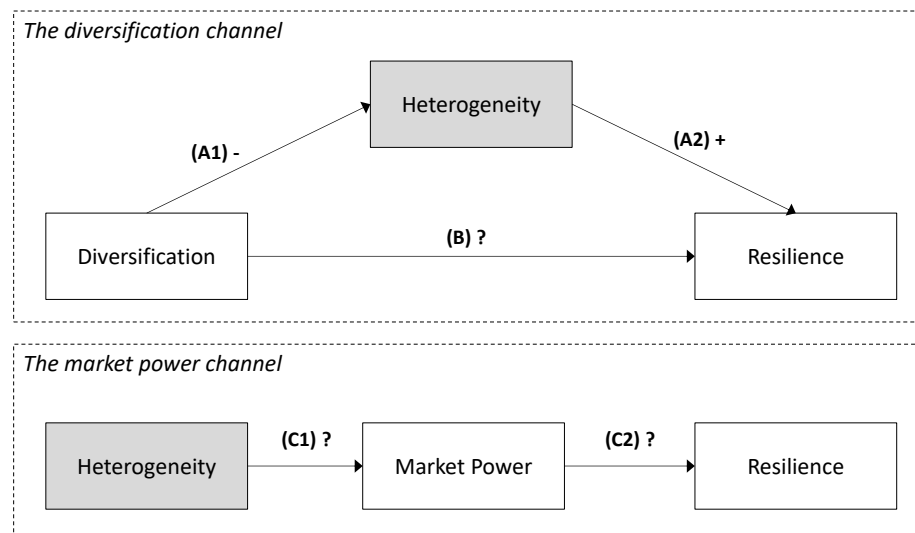
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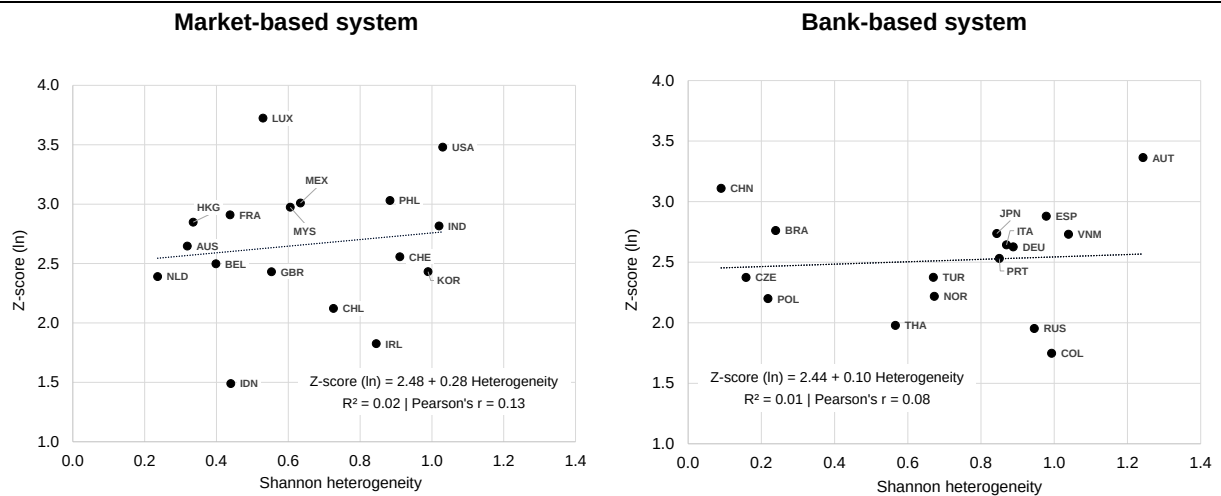
Figures

Figure 1. 'Diversification-resilience' and 'market power-resilience' channels: an overview



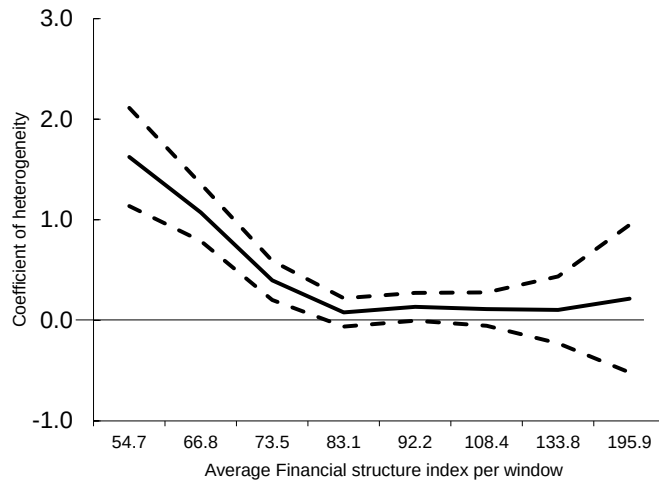
Notes: The relationships mapped in this figure stem from the literature review. The codes attributed to each relationship (A1, A2, B, C1, C2) are identified in the main text. The expected sign of each relationship is identified whenever literature offers a clear prediction.

Figure 2. Business model heterogeneity and resilience per type of financial system



Legend: Market-based system (LHS): AUS - Australia, BEL - Belgium, CHE - Switzerland, CHL - Chile, FRA - France, GBR - United Kingdom, HKG - Hong Kong, IDN - Indonesia, IND - India, IRL - Ireland, KOR - Korea, LUX - Luxembourg, MEX - Mexico, MYS - Malaysia, NLD - Netherlands, PHL - Philippines, USA - United States of America. | Bank-based systems (RHS): AUT - Austria, BRA - Brazil, CHN - China, COL - Colombia, CZE - Czech Republic, DEU - Germany, ESP - Spain, ITA - Italy, JPN - Japan, NOR - Norway, POL - Poland, PRT - Portugal, RUS - Russia, THA - Thailand, TUR - Turkey, VNM - Vietnam.

Figure 3. Impact of heterogeneity on resilience per type of financial system



Notes: We report the coefficients of heterogeneity on Z-score obtained for a set of rolling regression using the baseline 3SLS regression specification and the level of financial structure index to construct each rolling window. X-axis: average value of the financial structure index per sub-sample. A total of 8 sub-samples (windows) are identified at the country-level. Namely, each window includes 17 countries (i.e., 1/2 of total number of countries). The step size is 3 $[(33-12)/(8-1)]$. The number of observations per window varies between 169 and 188. The full line represents the coefficient estimates; the bottom and upper dotted lines represent the 10% and 90% confidence intervals.

Tables

Table 1. Variables description

			Description	Source
Resilience	ZSC	Z-score (ln)	Natural log of: the ratio of total equity to total assets plus ROA, divided by the standard deviation of ROA, using the full sample period at the bank-level. Aggregation at country level is obtained using the median value.	Authors' calculation
	RACAR	Risk-adj. capital ratio (ln)	Natural log of total equity to total assets, divided by the standard deviation of ROA.	Authors' calculation
	RAROA	Risk-adj. ROA (ln)	Natural log of ROA, divided by the standard deviation of ROA.	Authors' calculation
Heterogeneity	SHE	Shannon heterogeneity	Calculated as: $-\sum p_i \ln(p_i) = -[p_1 \ln(p_1) + \dots + p_j \ln(p_j)]$, where i is the business model, j is the total number of business models, and p_i is the proportion of abundance of business model i in a country, computed as the share of a country's total bank assets of banks with business model i .	Authors' calculation
Country controls	DIV	Revenue diversification	For each bank: 1 minus the sum of squared of four components of total operating income (TOR): net interest income (NII), net fees and commissions (NFC), net trading income (NTI) and other income (OTH). Absolute values of each component are used: $[1 - [(NII/TOR)^2 + (NFC/TOR)^2 + (NTI/TOR)^2 + (OTH/TOR)^2]]$. Country-level aggregation using mean value.	Authors' calculation
	LI	Lerner index	Output prices minus marginal costs, divided by output prices. The prices are proxied by total operating revenues divided by total assets. The marginal costs are obtained using a translog cost function with respect to output. A higher value of LI indicates higher market power.	Authors' calculation
	FSI	Financial system index	Ratio between the banks' total assets and the sum of the outstanding domestic and international private debt securities and total stock market capitalization (%).	GFDD (World Bank)
	CON	Concentration	Share of total assets held by 5 largest banks in each country (%).	Authors' calculation
	ARI	Activity restriction index	This index assesses the ability of banks to engage in activities related with securities, insurance, and real estate. The index is built using the World Bank's 'Bank Regulation and Supervision Survey' of 2007, 2011 and 2017. A higher value equates to greater activity restrictions.	BRSS (World Bank)
	STK	Stakeholder	Share of a country's total bank assets held by cooperative or savings banks (%).	Authors' calculation
	ERI	Entry requirements index	This index assesses the number of entry requirements imposed by a country's banking supervisory agency. The following 10 requirements are assessed (e.g. including draft inflows, financial information on main potential shareholders). A higher value equates to greater entry barriers.	BRSS (World Bank)
	BCL	Business cycle	Annual growth of GDP per capita (%).	GFDD (World Bank)
	SIZ	Size of the banking sector	Total assets held by deposit money banks as a share of GDP (%).	GFDD (World Bank)
	NPL	Non-performing loans	Non-performing loans to gross loans to customers (%).	GFDD (World Bank)
Business model	GLC	Gross loans to customers	Gross loans and advances to customers divided by total assets (%).	Bankscope/Orbis
	IL	Interbank lending	Net loans and advances to banks, reverse repos, securities borrowed, cash collateral divided by total assets (%).	Bankscope/Orbis
	TA	Trading assets	Financial assets trading and at fair value through profit or loss, divided by total assets (%).	Bankscope/Orbis
	CD	Customer deposits	Customer deposits, divided by total assets (%).	Bankscope/Orbis
	IB	Interbank borrow	Bank deposits, repurchase agreements, securities loaned, cash collateral, divided by total assets (%).	Bankscope/Orbis
	WF	Wholesale funding	Sum of other deposits, short-term funding and debt securities (maturity < 1 year), long-term borrowings and debt securities at historical cost, subordinated liabilities, other long-term borrowing, divided by total assets (%).	Bankscope/Orbis
	TD	Total derivatives	Sum of asset and liability derivative financial instruments, divided by total assets (%).	Bankscope/Orbis
	TA	Total assets	Log of average assets in thousand euros.	Bankscope/Orbis
	TE	Total equity	Total equity divided by total assets (%).	Bankscope/Orbis

Notes: GFDD – World Bank's Global Financial Development Database. BRSS – World Bank's Bank Regulation and Supervision Survey.

Table 2. Banking business models: popularity and composition

	BM1	BM2	BM3	BM4
Number of banks	570	296	294	108
Share of total banks	45.0	23.3	23.2	8.5
Share of total assets	15.0	17.5	34.1	33.5
Market-based systems	18.4	23.3	12.4	45.8
Bank-based systems	12.2	12.8	51.5	23.5
Gross loans to customers	61.8 (12.8) ⁺⁺⁺	69.7 (11.7)⁺⁺⁺	44.2 (15.3) ⁺⁺⁺	38.9 (17.9) ⁺⁺⁺
Interbank lending	7.3 (8.3) ⁺⁺	5.7 (4.4) ⁺⁺	18.2 (15.6)⁺⁺	17.4 (11.3) ⁺⁺
Trading assets	1.3 (2.8) ⁺⁺	1.6 (2.3) ⁺⁺	3.2 (4.8) ⁺⁺⁺	10.7 (8.0)⁺⁺⁺
Customer deposits	77.9 (11.3)⁺⁺⁺	56.9 (17.7) ⁺⁺	54.1 (19.3) ⁺⁺	33.3 (18.3) ⁺⁺⁺
Interbank borrowing	5.5 (6.3) ⁺⁺⁺	8.0 (8.1) ⁺⁺⁺	19.8 (13.6) ⁺⁺	21.2 (12.3)⁺⁺
Wholesale funding	4.4 (4.6) ⁺⁺⁺	18.5 (15)⁺⁺⁺	8.4 (10.6) ⁺⁺⁺	15.4 (12.9) ⁺⁺⁺
Total derivatives	0.7 (1.9) ⁺⁺	1.5 (2.2) ⁺	2 (4.4) ⁺⁺	14.2 (12.3)⁺⁺⁺
Revenue diversification	39.3 (13.7) ⁺⁺⁺	44.2 (10.7) ⁺⁺	42.3 (13.4) ⁺⁺	54.8 (9.1)⁺⁺⁺
Total assets	7.1 (0.4) ⁺⁺⁺	7.3 (0.5) ⁺⁺	7.4 (0.7) ⁺⁺	7.9 (0.8)⁺⁺⁺
Total equity	8.3 (3.5) ⁺	8.9 (3.3) ⁺	8.9 (4.3) ⁺	6.9 (3.6) ⁺⁺⁺

Notes: Mean values and standard deviations in parentheses. All variables computed as percentage of total assets, except number of banks (count), revenue diversification (HHI) and total assets (log). For each variable, we compute the Tuckey HSD test for comparison of means per pair of business models. The number of (+) indicates the number of pairwise comparisons statistically different at the 5% level. Values in **bold** indicate the business models with the highest mean values for each variable when the number of plus signs is (++) or (+++).

Table 3. Descriptive statistics

	Mean	SD within	SD between	Min	Max
<i>Panel A: All financial systems (n=496)</i>					
Z-score (ln)	2.96***	0.21	0.60	-0.70	4.13
Shannon heterogeneity	0.68**	0.08	0.31	0.05	1.28
Revenue diversification	46.01*	3.74	6.26	27.34	63.17
Lerner index	0.25	0.10	0.07	-0.90	1.36
Activity restriction index	6.30***	1.01	1.84	3.00	12.00
Business cycle	1.85	3.11	1.59	-11.76	23.20
Concentration	72.71	3.76	11.88	44.35	98.22
Entry requirements index	7.53***	1.10	1.22	0.00	9.00
Stakeholder	8.93***	3.50	11.13	0.00	45.55
Financial system	113.02***	36.75	86.39	11.76	742.00
Non-performing loans	3.38***	2.22	2.64	0.10	25.71
<i>Panel B: Market-based systems (n=258)</i>					
Z-score (ln)	3.04	0.26	0.68	-0.70	4.13
Shannon heterogeneity	0.65	0.07	0.26	0.17	1.05
Revenue diversification	45.42	3.78	5.47	28.77	60.24
Lerner index	0.24	0.12	0.07	-0.90	1.36
Activity restriction index	6.07	0.92	2.09	3.00	12.00
Business cycle	1.85	3.22	1.34	-11.36	23.20
Concentration	73.40	3.61	12.16	44.35	97.67
Entry requirements index	7.20	1.46	1.61	0.00	9.00
Stakeholder	5.13	1.66	10.31	0.00	34.48
Financial system	61.12	12.29	18.17	11.76	124.17
Non-performing loans	2.68	2.37	2.39	0.10	25.71
<i>Panel C: Bank-based system (n=238)</i>					
Z-score (ln)	2.88	0.13	0.50	1.45	3.63
Shannon heterogeneity	0.71	0.08	0.35	0.05	1.28
Revenue diversification	46.64	3.70	7.15	27.34	63.17
Lerner index	0.25	0.06	0.07	-0.31	0.46
Activity restriction index	6.56	1.11	1.55	4.00	11.00
Business cycle	1.85	3.01	1.87	-11.76	10.51
Concentration	71.97	3.93	11.87	49.11	98.22
Entry requirements index	7.88	0.43	0.38	6.00	9.00
Stakeholder	13.04	4.76	11.37	0.00	45.55
Financial system	169.28	51.55	98.32	44.49	742.00
Non-performing loans	4.12	2.06	2.74	0.50	18.06

Notes: Countries with a market (bank) based financial system are below (above) the cross-section median value of the financial system index (82.7%). In Panel A, column 'Mean', we report the results of a Tuckey HSD test to compare means between market and bank-based systems. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively. Variables winsorized at 1 and 99 percentiles.

Table 4. 3SLS regressions: baseline results

	Shanon Het. (1a)	Lerner index (1b)	Z-score (1c)	RACAR (2)	RAROA (3)
Shanon heterogeneity		0.374***	0.554**	0.482***	-0.096
Revenue diversification	-0.017***		-0.012*	-0.003	-0.007
Lerner index			0.017	-0.317	0.361
Activity Restriction index	-0.004				
Stakeholder	0.016***				
Entry Requirements index		0.029***			
Concentration		-0.002			
Business cycle		-0.002	0.007*	0.000	0.004**
Size of banking sector			-0.005***	-0.002***	-0.001***
Non-performing loans			-0.002	0.003	-0.010***
Number of observations		496		496	496
McElroy System R-squared		0.209		0.244	0.263
Sargan-Hansen test (p-value)		0.967		0.904	0.963

Notes: Columns (1a) to (1c) correspond to the estimation of the baseline 3SLS model with fixed-effects (within) and year dummies – as defined in **section 3.2**. Columns (2) and (3) we re-run the model decomposing the dependent variable in the ‘Resilience’ equation (Z-score) into the ‘Risk-adjusted Capital ratio’ (RACAR) and the ‘Risk-adjusted ROA’ (RAROA), respectively. For brevity reasons, in the decomposed dependent variable regressions, presented in columns (2) and (3), we only report the results of the ‘Resilience’ equation of the systems of equations [*vide equation (4)*], which corresponds to column (1c) of the baseline regression. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively.

Table 5. 3SLS regressions: market versus bank-based systems

	Z-score (ln) (1)	RACAR (ln) (2)	RAROA (ln) (3)
<i>Panel A: Market-based systems</i>			
Shanon heterogeneity	1.133***	0.822***	0.147
Revenue diversification	0.006	0.006	-0.006
Lerner index	0.948	-0.230	0.319
Business cycle	0.007	-0.001	0.007**
Size of banking sector	-0.006***	-0.002***	-0.002***
Non-performing loans	0.013**	0.007***	-0.007*
Number of observations	258	258	258
McElroy System R-squared	0.355	0.409	0.287
Sargan-Hansen test (p-value)	0.160	0.122	0.157
	Z-score (ln) (4)	RACAR (ln) (5)	RAROA (ln) (6)
<i>Panel B: Bank-based systems</i>			
Shanon heterogeneity	0.126	-0.140	-0.201
Revenue diversification	0.001	0.006	-0.003
Lerner index	0.342	0.902	0.335
Business cycle	0.001	0.000	0.003
Size of banking sector	-0.004***	-0.001***	-0.001***
Non-performing loans	-0.016***	0.000	-0.009**
Number of observations	238	238	238
McElroy System R-squared	0.437	0.511	0.362
Sargan-Hansen test (p-value)	0.307	0.209	0.167

Notes: Countries with market (bank) oriented financial systems are below (above) the median of the Financial system index. Values presented are the coefficient estimates of using three-stages least squares (3SLS). For brevity, we only report the results of the 'Resilience' equation of the systems of equations [*vide equation (4)*], which corresponds to column (1c) of **Table 4**. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively.

Table 6. Robustness checks

	SURE	Dyn. GMM	SYSRISK	CAR	NPL
	(1)	(2)	(3)	(4)	(5)
Shannon heterogeneity	0.425***	0.366*	-5.799***	4.72*	6.066
Number of observations	463	463	496	496	496
Log pseudo-likelihood	1428.5				
Wald Chi-squared (p-value)	0.000				
Hansen's J test (p-value)		0.006			
AR (1)		0.136			
AR (2)		1.000			
McElroy System R-squared			0.278	0.257	0.151
Sargan-Hansen test (p-value)			0.960	0.966	0.999
	BCRISIS	Simpson het.	Shan. even.	Gov. Qual.	Excl. China
	(6)	(7)	(8)	(9)	(10)
Shannon heterogeneity	-7.451**			0.558**	0.538**
Simpson heterogeneity		0.237*			
Shannon evenness			5.728***		
Shannon heterog.*Gov. qual.				-0.010	
Number of observations	496	496	496	496	486
Wald Chi-squared (p-value)	0.012				
Likelihood ratio (p-value)	0.000				
McElroy System R-squared		0.214	0.173	0.210	0.218
Sargan-Hansen test (p-value)		0.997	0.979	0.971	0.984
	Excl. US	2005-16	2008-19	2010-21	
	(11)	(12)	(13)	(14)	
Shannon heterogeneity	0.602**	0.652**	0.455**	0.654**	
Number of observations	479	336	371	385	
McElroy System R-squared	0.196	0.097	0.187	0.075	
Sargan-Hansen test (p-value)	0.982	0.692	0.670	0.537	

Notes: Regressions estimated using the system of equations (2 to 4) (**Section 3**), except for regression (7) for which only equation (4) was estimated. Regression (1): Unrelated Regressions (SURE), with Huber-White robust standard errors [48], using the conditional mixed-process regression approach [49]. Regression (2): dynamic GMM with robust standard errors. Regression (3): explanatory variable is the natural log of V-lab's Systemic Risk. Regression (4): explanatory variable is the capital ratio, i.e., total equity divided by total assets. Regression (5): explanatory variable is non-performing loans to total assets. Regression (6): explanatory variable is a dummy, 1 if the country experienced a systemic banking crisis in year t [52]; estimated using logit model with year-fixed effects. Regression (7): Simpson heterogeneity is calculated as one divided by the HHI of total assets' market shares of each business model. Regression (8): Shannon evenness computed as the ratio between the Shannon heterogeneity and the number of business models in each country. Regression (9): we interact heterogeneity with the index of governance quality [54]. Regressions (10) and (11): exclude the most dominant countries in each type of financial system – China (39.9% of total assets of bank-based systems) and US (21.1% of total assets of market-based systems). Regressions (12) to (15): we re-run the baseline regressions using rolling period sub-samples of 12 years, namely 2005-16 (12), 2008-19 (13) and 2010-21 (14).

Supplementary material

Table A1. Sample composition: number of observations per country and region

	Banks	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	Bank-year obs.	Country- year obs.
<i>Europe (N=17)</i>																				
Austria	38	27	33	34	34	34	33	34	35	36	37	37	37	38	38	36	35	34	587	17
Belgium	12		9	9	9	9	9	11	11	12	12	12	12	11	11	11	11	10	169	16
Czech Republic	10	7	7	7	8	8	8	8	8	9	10	10	10	10	10	10	10	10	150	17
France	58						46	49	50	52	58	58	58	56	55	55	55	55	647	12
Germany	76	54	65	65	69	70	71	71	73	75	76	75	75	69	65	63	64	63	1,158	17
Ireland	10	8	8	8	8	8	9	9	9	10	10	10	10	9	9	9	8	6	142	16
Italy	51	41	45	46	49	49	49	51	51	51	51	51	51	40	36	33	32	30	661	14
Luxembourg	24	17	17	21	22	22	22	23	23	24	24	23	23	23	22	20	19	19	361	17
Netherlands	19								17	18	19	18	17	16	14	14	13	13	159	10
Norway	16		12	13	14	15	15	15	15	16	16	16	16	15	15	15	14	14	236	16
Poland	13	10	11	11	11	12	12	13	13	13	13	13	12	12	11	11	11	11	200	17
Portugal	10	8	9	9	9	9	9	9	9	9	10	10	10	10	9	9	9	9	156	17
Russia	31		22	22	25	27	29	31	31	31	31	31	31	29	25	24	23	13	412	15
Spain	25						21	23	23	25	25	25	25	23	21	21	21	18	271	12
Switzerland	34	30	30	30	30	30	32	32	33	34	34	34	33	31	31	31	30	31	535	17
Turkey	14			13	13	13	13	13	14	14	14	14	14	14	14	14	14	14	205	15
United King.	44	35	37	37	38	37	37	42	43	43	43	43	43	41	40	40	40	40	674	17
Europe total	485																		6,723	262
<i>Asia (N=11)</i>																				
Australia	18		18	18	18	18	18	18	18	18	18	18	18	18	18	18	18	18	288	16
China	157								121	153	157	157	157	147	146	147	145	141	1,448	10
Hong Kong	21	19	19	19	19	19	19	19	19	20	21	21	21	21	21	21	21	20	339	17
India	43	35	37	38	40	40	41	41	42	43	43	43	43	39	37	30	31	33	650	17
Indonesia	20	15	16	16	16	17	17	18	19	20	20	20	19	19	18	17	17	17	298	17
Japan	182	166	167	169	171	172	176	179	180	180	182	182	181	169	167	146	139	139	2,848	17
Korea	17						13	15	14	15	16	16	16	17	17	16	16	16	185	12
Malaysia	17							17	17	17	17	17	17	16	16	16	16	16	182	11
Philippines	12	11	11	11	11	11	11	12	12	12	12	12	12	12	12	12	12	11	197	17
Thailand	19			15	15	16	18	19	19	19	19	19	18	16	15	15	16	15	252	15
Vietnam	13		10	11	12	12	12	12	13	13	13	13	13	13	13	13	13	13	199	16
Asia total	519																		6,886	165
<i>Americas (N=5)</i>																				
Brazil	28						23	27	27	28	27	27	27	28	28	28	28	27	320	12
Chile	10						10	10	10	10	10	10	10	10	9	8	8	8	113	12
Colombia	10							10	10	10	10	10	10	10	10	10	10	10	110	11
Mexico	15	14	15	15	15	15	15	15	15	15	15	15	15	15	14	14	14	14	250	17
United States	201	164	165	165	166	169	170	198	201	201	201	201	201	174	174	174	174	174	3,072	17
Americas total	264																		3,865	69
Total (N=33)	1,268																		17,474	496

i. Table A2. Number of business models per region: selection criteria

	Europe				Asia				America			
	ASW	CHI	DBI	DI	ASW	CHI	DBI	DI	ASW	CHI	DBI	DI
FCM												
J=3	0.149	113.30	1.64	0.024	0.230	110.49	1.76	0.020	0.280	104.48	1.50	0.045
J=4	0.170	121.95	1.53	0.039	0.211	108.21	1.54	0.021	0.297	109.26	1.19	0.036
J=5	0.088	105.80	1.82	0.025	0.211	96.33	1.67	0.020	0.190	94.58	1.46	0.019
J=6	0.127	101.01	1.63	0.033	0.143	84.67	1.67	0.021	0.181	89.46	1.45	0.015
SOM												
J=3	0.154	103.97	1.75	0.025	0.105	94.10	2.15	0.024	0.272	93.30	1.46	0.041
J=4	0.173	118.07	1.53	0.035	0.208	107.51	1.64	0.034	0.266	85.894	1.27	0.051
J=5	0.145	102.21	1.71	0.022	0.153	84.02	1.87	0.021	0.215	78.28	1.61	0.037
J=6	0.069	84.43	1.75	0.029	0.109	81.19	1.70	0.026	0.210	61.23	1.66	0.034
PAM												
J=3	0.176	115.28	1.63	0.022	0.187	110.69	1.43	0.035	0.375	102.95	1.17	0.069
J=4	0.204	128.14	1.48	0.035	0.221	106.96	1.50	0.028	0.315	109.53	1.18	0.039
J=5	0.203	118.18	1.39	0.029	0.254	123.66	1.30	0.029	0.183	93.08	1.35	0.029
J=6	0.209	116.42	1.36	0.029	0.223	113.66	1.36	0.025	0.198	92.11	1.33	0.037
Count of #1 rank (considering all criteria, per region)												
J=3	0				3				6			
J=4	10				6				6			
J=5	0				3				0			
J=6	2				1				0			

Notes: Results of running the PAM, SOM and FCM algorithms on the full period average sample, with inputs PC1 to PC5 for different number of clusters (J). Selection criteria: Average Silhouette Width (ASW), Calinski-Harabasz Index (CHI), Davies-Bouldin Index (DBI) and Dunn Index (DI). The partitions with the top values (#1) for each criterion are presented in **bold**. Note that the best partitions minimize SW<0 and DBI and maximize the remaining criteria.

ii. *Table A3. Top versus bottom resilient systems*

	Top	Bottom	Diff.
	(1)	(2)	(3)
Number of country-year obs.	118	119	
Z-score (ln)	3.23	1.94	1.29***
Shannon heterogeneity	0.73	0.65	0.08*
Revenue diversification	47.40	45.99	1.41
Lerner index	0.25	0.28	-0.03*

Notes: Country-year observations labelled as 'Top' ('Bottom') refer to observations recorded by countries located in the top (bottom) quartile of cross-section Z-score per type of financial system. In column (1) and (2) we present mean values, in column (3) we present the difference between (1) and (2) as well as the p-value of the Tuckey HSD test for equality of means. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively.

iii. *Table A4. Top versus bottom resilient systems per type of financial system*

	Top	Bottom	Diff.
	(1)	(2)	(3)
<i>Panel A: Market-based systems</i>			
Number of country-year obs.	68	55	
Z-score (ln)	3.31	1.89	1.42***
Shannon heterogeneity	0.77	0.58	0.19***
Revenue diversification	45.84	43.74	2.10*
Lerner index	0.25	0.25	0.00
<i>Panel B: Bank-based systems</i>			
Number of country-year obs.	51	58	
Z-score (ln)	3.06	1.99	1.07***
Shannon heterogeneity	0.72	0.64	0.08
Revenue diversification	49.13	49.24	-0.11
Lerner index	0.22	0.29	-0.07***

Notes: Countries with a market (bank) based financial system are below (above) the cross-section median value of financial system (82.7%). Country-year observations labelled as 'Top' ('Bottom') refer to observations recorded by countries located in the top (bottom) quartile of cross-section Z-score per type of financial system. In column (1) and (2) we present mean values, in column (3) we present the difference between (1) and (2) as well as the p-value of the Tuckey HSD test for equality of means. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively.