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DO NON-INTEREST INCOME ACTIVITIES MATTER FOR BANKING SECTOR EFFICIENCY? A NET INTEREST MARGIN PERSPECTIVE[3]

This paper explores the effects non-interest income (NII) generating activities on banking sector efficiency in 152 countries from 1996 to 2017. Contrary to existing studies that investigate the effects of diversification on banking performance at the micro-level, this study seeks to provide new insights by examining the effects of diversification at the aggregate level on bank efficiency. This 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, as a robustness check, we do not find a tipping point beyond which the efficiency benefits of NII activities have an adverse impact on banking sector efficiency. These results are shown to be insensitive to different groups of countries. Our findings generally suggest that the liberalization of bank activities is effective in enhancing banking sector efficiency. In this sense, the findings of this study support banking sector diversification policies that have been implemented in many countries since the 1980s and 1990s.

Keywords: Banks, Net interest margin, Non-interest income, Bank profitability

JEL Codes: E40, G21

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1. Introduction

Banks function as financial intermediaries in the re-allocation of funds from surplus units to deficit units. Some economists (e.g., Schumpeter, 1911; Levin, 1997) have argued that an efficient banking system can provide low-cost monetary payments and effectively mobilize deposits and re-allocate funds to finance public and private investments and spur sustainable economic growth. To achieve this and following the advice of Bretton Woods institutions,[4] 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.[5] 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 up a significant amount of banks' total income in many countries. For instance, as of 2017 (see Figure 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. Devereux and Smith (1994), Saint-Paul (1992) and Obstfeld (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 (Moudud-Ul-Huq et al., 2018, Doan 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.

By contrast, there is a strand of the theoretical literature that questions the beneficial role of bank diversification. As underlined by Klein and Saidenberg (1998), 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

[4] The World Bank and the International Monetary Fund (IMF)

[5] This includes the establishment of stock markets, the diversification of financial institutions, the removal of bank credit quotas, and the relaxation of interest rate controls.

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 and Stein, 2000), and informational asymmetries between divisional managers and head office (Harris et al., 1992). Some authors (including Adesina, 2021; DeYoung and Roland, 2001) 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 and Roland, 2001, Köhler, 2015), low bank valuation (Laeven and 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 and Huizinga 1999 and 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.[6] 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 and Heimeshoff 2009, Noss and Toffano 2014, and 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).[7] 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. Unlike previous studies (including Huang and Ji, 2017 and Ibrahim and Alagidede, 2018) that use a quadratic term to capture non-linearity in regressions, the threshold model does not impose any quadratic term since it uses a certain functional form that may not be the patterns in the dataset.

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

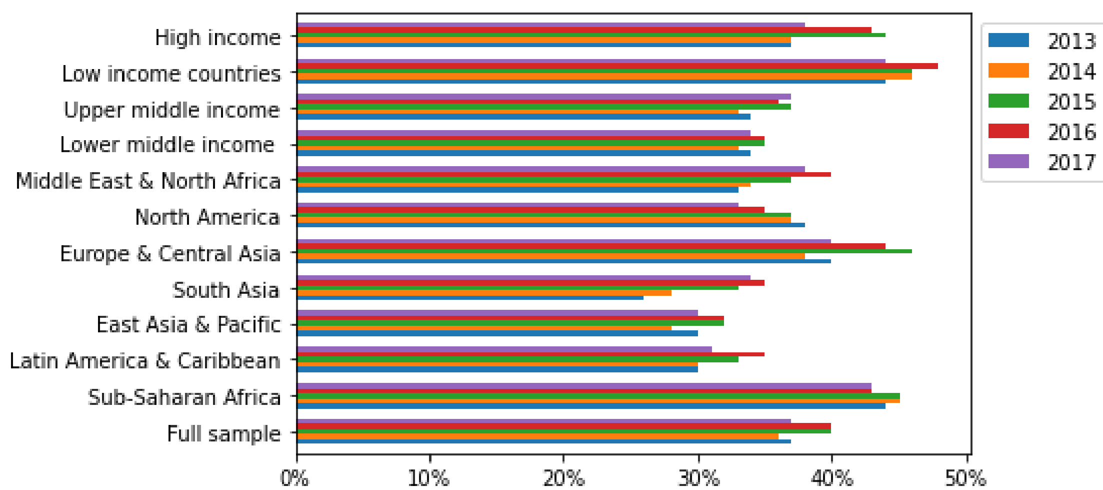
[6] The mixed findings on effects of diversification on NIM warrants more research.

[7] For example, Osiris provides data of a few Russian banks. Bankfocus data on NII and NIM are available for limited number of years.

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, the sample countries are also classified into six geographical regions (Appendix Table A.1 provides more details). In addition, using the most recent World Bank Regulation and Supervision Survey (2017 to 2019), 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.

This paper is organized as follows. Section 1 gives an introduction that covers the motivations behind this study along with a brief review of the theoretical and empirical literature analyzing the relationship between diversification and bank efficiency. 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.

Figure 1: Non-interest income to total income ratio



Notes: This figure presents the average of NII by income and regional country groups.
Source: Global Financial Development Database, 2021

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 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 (Chortareas et al. 2012, Barth et al. 2006). In the view of Claeys and 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., 2004).

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:

$$Eff_{i,t} = \beta_0 + \beta_1 EFF_{i,t-1} + \beta_2 NII_{i,t} + \beta_3 ConV_{i,t} + \alpha_i + \mu_t + \varepsilon_{i,t} \quad (1)$$

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[8] of country i in year t. $NII_{i,t}$ denotes the ratio of banking sector NII to total income (%). $ConV_{i,t}$ denotes a matrix of six country-level control variables: bank assets to GDP ratio (BAGDP), to control for banking system development;[9] Z-score,[10] 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; 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

[8] The country-level NIM is obtained from GFDD. GFDD calculates the aggregate NIM from underlying bank-by-bank unconsolidated data from Bankscope (now known as Bankfocus).

[9] We want to ensure that our dataset cover many countries. As a result of this, we drop other banking sector development variables because their data are not available for many countries.

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

deflator (annual %) and the economic growth rate, proxied by the gross domestic product growth rate (GDPG). Our control variables (BAGDP, BCrisis, Con, Z-score, Infl and GDPG) are included in the model because they have been found to affect bank performance (Chortareas et al., 2012; Doan et al., 2018; Demirgüç-Kunt et al., 2004; Köhler, 2015). Our model contains not only the six control variables but also time-specific effects (μ_t) and country-specific effects (α_i).[11] The model contains $EFF_{i,t-1}$ (lagged dependent variable), which measures the dynamic effects. β_0 and β_1, β_2, β_3 are, respectively, the constant and the parameters to be estimated. $\varepsilon_{i,t}$ is the error term.

Since $EFF_{i,t}$ is a function of $\varepsilon_{i,t}$ in Equation 1, $EFF_{i,t-1}$ is also a function of $\varepsilon_{i,t}$. Therefore, $EFF_{i,t-1}$ (the right-hand side variable) is correlated with the error term (the endogeneity problem), which might lead to biased estimation results in the dynamic panel data model. 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) estimator proposed by Kripfganz (2016) to estimate linear dynamic panel data models. QML-FE offers better finite sample performance than two-step system GMM (Moral-Benito, 2013). It also overcomes many other limitations of two-step system GMM (see 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. Roodman (2009) recommends the FE estimator for a panel data with large T.[12] Another drawback of using two-step GMM is that the number of instruments tends to increase as the time dimension increases. For this reason, since the T dimension of our panel data is greater than 21, it is appropriate to use the FE for a robustness check.

2.2.2 Dynamic panel threshold model

Given that our baseline model (Equation 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's 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

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

[12] This is because the number of the GMM instruments increases considerably as the time dimension increases.

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.

$$Eff_{i,t} = \beta_1 NII_{i,t} I(NII_{i,t} \leq \gamma) + \delta_1 I(NII_{i,t} \leq \gamma) + \beta_2 NII_{i,t} I(NII_{i,t} > \gamma) + \beta_3 X_{i,t} + \alpha_i + \mu_t + \varepsilon_{i,t} \quad (2)$$

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. $I(\cdot)$ is an indicator function, taking on the value of zero if the value of the threshold variable *NII* is above the threshold level and takes 1 otherwise. This splits the sample into two regimes, one with slope parameter β_1 and another with β_2.[13] δ_1 stands for the threshold intercept. Leaving out the threshold intercept may bias the estimated results (Bick, 2010). $X_{i,t}$ is a set of independent variables which can be divided into two subsets: $X_{1i,t}$ and $X_{2i,t}$. $X_{1i,t}$ is a subset of endogenous variables, while $X_{2i,t}$ is a subset of exogenous variables. The initial efficiency level is considered as an endogenous variable (i.e., $X_{1i,t} = Eff_{i,t-1}$), while $X_{2i,t}$ contains BAGDP, BCrisis, Con, 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. As suggested by 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:

$$\varepsilon^*_{i,t} = \sqrt{\frac{T-t}{T-t+1}}\left[\varepsilon_{i,t} - \frac{1}{T-t}\left(\varepsilon_{i(t+1)} + \cdots + \varepsilon_{i,T}\right)\right] \quad (3)$$

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,

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

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, 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[14] dataset of 152 countries,[15] which consists of 54 HICs, 24

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

[14] 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.

LICs, 40 UMICs and 34 LMICs[16] over the 1996–2017 period.[17] Using World Bank classifications, the sample countries are also classified into six geographical regions (Appendix Table A.1 provides more details). 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%).[18] 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) NII ranges from 36.36% (34.05%) in UMICs to 41.73% (42.16%) in LICs; the average 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.

Looking at Figure 2, we can observe that no two independent variables are highly correlated.[19] The correlation matrix also offers interesting preliminary insights on our main variables of interest. The correlation coefficient between NII and our measure of banking sector efficiency (NIM) is negative, indicating that a higher level of diversification is associated with a higher level of banking sector efficiency. To provide further insights, Figures 3 presents the scatter plots of the behavior of NII with respect to NIM. These scatter plots also suggest that NII has a negative relationship with NIM.

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[15] Data for our analysis is available for 152 (71.03%) out of the 214 countries in the GFDD. Appendix Table A.1 provides the list of the 152 countries. The exclusion of other countries is mainly due to the unavailability of their data for a significant number of years for all our variables.

[16] This is based on the classification used by the World Bank in the Global Financial Development Database.

[17] 2017 was the most recent year of data available at the time the study was conducted.

[18] This is relative to the total sample.

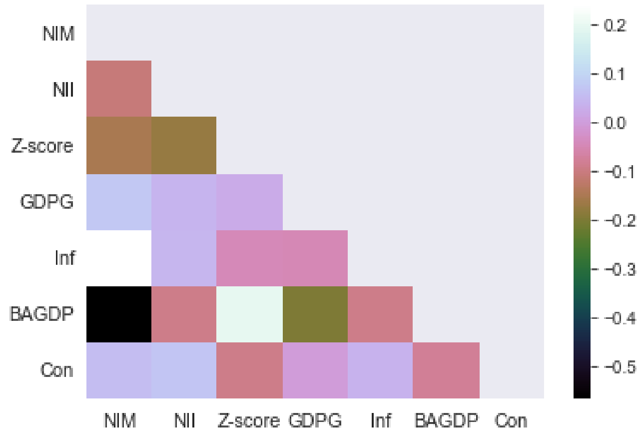
[19] Multicollinearity problem arises when the correlation coefficient is higher than 0.7 (Kennedy, 2008).

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
Med.	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
Min.	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
Max.	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
	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
Med.	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
Min.	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
Max.	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
	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
Med.	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
Min.	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
Max.	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
	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
Med.	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
Min.	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
Max.	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
	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
Med.	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
Min.	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
Max.	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
	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
Med.	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
Min.	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
Max.	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

Notes: This table provides the descriptive statistics (Mean, Med., Min., and Max.) of the variables used in the regression analyses by geographical region and income group over the 1996–2017 period. Med.: median; Min.: minimum; Max: maximum; NIM: net interest margin; NII: non-interest income to total income; GDPG: gross domestic product growth rate; Infl: inflation; BAGDP: the ratio of deposit money banks' assets to GDP; Con: bank concentration.

Figure 2: Correlation matrix



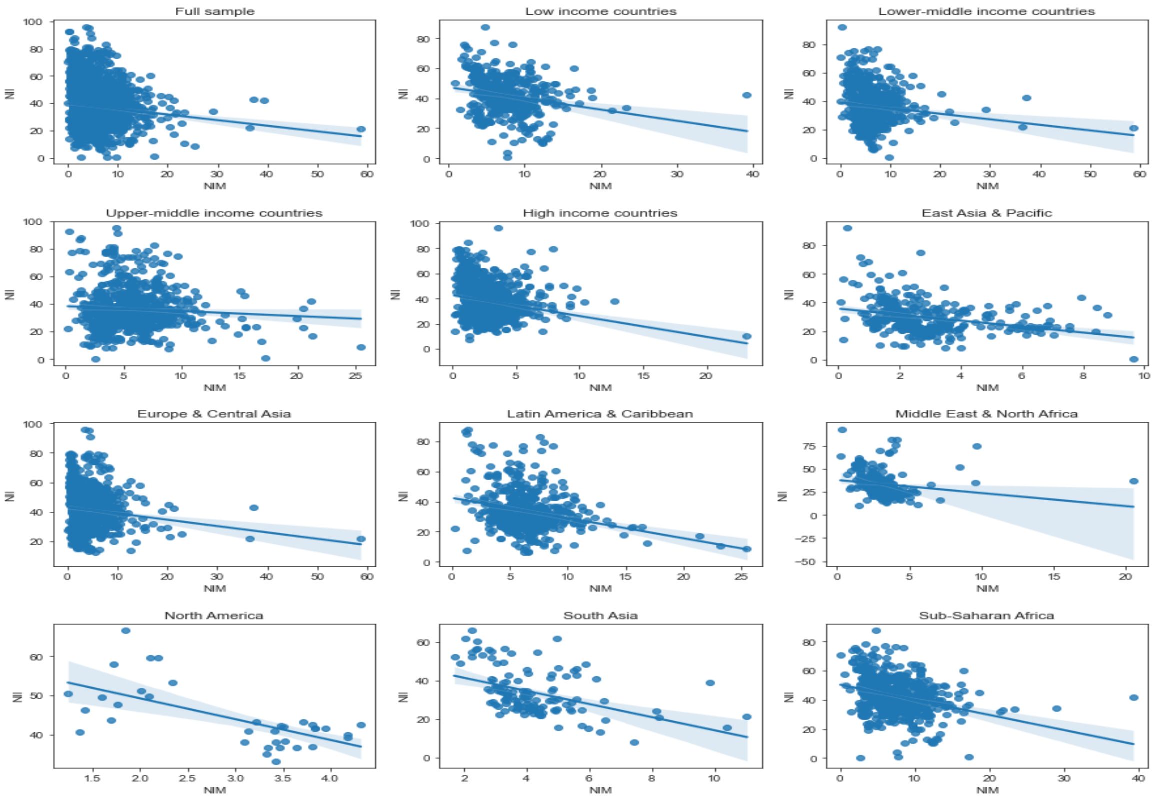
To avoid biased estimates of our regression models, we test the data for stationarity. Because we have unbalanced panel datasets that come in the form of relatively small T and large N, Augmented Dickey–Fuller (ADF) and Im, Pesaran and Shin (IPS) unit root tests are used as tests for the stationarity 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	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 tests. *** significant at the 1% level; ** significant at the 5% level; * significant at the 10% level. NIM: net interest margin; NII: non-interest income to total income; GDPG: gross domestic product growth rate; Infl: inflation; BAGDP: the ratio of deposit money banks' assets to GDP; Con: bank concentration.

Figure 3: Scatter plots of NII and NIM



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 NII 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 efficiency (Demirgüç-Kunt et al., 2004; Barth et al., 2013; Chortareas et al., 2012). Our finding that NII reduces NIM is largely supports the findings of bank-level panel data studies, e.g., Lepetit et al.'s (2008b) study of 602 European banks over the 1996–2002 period, Carbó et al.'s (2009) study of 1912 banks in 14 European countries and Demirgüç-Kunt and Huizinga's (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, 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 positively with NIM, although this is only significant in the GMM (1) 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 et al., 2004 and Demirgüç-Kunt and Huizinga, 1999), 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.

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

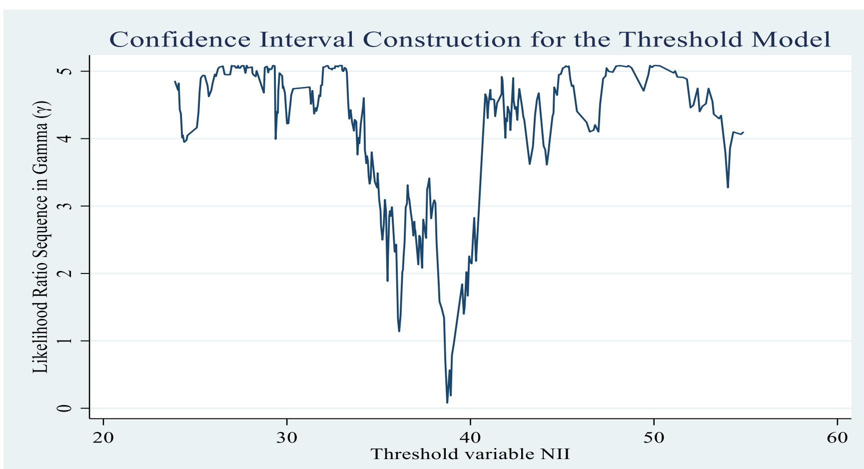
	GMM (1)	QML-FE (2)	FE (3)
Lagged Dep	0.4189***	0.4084***	
	(0.1056)	(0.0178)	
NII	–0.0078*	–0.0468***	–0.0600***
	(0.0042)	(0.0032)	(0.0038)
Z-score	0.0388***	0.0791***	0.0836***
	(0.0080)	(0.0093)	(0.0100)
GDPG	0.0198***	0.0007	0.0000
	(0.0066)	(0.0085)	(0.0085)
Infl	0.0044***	0.0138***	0.0102***
	(0.0016)	(0.0028)	(0.0007)
BAGDP	–0.0173***	–0.0047**	–0.0107***
	(0.0035)	(0.0019)	(0.0023)
Con	0.0273***	0.0193***	0.0151***
	(0.0048)	(0.0027)	(0.0034)
BCrisis	0.2234	0.0623	0.0631
	(0.1696)	(0.1371)	(0.1671)
Constant	0.0000	2.7510***	6.9668***
	(0.0000)	(0.3313)	(0.3760)
Country effect	Yes	Yes	Yes
Year effect	Yes	Yes	Yes
AR(1)	–4.32***		
AR(2)	0.45		
Sargan test	17.34		
Instruments	181		
R^2			0.2319
Observations	2,798	2,319	2,992
Countries	152	131	152

Notes: This table reports the GMM, QML-FE, and FE regressions results for the full sample. 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). Standard errors are shown in parentheses. *** significant at the 1% level; ** significant at the 5% level; * significant at the 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 percent 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 of $\hat{\beta}_1$ and $\hat{\beta}_2$ (in Panel B of Table 4) indicate that though NII has negative effects on NIM, the impacts vary with the level of NII, specifically, when the level of NII is low, the effect coefficient (i.e. $\hat{\beta}_1$) of NII on NIM is –0.0914, versus –0.0867 in the high NII regime (i.e. $\hat{\beta}_2$), demonstrating a scenario in which the absolute negative effect coefficient in the low bank diversification regime is higher than in the high diversification regime.[20] In other words, the magnitudes of the effects of $\hat{\beta}_1$ and $\hat{\beta}_2$ suggest that engaging in NII generating activities is a more important driver of efficiency for a less diversified banking sector. Nevertheless, since coefficients of both $\hat{\beta}_1$ and $\hat{\beta}_2$ have a negative sign in Table 4, 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.

Figure 3: Threshold Estimate of NII



[20] The threshold effect could be observed in Figure 3, which depicts the likelihood ratio (LR) sequence in Gama (γ) as a function of the threshold variable.

Table 4: Dynamic threshold regression results for the full sample

Panel A: Estimated NII threshold values	
Estimated threshold ($\hat{\gamma}$)	38.8071
95% confidence interval	[22.8031, 55.4788]
Panel B: Impact of NII	
$\hat{\beta}_1$(NII ≤ γ)	–0.0896***
	(0.0189)
$\hat{\beta}_2$ (NII > γ)	–0.0809***
	(0.0127)
Panel C: Impact of covariates	
Lagged Dep	0.1697***
	(0.0315)
Z-score	0.1484***
	(0.0424)
GDPG	0.0182
	(0.0217)
Infl	0.0017
	(0.0087)
BAGDP	–0.0418***
	(0.0106)
Con	0.0285***
	(0.0097)
BCrisis	0.1396
	(0.6128)
Country effect	Yes
Year effect	Yes
Observations	2,613
Countries	152

Notes: This table reports the dynamic threshold regression results for the full sample. 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). Standard errors are shown in parentheses. *** significant at the 1% level; ** significant at the 5% level; * significant at the 10% level.

4.3 Robustness checks: Subsample analyses

Our main results, through the application of four estimation techniques, show that the relationship between diversification and banking sector efficiency is positive and significant in 152 countries. However, despite providing consistent results in the previous sections, it is important to point out that 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. To start with, 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 5 report, respectively, the FE, two-step system GMM, QML-FE, and dynamic panel threshold regression results for the four income groups.[21] The coefficients of NII (including $\hat{\beta}_1$ and $\hat{\beta}_2$) presented in Panels A to D are significantly negative across all income groups. Thus, the results for the income groups corroborate our main results reported in the previous sections. Although, there are some variances between the estimation results in terms of magnitude of coefficients on NII. In FE regressions results, a 1% increase of NII in LICs, LMICs, UMICs and HICs leads, respectively, to 0.10%, 0.11%, 0.06% and 0.03% decrease of NIM. The GMM (QML-FE) regression results show that a 1% increase in NII in LICs, LMICs, UMICs and HICs leads, respectively, to 0.04% (0.10%), 0.05% (0.08%), 0.04% (0.08%) and 0.02% (0.03%) decrease of NIM. These variances demonstrate a scenario in which the absolute negative effect coefficients in HICs are smaller than in the LICs, LMICs and UMICs. Earlier we reported that the average NIM in HICs is the smallest among the income groups (Table 1). Such low NIM could contribute to a decrease in the reducing effects of NII in HICs.

Table 5: Regression results by country income group

	LICs	LMICs	UMICs	HICs
Panel A: FE results				
NII	–0.10***	–0.11***	–0.06***	–0.03***
	(0.01)	(0.01)	(0.01)	(0.00)
R^2	0.59	0.30	0.26	0.21
Observations	424	654	804	1,110
Countries	24	34	40	54
Panel B: GMM results				
Lagged Dep	0.28***	1.03***	0.58*	0.28**
	(0.08)	(0.23)	(0.35)	(0.12)
NII	–0.04***	–0.05**	–0.04***	–0.02**
	(0.01)	(0.02)	(0.02)	(0.01)
AR (1)	–3.72***	–2.31**	–1.79*	–3.23***
AR (2)	–0.19	0.02	0.91	–0.06
Sargan test	1.86	0.71	0.66	7.42
Observations	389	612	761	1,036
Countries	24	34	40	54
Panel C: QML-FE results				
Lagged Dep	0.08*	0.40***	0.33***	0.18***
	(0.05)	(0.03)	(0.03)	(0.04)
NII	–0.10***	–0.08***	–0.08***	–0.03***
	(0.01)	(0.01)	(0.01)	(0.00)
Observations	325	512	680	802
Countries	21	30	37	43
Panel D: Dynamic panel threshold regression				
Estimated threshold ($\hat{\gamma}$)	40.98	51.15	47.47	33.71
95% confidence interval	[39.10, 48.91]	[21.85, 54.11]	[22.73, 51.43]	[23.70, 50.44]
$\hat{\beta}_1$(NII ≤ γ)	–0.03*	–0.08***	–0.10***	–0.05***
	(0.02)	(0.02)	(0.02)	(0.01)
$\hat{\beta}_2$ (NII > γ)	–0.07***	–0.08***	–0.08***	–0.03***
	(0.01)	(0.01)	(0.02)	(0.01)
Lagged Dep	0.06	0.16***	0.31***	0.13**
	(0.05)	(0.05)	(0.04)	(0.05)
Observations	357	574	718	964
Countries	24	34	40	54

Notes: This table reports the GMM, QML-FE, FE, and dynamic panel threshold regressions results by country income group. 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). Standard errors are shown in parentheses. *** significant at the 1% level; ** significant at the 5% level; * significant at the 10% level.

[21] For space related reasons, only the coefficients of NII (our variable of interest) are reported in Table 5.

As a further robustness check, instead of dividing our sample countries according to their income groups, we classify them 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.[22] We re-estimate our baseline models for each of the geographical regions.[23] Countries according to region and income level are provided in Appendix Table A.1. Table 6 presents the results for our six geographical subsamples. In panels A, B, C, and D of Table 6, we can observe that the coefficients of NII (including $\hat{\beta}_1$ and $\hat{\beta}_2$) are negative with NIM across all geographical regions. Thus, the results for the geographical regions support our earlier findings that liberalization (less restrictions) of banking activities is effective in enhancing banking sector efficiency.

Table 6: Regression results by geographical region

	Europe & Central Asia	East Asia & Pacific	Middle East & North Africa	Latin America & Caribbean	Sub–Saharan Africa	South Asia
Panel A: FE results						
NII	–0.04***	–0.04***	–0.06***	–0.08***	–0.08***	–0.08***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
R^2	0.23	0.36	0.34	0.33	0.45	0.66
Observations	967	321	341	546	657	125
Countries	47	16	17	27	36	7
Panel B: GMM results						
Lagged Dep	1.31***	0.29**	0.30*	1.04***	0.96***	0.25
	(0.29)	(0.12)	(0.16)	(0.29)	(0.20)	(0.19)
NII	–0.07***	–0.01***	–0.01	–0.05**	–0.10***	–0.01
	(0.02)	(0.00)	(0.01)	(0.02)	(0.02)	(0.01)
AR (1)	–1.61	–2.42**	–1.85**	–2.40**	–2.60***	–1.75*
AR (2)	0.27	1.64	–1.51	–0.67	0.87	–0.41
Sargan test	7.37	0.22	3.82	6.14	1.81	1.12
Observations	907	295	322	516	607	118
Countries	47	16	17	27	36	7
Panel C: QML-FE results						
Lagged Dep	0.44***	0.27***	0.30***	0.27***	0.08**	0.18**
	(0.03)	(0.07)	(0.03)	(0.04)	(0.04)	(0.08)
NII	–0.05***	–0.03***	–0.07***	–0.06***	–0.08***	–0.07***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Observations	753	201	277	461	485	111
Countries	41	11	15	25	30	7
Panel D: Dynamic panel threshold regression						
Estimated threshold ($\hat{\gamma}$)	53.18	25.07	31.86	50.23	56.72	23.98
95% confidence interval	[27.00, 57.83]	[18.59, 42.04]	[22.08, 44.84]	[44.02, 50.23]	[30.12, 55.09]	[23.98, 25.08]
$\hat{\beta}_1$(NII ≤ γ)	–0.00	–0.02	–0.11***	–0.06***	–0.04*	–0.03*
	(0.02)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)
$\hat{\beta}_2$ (NII > γ)	–0.03***	–0.03***	–0.09***	–0.05***	–0.06***	–0.08***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)
Lagged Dep	0.32***	0.14**	0.35***	0.30***	–0.00	–0.00
	(0.05)	(0.07)	(0.04)	(0.06)	(0.06)	(0.08)
Observations	849	272	303	486	561	111
Countries	47	16	17	27	36	7

[22] 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).

[23] We exclude North America in our estimations because the number (35) of observations for the region is too small for any meaningful regression analysis (see North America in Table A.2 of the Appendix A).

Notes: This table reports the GMM, QML-FE, FE, and dynamic panel threshold regressions results by geographical region. 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). Standard errors are shown in parentheses. *** significant at the 1% level; ** significant at the 5% level; * significant at the 10% level.

To investigate whether the relationship between NII and NIM changes in different regulatory environments, we divide our sample countries according to the regulatory restrictions (Restriction) placed on banking activities in each country. 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.[24] 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.[25] As presented in Table 7, the coefficients on NII (including $\hat{\beta}_1$ and $\hat{\beta}_2$) are negative across all our estimations in both groups of countries. However, the absolute coefficients of NII in countries with limited restrictions are smaller than the absolute coefficients of NII in countries with high restrictions. This may suggest that the effects of fewer restrictions on NIM are subject to the diminishing returns within an industry.

[24] Information on Restriction come from the World Bank's most recent survey which was started in 2017 and completed in 2019.
[25] We exclude countries for which we have no information on Restriction.

Table 7: Regression results by bank activity restrictiveness

	Countries with limited restrictions	Countries with high restrictions
Panel A: FE results		
NII	–0.0549***	–0.0581***
	(0.0057)	(0.0049)
R^2	0.7075	0.8393
Observations	1,657	899
Countries	83	45
Panel B: GMM results		
Lagged Dep	0.4519***	0.2400***
	(0.1521)	(0.0742)
NII	–0.0384	–0.0401***
	(0.2225)	(0.0108)
AR (1)	–3.05***	–3.47***
AR (2)	1.23	1.67
Sargan test	13.31	7.21
Observations	1,548	847
Countries	83	45
Panel C: QML-FE results		
Lagged Dep	0.4576***	0.2879
	(0.0176)	(0.0000)
NII	–0.0392***	–0.0433***
	(0.0050)	(0.0084)
Observations	1,207	779
Countries	62	41
Panel D: Dynamic panel threshold regression		
Estimated threshold ($\hat{\gamma}$)	56.9838	21.7618
95% confidence interval	[25.308, 56.9838]	[20.4931, 49.2308]
$\hat{\beta}_1$(NII $\leq \gamma$)	–0.0616***	–0.1054***
	(0.0165)	(0.0221)
$\hat{\beta}_2$ (NII $> \gamma$)	–0.0490***	–0.0692***
	(0.0135)	(0.0092)
Lagged Dep	0.1975***	0.0426
	(0.0491)	(0.0393)
Observations	1,442	797
Countries	83	45

Notes: This table reports the GMM, QML-FE, FE, and dynamic panel threshold regressions results for two subsamples: countries with limited restrictions on banking activities and countries with high restrictions. 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). Standard errors are shown in parentheses. *** significant at the 1% level; ** significant at the 5% level; * significant at the 10% level.

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 proposed by Kripfganz (2016). 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 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 positive effects on banking sector efficiency. 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.

This study has its limitations. First, our study uses NIM to measure banking sector efficiency. This variable cannot capture all areas of banking sector efficiency, especially since there are different measures of banking sector efficiency. Therefore, further investigations could be carried out on the NII–banking sector efficiency nexus by using other measures of efficiency. Second, we acknowledge that this research uses a few (six) control variables in our econometric models. This is due to data limitations for some countries. The inclusion of variables (such as bank capitalization and liquidity) would have drastically reduced our sample countries and sample period. However, we have tried to ensure that our results are robust by using different subsamples, models, and estimation techniques. We suggest that future studies should be carried out with more control variables.

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Appendix A

Table A.1: List of sample countries

Country	Income	Region	Country	Income	Region	Country	Income	Region
Afghanistan	LIC	SA	Gabon	UMIC	SSA	New Zealand	HIC	EAP
Albania	UMIC	ECA	Gambia, The	LIC	SSA	Nicaragua	LMIC	LAC
Algeria	UMIC	MENA	Georgia	LMIC	ECA	Niger	LIC	SSA
Angola	LMIC	SSA	Germany	HIC	ECA	Nigeria	LMIC	SSA
Antigua and Barbuda	HIC	LAC	Ghana	LMIC	SSA	North Macedonia	UMIC	ECA
Argentina	HIC	LAC	Greece	HIC	ECA	Norway	HIC	ECA
Armenia	UMIC	ECA	Guatemala	UMIC	LAC	Oman	HIC	MENA
Australia	HIC	EAP	Guyana	UMIC	LAC	Pakistan	LMIC	SA
Austria	HIC	ECA	Haiti	LIC	LAC	Panama	HIC	LAC
Azerbaijan	UMIC	ECA	Honduras	LMIC	LAC	Paraguay	UMIC	LAC
Bahamas, The	HIC	LAC	Hong Kong	HIC	EAP	Peru	UMIC	LAC
Bahrain	HIC	MENA	Hungary	HIC	ECA	Philippines	LMIC	EAP
Bangladesh	LMIC	SA	Iceland	HIC	ECA	Poland	HIC	ECA
Barbados	HIC	LAC	India	LMIC	SA	Portugal	HIC	ECA
Belarus	UMIC	ECA	Indonesia	LMIC	EAP	Qatar	HIC	MENA
Belgium	HIC	ECA	Iraq	UMIC	MENA	Romania	UMIC	ECA
Belize	UMIC	LAC	Ireland	HIC	ECA	Russian Federation	UMIC	ECA
Benin	LIC	SSA	Israel	HIC	MENA	Rwanda	LIC	SSA
Bhutan	LMIC	SA	Italy	HIC	ECA	San Marino	HIC	ECA
Bolivia	LMIC	LAC	Jamaica	UMIC	LAC	Saudi Arabia	HIC	MENA
Bosnia and Herzegovina	UMIC	ECA	Japan	HIC	EAP	Senegal	LIC	SSA
Botswana	UMIC	SSA	Jordan	UMIC	MENA	Serbia	UMIC	ECA
Brazil	UMIC	LAC	Kazakhstan	UMIC	ECA	Sierra Leone	LIC	SSA
Bulgaria	UMIC	ECA	Kenya	LMIC	SSA	Singapore	HIC	EAP
Burkina Faso	LIC	SSA	Korea, Rep.	HIC	EAP	Slovak Republic	HIC	ECA
Burundi	LIC	SSA	Kuwait	HIC	MENA	Slovenia	HIC	ECA
Cabo Verde	LMIC	SSA	Kyrgyz Republic	LMIC	ECA	South Africa	UMIC	SSA
Cambodia	LMIC	EAP	Latvia	HIC	ECA	Spain	HIC	ECA
Cameroon	LMIC	SSA	Lebanon	UMIC	MENA	Sri Lanka	LMIC	SA
Canada	HIC	NA	Lesotho	LMIC	SSA	Sudan	LMIC	SSA
Chad	LIC	SSA	Libya	UMIC	MENA	Suriname	UMIC	LAC
Chile	HIC	LAC	Lithuania	HIC	ECA	Sweden	HIC	ECA
China	UMIC	EAP	Luxembourg	HIC	ECA	Switzerland	HIC	ECA
Colombia	UMIC	LAC	Macao SAR, China	HIC	EAP	Tajikistan	LIC	ECA
Congo, Dem. Rep.	LIC	SSA	Madagascar	LIC	SSA	Tanzania	LIC	SSA
Costa Rica	UMIC	LAC	Malawi	LIC	SSA	Thailand	UMIC	EAP
Côte d'Ivoire	LMIC	SSA	Malaysia	UMIC	EAP	Togo	LIC	SSA
Croatia	HIC	ECA	Mali	LIC	SSA	Trinidad and Tobago	HIC	LAC
Cyprus	HIC	ECA	Malta	HIC	MENA	Tunisia	LMIC	MENA
Czech Republic	HIC	ECA	Mauritania	LMIC	SSA	Turkey	UMIC	ECA
Denmark	HIC	ECA	Mauritius	UMIC	SSA	Uganda	LIC	SSA

Dominican Republic	UMIC	LAC	Mexico	UMIC	LAC	Ukraine	LMIC	ECA
Ecuador	UMIC	LAC	Moldova	LMIC	ECA	United Arab Emirates	HIC	MENA
Egypt, Arab Rep.	LMIC	MENA	Mongolia	LMIC	EAP	United Kingdom	HIC	ECA
El Salvador	LMIC	LAC	Montenegro	UMIC	ECA	United States	HIC	NA
Estonia	HIC	ECA	Morocco	LMIC	MENA	Uruguay	HIC	LAC
Eswatini	LMIC	SSA	Mozambique	LIC	SSA	Venezuela, RB	UMIC	LAC
Ethiopia	LIC	SSA	Myanmar	LMIC	EAP	Vietnam	LMIC	EAP
Finland	HIC	ECA	Namibia	UMIC	SSA	Yemen, Rep.	LIC	MENA
France	HIC	ECA	Nepal	LIC	SA	Zambia	LMIC	SSA
			Netherlands	HIC	ECA	Zimbabwe	LIC	SSA

Notes: Europe & Central Asia (ECA); East Asia & Pacific (EAP); Middle East & North Africa (MENA); Latin America & Caribbean (LAC); North America (NA); South Asia (SA); Sub-Saharan Africa (SSA); low income country (LIC); lower-middle income country (LMIC); upper-middle income country(UMIC); high income country (HIC).

Table A.2: Sample distribution by geographical region and income group

		LICs	LMICs	UMICs	HICs	EAP	ECA	LAC	MENA	NA	SA	SSA	Full sample
Countries		24	34	40	54	16	47	27	17	2	7	36	152
	%	15.79	22.37	26.32	35.53	10.53	30.92	17.76	11.18	1.32	4.61	23.68	100.00
Observations		424	654	804	1,110	321	967	546	341	35	125	657	2992
	%	14.17	21.86	26.87	37.10	10.73	32.32	18.25	11.40	1.17	4.18	21.96	100.00

Notes: low income countries (LICs); lower-middle income countries (LMICs); upper-middle income countries (UMICs); high income countries (HICs); Europe & Central Asia (ECA); East Asia & Pacific (EAP); Middle East & North Africa (MENA); Latin America & Caribbean (LAC); North America (NA); South Asia (SA); Sub-Saharan Africa (SSA).