Прикладная эконометрика, 2024, т. 73, с. 59–77.
Applied Econometrics, 2024, v. 73, pp. 59–77.
DOI: 10.22394/1993-7601-2024-73-59-77

K.S. Adesina, M. Semenova[1]

Do non-interest income activities matter for banking sector efficiency? A net interest margin perspective

This paper explores the effects of non-interest income (NII) generating activities on banking sector efficiency in 152 countries from 1996 to 2017. Contrary to previous studies that examine the effects of diversification on banking performance at the micro-level, this study seeks to provide new insights about the effects of diversification at the aggregate level on bank efficiency. This aspect offers a chance to capture the whole banking sector and provides a broader understanding of the effects of banking sector diversification. Our baseline results reveal that engaging in NII activities is positively associated with banking sector efficiency. Using the dynamic threshold regression method, we do not find a tipping point beyond which the benefits of NII activities have an adverse impact on banking sector efficiency. These results are insensitive to different groups of countries. Our findings generally suggest that banking liberalization contributes to the efficiency of the banking sector. In this sense, the findings of this study support banking sector diversification policies implemented in many countries since the 1980s and 1990s.

Keywords: banks; net interest margin; non-interest income; bank profitability.
JEL classification: E40; G21.

1. Introduction

Banks function as financial intermediaries in the re-allocation of funds from surplus units to deficit units. Some economists, e.g. Levine (1997), have argued that an efficient banking system can provide low-cost monetary payments and effectively mobilize deposits and reallocate funds to finance public and private investments and spur sustainable economic growth. To achieve this and following the advice of Bretton Woods institutions, over the past two decades, economic authorities in many countries have implemented financial sector reforms to liberalize financial markets and deregulate tightly controlled financial sectors. These reforms cover a wide range of sub-sectors, including insurance, banking, and stock markets. These changed the scope of bank activities in many countries enabling many banks to expand their business activities from traditional (loan-making) activities towards non-traditional financial services that generate commissions, fee income, trading revenue, and other kinds of non-interest income (NII). This diversification altered the income structure of the banking sector in many economies. NII now makes

[1] **Adesina, Kolade Sunday** — University of Milan, Italy; sunday.kolade@unimi.it.
Semenova, Maria — HSE University, Moscow, Russia; msemenova@hse.ru.

up a significant amount of banks' total income in many countries. For instance, as of 2017 (see Fig. 1), the average of NII to total income ratio is 37.60% in high income countries (HICs), 44.33% in low-income countries (LICs), 36.77% in upper-middle income countries (UMICs) and 33.65% in lower-middle income countries (LMICs). Figure 1 shows that various geographical regions also have high NII to total income ratios ranging from 30.35% average for East Asia and the Pacific to 42.91% average for Sub-Saharan Africa in 2017.

In the light of the recent global financial crisis, the implications of non-traditional banking activities have come under increased scrutiny. The arguments in the theoretical literature are, however, varied and sometimes conflicting. Levine (1997), for example, points out that diversified financial systems can accelerate technological change, and ultimately efficiency. Obstfeld (1994), Saint-Paul (1992), Devereux and Smith (1994) also posit that financial markets that ease diversification tend to induce a portfolio shift toward projects with lower costs and/or higher expected returns. There is another view that diversification is beneficial by enabling banks to benefit from cheaper costs of monitoring information and effective use of managerial skills (Abuzayed et al., 2018). Elsas et al. (2010) add to the argument by noting that diversification enables banks to benefit from superior resource allocation through internal capital markets, and economies of scale and scope. The empirical findings on the potential benefits of diversification are found in the forms of profitability (Elsas et al., 2010; Köhler, 2015), cost efficiency (Doan et al., 2018; Moudud-Ul-Huq et al., 2018), financial stability (Köhler, 2015; Moudud-Ul-Huq et al., 2018), and capital savings (Shim, 2013). To explain these findings, the authors mainly use the arguments of modern portfolio theory, the economies of scope, and an adequate banking regulatory framework.

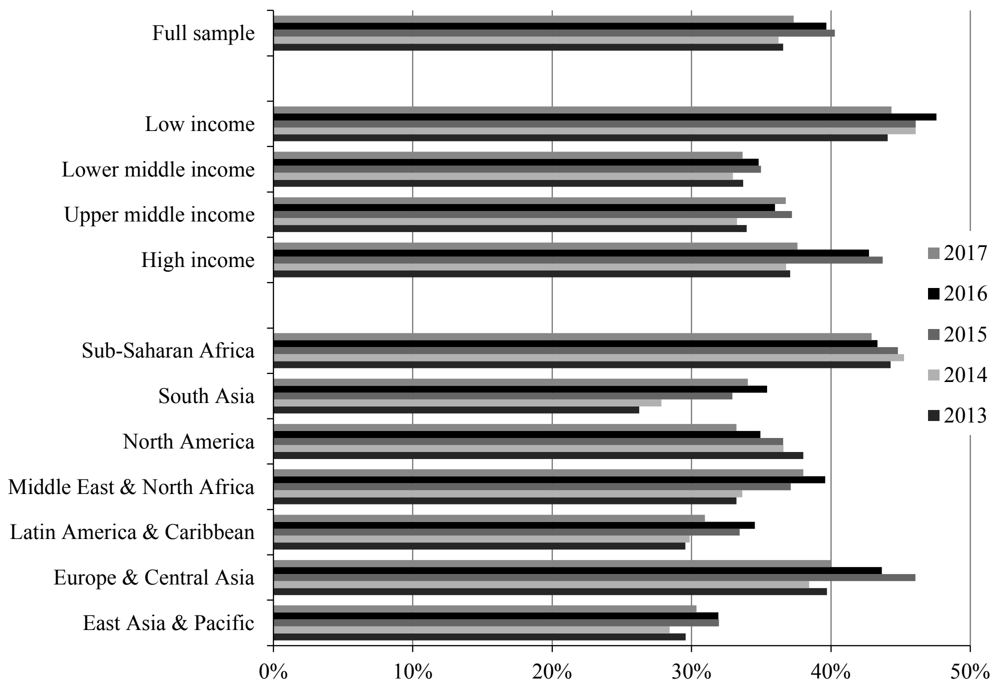

Fig. 1. The average of non-interest income to total income ratio

Source: Global Financial Development Database, 2021.

By contrast, there is a strand of the theoretical literature that questions the beneficial role of bank diversification. As underlined by Klein, Saidenberg (2000), increased NII generating activities may dilute the comparative advantage of bank management by operating outside their area of expertise. Some argue that diversification increases the vulnerability of the banking system to economic and financial crises. Other authors have also criticized bank diversification and claimed that inefficiency may stem from agency problems (Jensen, 1986; Meyer et al., 1992), increased incentives for rent-seeking behavior by managers (Scharfstein, Stein, 2000), and informational asymmetries between divisional managers and head office (Harris et al., 1982). Some authors (including DeYoung, Roland (2001), Adesina (2021)) add to the argument by providing empirical evidence that bank diversification is intrinsically associated with financial instability which may reduce bank efficiency. Other findings on the negative side of diversification are found in the forms of revenue volatility (DeYoung, Roland, 2001; Köhler, 2015), low bank valuation (Laeven, Levine, 2007), and risk amplification (Williams, 2016). These authors rely on agency theory and information asymmetries to explain their findings.

Researchers have also discussed the possible impacts of NII on the net interest margin (NIM), a measure of banking sector efficiency. Diversification triggers competition among financial intermediaries, which could bring about lower NIMs and innovation in the provision of banking services (see (Lepetit et al., 2008a)). As a result of cross-subsidization, NII generating activities may also cause a decrease in NIM since banks may be willing to forgo interest income from higher spreads. Whether NII generating activities decrease or increase bank NIM is ultimately an empirical question, which we explore.

For banks, in the Global North and the Global South, there are empirical studies, including (Demirgüç-Kunt, Huizinga, 1999; Chortareas et al., 2012), that use bank-level (i.e. micro-level) data to examine the effects of NII generating activities on NIM. Although we have learned from existing studies, this study takes a different approach and seeks to provide new insights. Rather than using bank-level data, we investigate the effects of NII generating activities at an aggregate level (country-wide NII) on NIM. In doing so, we follow the approach of studies that are based on aggregate banking data (Uhde, Heimeshoff, 2009; Noss, Toffano, 2016; Ghosh, 2015). Using aggregate data offers a chance to capture the whole banking sector and provides a broader understanding of the effects of non-traditional banking activities. The use of aggregate data also enables us to cover many countries avoiding representativeness bias appearing in the bank-level databases (such as Bankfocus and Osiris). International financial institutions (including the World Bank and IMF) commonly use aggregate NII to assess the level of banking sector diversification in each country. To our knowledge, this study is the first attempt to use aggregated country-level data to analyze banking sector diversification and efficiency (measured by NIM). In addition to this contribution, for robustness purposes, we use four different estimation techniques, including the dynamic panel threshold regression method. This is the first study to use a dynamic panel threshold model suggested by Kremer et al. (2013) to examine the bank diversification-efficiency nexus.

We follow the literature in using the NII to total income ratio to measure bank NII activities. Bank diversification in many countries provides us with an ideal opportunity to use country-level data to examine the impact of bank NII activities on banking sector efficiency. For this purpose, this study uses a global panel dataset of 152 countries, which consists of 54 high-income countries, 24 low-income countries, 40 upper-middle-income countries, and 34 lower-middle-income countries over the 1996–2017 period. Using World Bank (2017) classifications[2], the sample

[2] https://www.worldbank.org/en/publication/gfdr/data/global-financial-development-database.

countries are also classified into six geographical regions. In addition, using the most recent World Bank Regulation and Supervision Survey (2017 to 2019)[3], we divide our sample countries according to the regulatory restrictions placed on bank activities in each country. To study the effects of non-traditional banking activities on banking sector efficiency, we estimate panel regressions for each subsample and for pooled data. By and large, despite splitting our sample countries into different groups, we find that, overall, a larger share of bank NII is associated with a higher level of banking sector efficiency (measured by NIM). This finding supports banking sector diversification policies that have been implemented in many countries since the 1980s and 1990s. This is critical information for bank management and financial regulatory authorities to formulate effective policies.

The remaining part of this paper is organized as follows. Section 2 explains our empirical methodology, consisting of model specifications and estimation techniques. Section 3 describes our datasets, including their summary statistics and preliminary analyses. Baseline results and robustness checks are presented in Section 4. Section 5 concludes and provides policy implications.

2. Methodology

2.1. Bank non-interest income generating activities and efficiency measures

Sources of banks' operating income can be classified into two classes: net-interest income and non-interest income. Interest income is defined as interest income on loans and other interest income. As stated earlier, bank NII includes net fees and commissions, net gains on financial securities, and other kinds of NII. Based on this classification, we measure bank NII generating activities using the ratio of the aggregate banking sector NII to total income, where total income is net-interest income plus NII. The NII ratio measures the degree to which banks diversify between traditional and non-traditional banking activities. The higher the value, the more the banks engage in non-traditional banking activities.

Our dependent variable or, more precisely, banking sector efficiency, is measured by the aggregate banking sector NIM, which equals the ratio of banks' net interest income (i. e. net value of interest income and interest expense) to total average interest-bearing assets. While there may be different reasons for an increase in NIM, a higher value of this variable is a signal of inefficient financial intermediation and monopoly power that allows banks to charge higher margins (Barth et al., 2008; Chortareas et al., 2012). In the view of (Claeys, Vander Vennet, 2008), a higher NIM value is indicative of a high degree of information asymmetry and an inadequate banking regulatory framework. Podpiera (2004) also asserts that a higher NIM value is a signal of inefficient banking operation and high risks in lending, since it indicates the cost of banking intermediation that needs to be paid by banks' customers. The "efficient-structure" theory states that more efficient banks have lower costs of intermediation and garner higher market share (Demirgüç-Kunt et al., 2003).

[3] https://www.worldbank.org/en/research/brief/BRSS.

2.2. Model specifications

2.2.1. Linear dynamic panel model. Our empirical analysis of the banking sector efficiency effects of NII generating activities begins by specifying a linear dynamic panel data model of the form:

$$Eff_{i,t} = \beta_1 Eff_{i,t-1} + \beta_2 NII_{i,t-1} + \sum \beta_j ConV_{i\,t} + \alpha_i + \mu_t + \varepsilon_{i\,t}, \quad (1)$$

where $t = 1996,...,2017$ represents the year and $i = 1,...,152$ indexes the 152 countries in the sample. $Eff_{i,t}$ is the level of banking sector efficiency as proxied by the NIM[4] of country *i* in year *t*. $NII_{i,t-1}$ denotes the ratio of banking sector NII to total income (%). $ConV^j_{i,t}$ denotes a set of six country-level control variables:

– bank assets to GDP ratio (*BAGDP*), to control for banking system development;

– *bank Z-score*[5], to capture the probability of default of a country's banking system;

– banking crisis dummy (*BCrisis*), which is set to 1 for a banking crisis period and 0 otherwise, controls for those years when a country's banking system is in financial distress (Nguyen et al., 2016);

– the assets of three largest commercial banks to total commercial banking assets ratio, to measure bank competition and concentration (*Con*);

– inflation (*Infl*), measured by the GDP deflator (annual %) and

– the economic growth rate, proxied by the gross domestic product growth rate (*GDPG*).

Our control variables (*BAGDP*, *BCrisis*, *Con*, *bank Z-score*, *Infl* and *GDPG*) are included in the model because they have been found to affect bank performance (Demirgüç-Kunt et al., 2003; Chortareas et al., 2012; Köhler, 2015; Doan et al., 2018). Our model contains not only the six control variables but also time-specific effects (μ_t) and country-specific effects (α_i)[6]. To mitigate possible reverse causality, we lag banking sector variables (*NII*, *BAGDP*, *BCrisis*, *Con*, and *bank Z-score*) by one year (Fungáčová et al., 2017). The model contains $Eff_{i,t-1}$ (lagged dependent variable), which measures the dynamic effects, $\beta_1, \ldots, \beta_8$ are the parameters to be estimated, $\varepsilon_{i,t}$ is a stochastic error term. Since $Eff_{i,t}$ is a function of the fixed effects (α_i and μ_t) in equation (1), $Eff_{i,t-1}$ is also a function of the fixed effects. Therefore, the probability of $Eff_{i,t-1}$ being correlated with the fixed effects is high (endogeneity problem) and this might lead to biased estimation results when applying pooled ordinary least squares (OLS) or fixed-effect estimation technique to the dynamic panel data model (Roodman, 2009). To overcome this, we employ the two-step system generalized method of moments (GMM) estimation technique. This technique also addresses potential heteroscedasticity and autocorrelation in the data. However, as Roodman (2009) has pointed out, two-step system GMM may suffer from weak instrument problems. Therefore, for robustness, we further use the fixed effects quasi-maximum likelihood (QML-FE) technique to estimate linear dynamic panel data models, see (Kripfganz, 2016). QML-FE offers better finite sample

[4] The country-level NIM is obtained from the World Bank's Global Financial Development Database (GFDD). GFDD calculates the aggregate NIM from underlying bank-by-bank unconsolidated data from Bankscope (now known as BankFocus). See https://www.worldbank.org/en/publication/gfdr/gfdr-2016/data/global-financial-development-database.

[5] The country-level data of bank Z-score is obtained from GFDD.

[6] α_i is used to capture the heterogeneity of countries' policies, risk culture or industry exposure.

performance than two-step system GMM (Moral-Benito, 2013). It also overcomes many other limitations of two-step system GMM (Hsiao et al., 2002).

Additional evidence on the effects of NII on NIM is provided by using fixed effects (FE) to estimate the static version of our baseline (dynamic) model. If the time dimension of a panel data is large, dynamic panel bias becomes insignificant, and a more straightforward FE estimator works (Roodman, 2009). For this reason, since the time dimension of our panel data is greater than 21, it is appropriate to use the FE for a robustness check. Meanwhile, a key challenge of using the two-step GMM is that the number of instruments tends to increase as the time dimension increases.

2.2.2. Dynamic panel threshold model. Given that our baseline model (1) only verifies the linear association between EFF and NII, it is worth exploring whether there is a non-linear association between the two variables. As a result of competition, NII generating activities can enhance banking sector efficiency. However, NII generating activities could have an adverse effect when banks become extremely large and over diversified owing to monopoly rents. Thus, we expect a non-linear relationship between NII and NIM.

To examine non-linear relationships, many empirical studies use the static threshold model suggested by Hansen (1999). This model uses the FE estimation technique and requires all explanatory variables to be exogenous. Most empirical studies on thresholds using the Hansen model ignore the possible endogeneity problem (Kremer et al., 2013), which may bias their estimates. Hence, to examine the possible non-linear association between EFF and NII outlined in Section 2.2.1 and to address the possible endogeneity problem, we use the method of (Kremer et al., 2013) and construct a dynamic panel threshold model, which can detect the impact of NII on EFF before and after a certain threshold point of NII. The model is provided in equation (2) below:

$$\begin{aligned} Eff_{i,t} &= \beta_1 NII_{i,t-1} \mathrm{I}\left(NII_{i,t-1} \le \gamma\right) + \delta_1 \mathrm{I}\left(NII_{i,t-1} \le \gamma\right) + \\ &+ \beta_2 NII_{i,t-1} \mathrm{I}\left(NII_{i,t-1} > \gamma\right) + \sum_{j=3}^{8} \beta_j X_{i,t}^{j} + \alpha_i + \mu_t + \varepsilon_{i,t}, \end{aligned} \tag{2}$$

where Eff is the measure of banking sector efficiency as shown in equation (1); *NII* represents the threshold variable that switches between two regimes; γ is the threshold level of *NII*; $\mathrm{I}(\cdot)$ is an indicator function, taking the values 0 and 1. This splits the sample into two regimes, one with slope parameter β_1 and another with β_2[7]. δ_1 stands for the threshold intercept. Leaving out the threshold intercept may bias the estimated results (Bick, 2010). $X_{i,t}^{j}$ are the independent variables: *BAGDP*, *BCrisis*, *Con*, *bank Z-score*, *Infl* and *GDPG*.

In the first step of the model estimation procedure, we need to eliminate country-specific effects (α_i) in the dynamic panel threshold model. Following Kremer et al. (2013), we use the forward orthogonal deviations transformation to eliminate the country-fixed effects. This transformation method works by subtracting the mean of all future observations from the current observation. Thus, the error term is given by:

$$\varepsilon_{i,t}^{*} = \sqrt{\frac{T-t}{T-t+1}} \left[\varepsilon_{i,t} - \frac{1}{T-t} \left(\varepsilon_{i,t+1} + \ldots + \varepsilon_{i,T} \right) \right], \; t = 1,\ldots,T-1, \tag{3}$$

[7] If β_1 is significantly positive (negative) while β_2 is significantly negative (positive), the relationship between *NII* and *Eff* is non-linear.

where $\varepsilon^*_{i,t}$ stands for transformed errors and $\varepsilon_{i,t}$ denotes original errors in the regression. The distinguishing feature of the above forward orthogonal transformation is that it ensures that the error terms are not serially correlated, that is,

$$\operatorname{Var}(\varepsilon_i) = \sigma^2 I_T \quad \Rightarrow \quad \operatorname{Var}(\varepsilon^*_i) = \sigma^2 I_{T-1}, \tag{4}$$

where ε_i and ε^*_i are vectors of $\varepsilon_{i,t}$ and $\varepsilon^*_{i,t}$, and I_T, I_{T-1} are unit matrices.

3. Data and preliminary analysis

As mentioned, our aim is to investigate the banking sector efficiency effects of NII generating activities. Other than lagged efficiency, country fixed effects, and year effects, our estimation models include NIM, which measures banking sector efficiency, and a set of explanatory variables: *NII*, *bank Z-score*, *GDPG*, *Infl*, *BAGDP*, *Con*, and *BCrisis*. The data for these variables come from the World Bank's Global Financial Development Database (GFDD) and World Development Indicators (WDI). Given that information is not available for all years for all countries, we use an unbalanced panel dataset of 152 countries, which consists of 54 HICs, 24 LICs, 40 UMICs and 34 LMICs (based on the World Bank classification) over the 1996–2017 period[8]. Using World Bank classifications, the sample countries are also classified into six geographical regions. The exclusion of other countries is mainly due to the unavailability of their data for a significant number of years for all our variables. In order to ensure that we have sufficient observations to examine threshold effects, we require each country to have a minimum of eight observations from 1996 to 2017. 2017 was the most recent year of data available at the time the study was conducted. Table 1 shows some commonly used descriptive statistics (mean, median, minimum, and maximum) of the data. We organize the descriptive statistics by income groups and geographical regions. Among the income groups, the average NIM in LICs is the highest (7.47%), followed by LMICs (6.19%), UMICs (5.67%), and HICs (2.66%)[9]. We also observe that the medians follow this pattern. It seems that the NIM decreases as the country's income level increases.

Table 1 shows the average (median in parentheses) NII ranges from 36.36% (34.05%) in UMICs to 41.73% (42.16%) in LICs; the average bank Z-score ranges from 10.78 in LICs to 14.79 in LMICs; average GDPG ranges from 3.07% in HICs to 5.75% in LMICs. Average Infl (BAGDP) varies significantly from 3.19% (17.70%) in HICs (LICs) to 16.30% (90.28%) in LICs (HICs). The lowest average of Con is found for LMICs, while LICs have the highest (79.18%). Concerning the geographical regions, Sub-Saharan Africa has the highest average NIM (7.23%), reflecting the high cost of banking intermediation in many Sub-Saharan African countries. The average NIM in North America is the lowest (2.94%), followed by East Asia & Pacific (2.96%), Middle East & North Africa (3.04%), Europe & Central Asia (4.00%), South Asia (4.21%), and Latin America & Caribbean (6.38%). Disparities can also be observed in other variables across regions. As shown by the within- and between-countries variation, the variables exhibit variation over time and across countries.

To avoid spurious regression, we test the data for stationarity. Because we have unbalanced panel datasets that come in the form of relatively small time period and large number of cross-sectional

[8] Data for our analysis is available for 152 (71.03%) out of the 214 countries in the GFDD.

[9] This is relative to the total sample.

Table 1. Descriptive statistics by geographical region and country income group (1996–2017)

	NIM	*NII*	*Z-score*	*GDPG*	*Infl*	*BAGDP*	*Con*	*NIM*	*NII*	*Z-score*	*GDPG*	*Infl*	*BAGDP*	*Con*
	Low-income countries							*Lower-middle income countries*						
Mean	7.47	41.73	10.78	4.73	16.30	17.70	79.18	6.19	36.48	14.79	4.75	11.08	35.72	65.18
Median	6.72	42.16	10.36	4.92	6.37	15.37	85.47	5.60	34.62	12.82	4.78	6.64	31.65	63.26
Minimum	0.75	0.70	2.20	–27.99	–27.05	0.38	17.16	0.07	0.71	0.11	–14.76	–16.76	1.80	22.28
Maximum	39.21	87.75	33.17	33.63	2630.12	85.42	100.00	58.63	92.23	44.36	18.36	557.50	137.43	100.00
Standard deviation	3.73	12.85	5.25	5.00	123.01	11.85	18.57	4.21	12.98	8.86	3.45	28.77	22.91	20.58
Between variation	2.76	8.90	4.70	2.09	38.18	9.17	15.51	2.82	10.31	8.66	1.70	13.62	19.92	16.65
Within variation	2.49	9.24	2.19	4.57	116.86	7.36	10.62	3.06	8.67	2.79	3.05	25.45	12.86	13.49
	Upper-middle income countries							*High income countries*						
Mean	5.67	36.36	14.01	4.22	11.31	49.08	65.44	2.66	38.28	14.44	3.07	3.19	90.28	69.85
Median	5.28	34.05	12.09	3.86	5.98	37.95	64.69	2.39	36.29	13.42	3.00	2.08	81.53	71.38
Minimum	0.22	0.40	0.13	–62.08	–26.30	2.02	20.85	0.15	7.18	0.02	–21.59	–27.63	11.18	20.19
Maximum	25.47	95.26	96.68	123.14	914.13	174.54	100.00	23.17	96.17	48.52	26.76	71.91	261.42	100.00
Standard deviation	2.89	14.64	9.96	7.52	37.07	36.84	18.97	1.66	12.64	8.63	3.98	6.04	45.47	18.89
Between variation	2.01	10.78	8.74	1.97	11.79	33.70	15.45	1.27	8.81	7.93	1.65	2.51	37.76	17.03
Within variation	2.09	10.30	4.83	7.26	35.19	13.48	11.84	1.07	9.17	3.37	3.66	5.50	24.90	8.46
	East Asia & Pacific							*Europe & Central Asia*						
Mean	2.96	29.41	14.63	5.13	4.69	96.73	65.81	4.00	41.37	10.23	3.34	7.95	71.98	68.74
Median	2.53	27.44	14.58	5.19	3.07	101.40	63.76	3.23	39.58	8.58	3.17	2.86	61.96	68.29
Minimum	0.07	0.71	0.11	–21.59	–6.01	3.33	25.88	0.18	12.16	0.02	–14.84	–18.90	2.02	20.85
Maximum	9.64	92.23	34.27	26.76	75.27	257.23	100.00	58.63	96.17	47.57	88.96	914.13	261.42	100.00
Standard deviation	1.72	11.32	7.37	4.45	7.15	55.88	21.63	3.89	13.26	6.22	5.12	33.17	48.12	18.28
Between variation	1.44	6.28	6.76	2.29	4.56	52.88	17.45	2.88	8.95	5.54	1.97	11.37	41.89	15.13
Within variation	1.08	9.53	3.56	3.87	5.69	23.51	13.76	2.64	9.96	2.99	4.74	31.19	24.71	10.80

The end of Table 1

	NIM	*NII*	*Z-score*	*GDPG*	*Infl*	*BAGDP*	*Con*	*NIM*	*NII*	*Z-score*	*GDPG*	*Infl*	*BAGDP*	*Con*
	Latin America & Caribbean							*Middle East & North Africa*						
Mean	6.38	33.82	15.36	3.21	8.12	42.43	66.19	3.04	33.47	24.68	4.35	5.68	69.75	69.85
Median	6.01	31.48	14.90	3.49	5.68	38.13	63.30	2.88	32.45	23.45	3.89	3.82	65.46	73.94
Minimum	0.22	6.12	1.15	–11.96	–27.63	9.06	24.28	0.26	10.49	5.20	–62.08	–26.10	4.30	32.69
Maximum	25.47	88.04	48.52	18.29	174.86	110.53	100.00	20.50	92.75	63.41	123.14	91.50	173.54	100.00
Standard deviation	2.64	13.39	8.51	3.40	12.80	20.98	19.63	1.44	11.39	11.12	9.40	11.86	38.28	16.24
Between variation	1.82	9.46	8.00	1.18	6.42	19.22	18.24	1.12	9.21	9.91	2.00	3.61	36.18	15.33
Within variation	1.96	9.42	2.73	3.20	11.24	9.56	9.65	1.10	8.33	5.42	9.21	11.32	16.33	5.88
	North America							*South Asia*						
Mean	2.94	44.25	22.73	2.47	1.91	78.29	42.62	4.21	33.76	14.32	5.75	7.09	40.00	56.77
Median	3.34	42.14	23.52	2.83	1.84	61.81	35.05	3.96	30.21	12.57	5.36	6.19	37.04	57.52
Minimum	1.24	33.23	12.01	–3.85	–2.32	52.70	20.19	1.69	7.73	5.34	–1.55	–2.20	3.43	17.16
Maximum	4.32	66.65	29.94	6.87	9.69	137.42	86.85	11.03	65.98	33.41	21.39	38.51	85.42	100.00
Standard deviation	0.95	7.81	5.78	2.05	1.72	29.55	20.77	1.54	11.75	6.60	3.02	5.06	17.39	23.25
Between variation	1.29	8.81	7.44	0.01	0.07	37.88	24.48	1.40	9.79	6.63	1.44	1.68	16.25	20.61
Within variation	0.33	4.88	2.60	2.05	1.72	13.56	11.96	1.07	8.40	3.32	2.73	4.81	11.25	16.25
	Sub-Saharan Africa							*Full sample*						
Mean	7.23	42.90	11.51	4.56	15.87	23.12	76.40	4.92	37.86	13.88	4.00	9.11	56.99	68.96
Median	6.62	42.15	10.55	4.63	6.53	17.17	79.27	4.15	35.88	12.33	3.92	4.23	44.34	68.64
Minimum	0.07	0.40	2.20	–20.60	–27.05	0.38	22.28	0.07	0.40	0.02	–62.08	–27.63	0.38	17.16
Maximum	39.21	87.75	96.68	33.63	2630.12	121.75	100.00	58.63	96.17	96.68	123.14	2630.12	261.42	100.00
Standard deviation	3.63	12.12	6.40	4.25	103.38	20.45	18.75	3.52	13.42	8.77	5.25	53.90	44.85	19.79
Between variation	2.74	8.14	5.51	1.69	33.41	20.01	15.03	2.81	9.83	7.99	1.95	17.97	40.98	16.76
Within variation	2.40	9.34	3.93	3.92	97.79	7.39	11.39	2.13	9.39	3.59	4.89	50.77	17.96	10.95

units, ADF–Fisher Chi-square and Im, Pesaran and Shin (IPS) unit root tests are used as tests for the stationarity of the series; we find no presence of unit roots (see Table 2).

Table 2. Unit root tests at level

	NIM	*NII*	*Z-score*	*GDPG*	*Infl*	*BAGDP*	*Con*	*BCrisis*
IPS	–14.75***	–5.87***	–10.14***	–21.01***	–27.37***	–2.17**	–6.20***	–4.22***
ADF–Fisher Chi-square	807.97 ***	523.19***	660.34***	1207.36***	1270.44***	457.105***	528.74***	136.44***

Notes. The unit root tests were performed with individual intercept and trend. In all cases, the optimal lag length is chosen automatically using the Schwarz Info Criterion (SIC). The null hypothesis is a unit root for all the panels. *** — significant at the 1% level, ** — significant at the 5% level.

4. Results

4.1. Linear dynamic panel regression analysis

To estimate our linear panel model, as a starting point, FE, two-step system GMM, and QML-FE techniques were employed. The results are reported in Table 3. We can observe that the estimation results are qualitatively the same in the FE, GMM, and QML-FE estimators. As reported, the lagged coefficients of NIM are significantly positive, implying that banking sector efficiency persists from one year to the next. The coefficients of *NII* are significantly negative, implying that increased NII generating activities help reduce intermediation costs (NIM). This result supports the claim that liberalization of banking activities is effective in enhancing banking sector (Demirgüç-Kunt et al., 2003; Chortareas et al., 2012; Barth et al., 2013). Our finding that NII reduces NIM largely supports the findings of bank-level panel data studies, e. g. (Lepetit et al., 2008b) study of 602 European banks over the 1996–2002 period, (Carbó et al., 2009) study of 1912 banks in 14 European countries and (Demirgüç-Kunt, Huizinga, 1999) study of commercial banks in 80 countries. This finding is also consistent with Levine's (1997) argument that financial systems that ease diversification can accelerate technological change and efficiency. Another potential explanation for our finding is the view that diversification triggers competition among financial intermediaries, which could bring about innovation and efficiency in the provision of banking services (see (Lepetit et al., 2008a)).

Table 3 further reveals other factors that affect banking sector efficiency. The coefficients of the financial stability variable, *bank Z-score*, are significant and positive, suggesting that the NIM appetite of banks increases as their financial stability improves. As for *GDPG*, the results show the variable correlates negatively with NIM, although this is only significant in the GMM regression at the 1% level. The coefficients of *Con* are significantly positive with NIM, indicating that market concentration impedes banking sector efficiency (supported by Nguyen (2012)). This finding suggests that banks may charge lower interest rates if they face high competition. Banking sector development as proxied by the ratio of bank assets to GDP (*BAGDP*) displays negative and significant coefficients in all regressions. This indicates that banks operating in a developed banking sector are more likely to reduce their NIM, which supports the findings of (Chortareas et al., 2012). This is not surprising because banks operating in developed financial systems have better access to technology which can reduce their intermediation costs. As for national inflation, unsurprisingly, the variable exhibits a positive and significant relationship with NIM (supported by Demirgüç-Kunt and Huizinga (1999), Demirgüç-Kunt et al. (2003)), indicating that inflation is an impediment to an efficient banking system. Consistent with the literature, the positive coefficients of *BCrisis* indicate that banking crisis is negatively related to banking sector efficiency. The Hansen test of over-identifying restrictions points to the validity of the instruments employed in the GMM estimation. The AR(2) shows the absence of second-order autocorrelation.

Table 3. GMM, QML-FE, and FE regression results for the full sample

	GMM	QML-FE	FE
Dep_{t-1}	0.1469***	0.4577***	
	(0.0127)	(0.0204)	
NII_{t-1}	–0.0099**	–0.0080**	–0.0334***
	(0.0050)	(0.0035)	(0.0075)
$Z\text{-}score_{t-1}$	0.0361**	0.0168*	0.0498***
	(0.0174)	(0.0098)	(0.0140)
$GDPG_t$	–0.0126*	–0.0055	–0.0018
	(0.0073)	(0.0090)	(0.0093)
$Infl_t$	0.0026	0.0129***	0.0021
	(0.0041)	(0.0030)	(0.0035)
$BAGDP_{t-1}$	–0.0008	–0.0050**	–0.0096***
	(0.0054)	(0.0021)	(0.0029)
Con_{t-1}	0.0319***	0.0159***	0.0223***
	(0.0049)	(0.0029)	(0.0068)
$BCrisis_{t-1}$	0.1068	0.0756	0.1766
	(0.2578)	(0.1401)	(0.2516)
Constant	2.2654	2.3449***	4.9464***
	(1.3893)	(0.3804)	(0.5491)
Country effect	Yes	Yes	Yes
Year effect	Yes	Yes	Yes
AR(1)	–4.55***		
AR(2)	–0.59		
Hansen test	86.61		
Instruments	309		
Within R^2			0.1226
Between R^2			0.0706
Overall R^2			0.0929
Observations	2798	2319	2798
Countries	152	131	152

Notes. The dependent variable is aggregate banking sector NIM. The main explanatory variable is the aggregate banking sector non-interest income to total income (*NII*). The control variables include *country effect*, *year effect*, *Z-score*, *GDPG*, *Infl*, *BAGDP*, *Con*, and *BCrisis*. Standard errors are shown in parentheses. ***, **, * — significant at the 1, 5 and 10% level.

4.2. Dynamic panel threshold regression analysis

To check whether there is a threshold above which the negative effect of *NII* on NIM (see Table 3) changes to positive effect, we employ a dynamic panel threshold model (equation (2)), where the GMM-type technique is used to deal with the endogeneity problem. Kremer et al. (2013) provide details of this technique. Table 4 presents the results from estimating our dynamic threshold model using *NII* as a threshold variable. Panel A of the table displays the estimated *NII* threshold values and the corresponding 95% confidence intervals. In Panel B, $\hat{\beta}_1$ and $\hat{\beta}_2$ show the effects of *NII* on banking sector efficiency in the low- and high-diversification regimes, respectively. Panel C shows the coefficients of the control variables. The coefficients on both $\hat{\beta}_1$ and $\hat{\beta}_2$ (in Panel B of Table 4) are significantly negative, suggesting that a U-shaped relationship cannot be established between *NII* and banking sector efficiency. The results for our control variables (except *Infl*) remain consistent with those obtained in the linear model.

Table 4. Dynamic threshold regression results for the full sample

Panel A: Estimated NII threshold values	
Estimated threshold ($\hat{\gamma}$)	41.28
95% confidence interval	[36.60, 55.48]
Panel B: Impact of NII	
$\hat{\beta}_1$ $(NII_{t-1} \le \gamma)$	–0.0874*** (0.0209)
$\hat{\beta}_2$ $(NII_{t-1} > \gamma)$	–0.0534*** (0.0144)
Panel C: Impact of covariates	
Dep_{t-1}	0.2087*** (0.0353)
$Z\text{-}score_{t-1}$	0.0451 (0.0418)
$GDPG_t$	0.0015 (0.0240)
$Infl_t$	–0.0183* (0.0098)
$BAGDP_{t-1}$	–0.0577*** (0.0101)
Con_{t-1}	0.0404*** (0.0104)
$BCrisis_{t-1}$	0.2998 (0.6525)
Constant	7.4877*** (1.3664)
Country effect	Yes
Year effect	Yes
Observations	2798
Countries	152

Notes. See Notes to the Table 3.

4.3. Robustness checks: Subsample analyses

Our 152 sample countries are heterogeneous and diverse in terms of geographical areas, income groups, and regulatory environments. To take these into consideration, and to examine the sensitivity of our main results, we divide our full sample into different subsamples using the different country-specific characteristics. First, we split the sample countries according to their income groups using World Bank classifications, which categorize countries into four income groups: HICs, LICs, UMICs, and LMICs. Panels A, B, C, and D of Table A1 in Appendix A report, respectively, the FE, two-step system GMM, QML-FE, and dynamic panel threshold regression results for the four income groups, appearing in columns I, II, III and IV respectively[10]. Second, we divide our sample countries according to the regulatory restrictions (Restriction) placed on banking activities in each country[11]. Table A1 in Appendix A provides the results for countries with limited restrictions (column V) and countries with limited restrictions (column VI). Third, we classify our sample countries according to their geographical regions using World Bank classifications, which categorize our sample countries into 6 geographical regions: Europe and Central Asia, East Asia and Pacific, Middle East and North Africa, Latin America and Caribbean, Sub-Saharan Africa, and South Asia[12]. We re-estimate our baseline models for each of the geographical regions[13]. Table A2 in Appendix A presents the results for our six geographical subsamples. Findings for the different subsamples (in Appendix A) corroborate our main results reported in the previous sections.

5. Conclusion

Understanding whether NII generating activities can enhance banking sector efficiency is critical information for bank management and financial regulatory authorities in order to formulate effective policies. Several studies have analyzed the diversification-efficiency nexus for different countries using bank-level data and various estimation techniques. In this paper, we add to the empirical literature by analyzing the effects of NII generating activities on banking sector efficiency using aggregated country-level data. Using this approach enables us to capture the whole banking industrial sector and gives a broader understanding of the effects of bank NII generating activities. To this end, in addition to the widely used FE and system GMM methods, we employ the QML-FE estimator. This technique, which addresses potential endogeneity issues and accounts for the persistence of the banking sector efficiency, offers better finite sample performance than system GMM. The benchmark regression results show that NII enhances banking sector efficiency, measured by NIM.

As a robustness check of the benchmark results, we use the dynamic panel threshold model, which incorporates the GMM method, to examine the possible negative or insignificant relationship

---

[10] For space related reasons, only the coefficients of *NII* (our variable of interest) are reported in Table A1.

[11] See Appendix B for a detailed description of the classification.

[12] Each of these geographical regions has a relatively homogeneous sample of countries (in terms of similar culture, GDP per capital, and stock market/banking sector development).

[13] We exclude North America in our estimations because the number of observations (35) for the region is too small for any meaningful regression analysis.

between diversification and banking sector efficiency. The dynamic panel threshold regressions results do not show a tipping point beyond which the efficiency benefits of NII have an adverse impact on banking sector efficiency. Thus, all our estimation techniques confirm that NII has significant negative effects on NIM. This finding is robust to various subsample countries (whether developed or developing). In terms of policy recommendation, the finding highlights the importance of liberalizing bank activities (less restriction), as this is effective in enhancing banking sector efficiency. This is critical information for bank management, financial authorities, and governments in order to formulate policies to promote banking sector efficiency.

Acknowledgement. The paper was prepared within the framework of the Basic Research Program at the National Research University Higher School of Economics (HSE University).

References

Abuzayed B., Al-Fayoumi N., Molyneux P. (2018). Diversification and bank stability in the GCC. *Journal of International Financial Markets, Institutions and Money*, 57, 17–43. DOI: 10.1016/J.INTFIN.2018.04.005.

Adesina K. S. (2021). How diversification affects bank performance: The role of human capital. *Economic Modelling*, 94, 303–319. DOI: 10.1016/J.ECONMOD.2020.10.016.

Barth J. R., Caprio G., Levine R. (2008). *Rethinking bank regulation: Till angels govern*. Cambridge University Press.

Barth J. R., Caprio G. Jr., Levine R. (2013). Bank regulation and supervision in 180 countries from 1999 to 2011. *Journal of Financial Economic Policy*, 5 (2), 111–219. DOI: 10.1108/17576381311329661.

Carbó S., Humphrey D., Maudos J., Molyneux P. (2009). Cross-country comparisons of competition and pricing power in European banking. *Journal of International Money and Finance*, 28 (1), 115–134. DOI: 10.1016/J.JIMONFIN.2008.06.005.

Chortareas G. E., Girardone C., Ventouri A. (2012). Bank supervision, regulation, and efficiency: Evidence from the European Union. *Journal of Financial Stability*, 8 (4), 292–302. DOI: 10.1016/j.jfs.2011.12.001.

Claeys S., Vander Vennet R. (2008). Determinants of bank interest margins in Central and Eastern Europe: A comparison with the West. *Economic Systems*, 32 (2), 197–216. DOI: 10.1016/J.ECOSYS.2007.04.001.

Demirgüç-Kunt A., Huizinga H. (1999). Determinants of commercial bank interest margins and profitability: Some international evidence. *The World Bank Economic Review*, 13 (2), 379–408. DOI: 10.1093/WBER/13.2.379.

Demirgüç-Kunt A., Laeven L., Levine R. (2003). Regulations, market structure, institutions, and the cost of financial intermediation. *NBER Working Paper*, 9890. Cambridge, MA.

Devereux M. B., Smith G. W. (1994). International risk sharing and economic growth. *International Economic Review*, 35 (3), 535–550. DOI: 10.2307/2527072.

DeYoung R., Roland K. P. (2001). Product mix and earnings volatility at commercial banks: Evidence from a degree of total leverage model. *Journal of Financial Intermediation*, 10 (1), 54–84. DOI: 10.1006/JFIN.2000.0305.

Doan A. T., Lin K. L., Doong S. C. (2018). What drives bank efficiency? The interaction of bank income diversification and ownership. *International Review of Economics and Finance*, 55, 203–219. DOI: 10.1016/J.IREF.2017.07.019.

Elsas R., Hackethal A., Holzhäuser M. (2010). The anatomy of bank diversification. *Journal of Banking and Finance*, 34 (6), 1274–1287. DOI: 10.1016/J.JBANKFIN.2009.11.024.

Fungáčová Z., Shamshur A., Weill L. (2017). Does bank competition reduce cost of credit? Cross-country evidence from Europe. *Journal of Banking and Finance*, 83, 104–120. DOI: 10.1016/J.JBANKFIN.2017.06.014.

Ghosh A. (2015). Banking-industry specific and regional economic determinants of non-performing loans: Evidence from US states. *Journal of Financial Stability*, 20, 93–104. DOI: 10.1016/J.JFS.2015.08.004.

Hansen B. E. (1999). Threshold effects in non-dynamic panels: Estimation, testing, and inference. *Journal of Econometrics*, 93 (2), 345–368. DOI: 10.1016/S0304-4076(99)00025-1.

Harris M., Kriebel C. H., Raviv A. (1982). Asymmetric information, incentives and intrafirm resource allocation. *Management Science*, 28 (6), 604–620. DOI: 10.1287/MNSC.28.6.604.

Hsiao C., Pesaran M. H., Kamil Tahmiscioglu A. (2002). Maximum likelihood estimation of fixed effects dynamic panel data models covering short time periods. *Journal of Econometrics*, 109 (1), 107–150. DOI: 10.1016/S0304-4076(01)00143-9.

Jensen M. C. (1986). Agency costs of free cash flow, corporate finance, and takeovers. *The American Economic Review*, 76 (2), 323–329. http://www.jstor.org/stable/1818789.

Klein P. G., Saidenberg M. R. (2000). Diversification, organization, and efficiency: Evidence from bank holding companies. In: P. T. Harker and S. A. Zenios (eds.). *Performance of Financial Institutions: Efficiency, Innovation, Regulation*, 153–174. Cambridge University Press.

Köhler M. (2015). Which banks are more risky? The impact of business models on bank stability. *Journal of Financial Stability*, 16, 195–212. DOI: 10.1016/J.JFS.2014.02.005.

Kremer S., Bick A., Nautz D. (2013). Inflation and growth: New evidence from a dynamic panel threshold analysis. *Empirical Economics*, 44 (2), 861–878. DOI: 10.1007/S00181-012-0553-9.

Kripfganz S. (2016). Quasi-maximum likelihood estimation of linear dynamic short-T panel-data models. *The Stata Journal*, 16 (4), 1013–1038. DOI: 10.1177/1536867X1601600411.

Laeven L., Levine R. (2007). Is there a diversification discount in financial conglomerates? *Journal of Financial Economics*, 85 (2), 331–367. DOI: 10.1016/J.JFINECO.2005.06.001.

Lepetit L., Nys E., Rous P., Tarazi A. (2008a). Bank income structure and risk: An empirical analysis of European banks. *Journal of Banking and Finance*, 32 (8), 1452–1467. DOI: 10.1016/J.JBANKFIN.2007.12.002.

Lepetit L., Nys E., Rous P., Tarazi A. (2008b). The expansion of services in European banking: Implications for loan pricing and interest margins. *Journal of Banking and Finance*, 32 (11), 2325–2335. DOI: 10.1016/J.JBANKFIN.2007.09.025.

Levine R. (1997). Financial development and economic growth: Views and agenda. *Journal of Economic Literature*, 35, 688–726. DOI: 10.1596/1813-9450-1678.

Meyer M., Milgrom P., Roberts J. (1992). Organizational prospects, influence costs, and ownership changes. *Journal of Economics and Management Strategy*, 1 (1), 9–35. DOI: 10.1111/J.1430-9134.1992.00009.X.

Moral-Benito E. (2013). Likelihood-based estimation of dynamic panels with predetermined regressors. *Journal of Business and Economic Statistics*, 31 (4), 451–472. DOI: 10.1080/07350015.2013.818003.

Moudud-Ul-Huq S., Ashraf B. N., Gupta A. D., Zheng C. (2018). Does bank diversification heterogeneously affect performance and risk-taking in ASEAN emerging economies? *Research in International Business and Finance*, 46, 342–362. DOI: 10.1016/J.RIBAF.2018.04.007.

Nguyen J. (2012). The relationship between net interest margin and noninterest income using a system estimation approach. *Journal of Banking and Finance*, 36 (9), 2429–2437. DOI: 10.1016/J.JBANKFIN.2012.04.017.

Nguyen M., Perera S., Skully M. (2016). Bank market power, ownership, regional presence and revenue diversification: Evidence from Africa. *Emerging Markets Review*, 27, 36–62. DOI: 10.1016/j.ememar.2016.03.001.

Noss J., Toffano P. (2016). Estimating the impact of changes in aggregate bank capital requirements during an upswing. *Journal of Banking and Finance*, 62, 15–27. DOI: 10.1016/J.JBANKFIN.2015.09.020.

Obstfeld M. (1994). Risk-taking, global diversification, and growth. *The American Economic Review*, 85 (5), 1310–1329.

Roodman D. (2009). How to do xtabond2: An introduction to difference and system GMM in Stata. *The Stata Journal*, 9 (1), 86–136. DOI: 10.1177/1536867X0900900106.

Saint-Paul G. (1992). Technological choice, financial markets and economic development. *European Economic Review*, 36 (4), 763–781. DOI: 10.1016/0014-2921(92)90056-3.

Scharfstein D. S., Stein J. C. (2000). The dark side of internal capital markets: Divisional rent-seeking and inefficient investment. *The Journal of Finance*, 55 (6), 2537–2564. DOI: 10.1111/0022-1082.00299.

Shim J. (2013). Bank capital buffer and portfolio risk: The influence of business cycle and revenue diversification. *Journal of Banking and Finance*, 37 (3), 761–772. DOI: 10.1016/J.JBANKFIN.2012.10.002.

Uhde A., Heimeshoff U. (2009). Consolidation in banking and financial stability in Europe: Empirical evidence. *Journal of Banking and Finance*, 33 (7), 1299–1311. DOI: 10.1016/J.JBANKFIN.2009.01.006.

Williams B. (2016). The impact of non-interest income on bank risk in Australia. *Journal of Banking and Finance*, 73, 16–37. DOI: 10.1016/J.JBANKFIN.2016.07.019.

Received 04.04.2023; accepted 13.11.2023.

Appendix A

Tables in this Appendix report the GMM, QML-FE, FE, and dynamic panel threshold regressions results by country income group and by banking activities restrictions (Table A1), as well as by geographical region (Table A2). The dependent variable is aggregate banking sector NIM. The main explanatory variable is the aggregate banking sector non-interest income to total income (NII). The control variables include *country effect*, *year effect*, *Z-score*, gross domestic product growth rate (*GDPG*), inflation (*Infl*), the ratio of deposit money banks' assets to GDP (*BAGDP*), bank concentration (*Con*), and banking crisis dummy variable (*BCrisis*).

In all tables standard errors are shown in parentheses; ***, **, * — significance at the 1, 5 and 10% level, respectively.

Table A1. Regression results by country income group and banking activities restrictions

	LICs	LMICs	UMICs	HICs	Countries with limited restrictions	Countries with high restrictions
	I	II	III	IV	V	VI
			Panel A: FE results			
NII_{t-1}	–0.06***	–0.06***	–0.04***	–0.01***	–0.02***	–0.03***
	(0.01)	(0.01)	(0.01)	(0.00)	(0.005)	(0.005)
Within R^2	0.26	0.19	0.18	0.14	0.15	0.089
Between R^2	0.02	0.03	0.31	0.05	0.14	0.001
Overall R^2	0.04	0.09	0.27	0.07	0.15	0.01
Observations	389	612	761	1036	1548	847
Countries	24	34	40	54	83	45
			Panel B: GMM results			
Dep_{t-1}	0.27	0.71***	0.91*	0.56***	0.42***	0.97***
	(0.16)	(0.18)	(0.50)	(0.18)	(0.06)	(0.000)
NII_{t-1}	–0.01*	–0.04	–0.05	–0.04***	–0.03***	–0.008***
	(0.01)	(0.03)	(0.08)	(0.01)	(0.01)	(0.000)
AR(1)	–2.89***	–2.23**	–2.02**	–2.56**	–3.94***	–3.67***
AR(2)	–0.79	0.11	1.38	0.02	0.84	–0.23
Hansen test	0.00	0.00	0.00	99.24***	0.00	617.64
Observations	389	612	761	1036	1548	847
Countries	24	34	40	54	83	45
			Panel C: QML-FE results			
Dep_{t-1}	0.08*	0.40***	0.33***	0.18***	0.54***	0.31
	(0.05)	(0.03)	(0.03)	(0.04)	(0.03)	(0.000)
NII_{t-1}	–0.10***	–0.08***	–0.08***	–0.03***	–0.005	–0.03***
	(0.01)	(0.01)	(0.01)	(0.00)	(0.005)	(0.000)
Observations	325	512	680	802	1256	738
Countries	21	30	37	43	70	41
			Panel D: Dynamic panel threshold regression			
Estimated threshold ($\hat{\gamma}$)	30.48	28.49	41.94	30.08	41.92	36.80

The end of Table A1

	LICs	LMICs	UMICs	HICs	Countries with limited restrictions	Countries with high restrictions
	I	II	III	IV	V	VI
95% confidence interval	[25.02, 57.52]	[24.95, 31.85]	[40.45, 42.02]	[29.58, 34.21]	[25.68, 56.98]	[20.64, 48.93]
$\hat{\beta}_1$ ($NII_{t-1} \le \gamma$)	–0.06**	0.02	–0.10***	0.03**	–0.01	0.03
	(0.03)	(0.02)	(0.02)	(0.01)	(0.019)	(0.018)
$\hat{\beta}_2$ ($NII_{t-1} > \gamma$)	–0.05***	–0.00	–0.06***	0.01	–0.005	0.008
	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)
Dep_{t-1}	0.06	0.30***	0.28***	0.21***	0.24***	0.05
	(0.07)	(0.06)	(0.05)	(0.06)	(0.05)	(0.05)
Observations	357	574	718	964	1442	797
Countries	24	34	40	54	83	45

Table A2. Regression results by geographical region

	Europe and Central Asia	East Asia and Pacific	Middle East and North Africa	Latin America and Caribbean	Sub-Saharan Africa	South Asia
			Panel A: FE results			
NII_{t-1}	–0.01*	–0.00	–0.07***	–0.06***	–0.04***	–0.05***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Within R^2	0.21	0.25	0.38	0.21	0.18	0.45
Between R^2	0.04	0.21	0.00	0.17	0.22	0.16
Overall R^2	0.01	0.02	0.11	0.19	0.19	0.27
Observations	907	295	322	516	607	118
Countries	47	16	17	27	36	7
			Panel B: GMM results			
Dep_{t-1}	0.72***	–0.03	0.28	0.16	0.05	0.79***
	(0.01)	(0.29)	(0.22)	(0.17)	(0.17)	(0.22)
NII_{t-1}	–0.02***	0.01*	–0.01	–0.07***	–0.13***	–0.02*
	(0.00)	(0.01)	(0.01)	(0.03)	(0.04)	(0.01)
AR(1)	–2.85***	–1.32	–1.97**	–2.86***	–3.47***	–1.46
AR(2)	0.01	0.75	–1.69	–1.13	–0.10	0.54
Hansen test	0.00	0.00	0.00	0.00	0.00	0.00
Observations	907	295	322	516	607	118
Countries	47	16	17	27	36	7
			Panel C: QML-FE results			
Dep_{t-1}	0.44	0.25	0.30	0.48	0.17	0.30
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
NII_{t-1}	–0.01***	–0.03***	–0.04***	–0.08	–0.07***	–0.07***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Observations	753	201	277	461	485	111
Countries	41	11	15	25	30	7

The end of Table A2

	Europe and Central Asia	East Asia and Pacific	Middle East and North Africa	Latin America and Caribbean	Sub-Saharan Africa	South Asia
	Panel D: Dynamic panel threshold regression					
Estimated threshold ($\hat{\gamma}$)	41.90	32.24	31.78	43.76	37.05	33.07
95% confidence interval	[27.00, 58.10]	[22.77, 33.73]	[22.08, 44.84]	[20.74, 51.33]	[35.23, 39.10]	[22.54, 52.26]
$\hat{\beta}_1$ ($NII_{t-1} \le \gamma$)	–0.03	0.06***	–0.09***	–0.01	–0.03	–0.06**
	(0.02)	(0.01)	(0.01)	(0.02)	(0.02)	(0.03)
$\hat{\beta}_2$ ($NII_{t-1} > \gamma$)	–0.01	0.03***	–0.08***	–0.01	–0.03	–0.04*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)
Dep_{t-1}	0.40***	0.28***	0.11**	0.35***	0.01	0.37**
	(0.05)	(0.07)	(0.05)	(0.07)	(0.06)	(0.15)
Observations	849	272	303	486	561	111
Countries	47	16	17	27	36	7

Appendix B

Following Barth et al. (2013), Restriction is captured by considering whether a bank's engagement in real estate, insurance, securities, and the ownership of non-financial firms are unrestricted, permitted, restricted, or prohibited[14]. These activities are assigned values from 1 to 4. Unrestricted, permitted, restricted, and prohibited are, respectively, assigned 1, 2, 3 and 4. The aggregate value of Restriction varies from 4 to 16. Higher values of the variable indicate greater restrictions. We divide our sample countries into two subsamples: countries with limited restrictions (on banking activities) include banking markets with Restriction equal to or less than median value (10), and countries with high restrictions include banking markets with Restriction greater than 10. Based on this criterion, our subsamples comprise 83 countries with limited restrictions and 45 countries with high restrictions[15].

[14] Information on Restriction come from the World Bank's most recent survey which was started in 2017 and completed in 2019. See https://www.worldbank.org/en/research/brief/BRSS.

[15] We exclude countries for which we have no information on Restriction.