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Impact of Innovation on Nonperforming Loans of the Banking System: Evidence from International Countries

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Abstract: This paper examines the impact of innovation on non-performing loans in the banking sector. Specifically, innovation has the potential to either limit banks' lending activities or enhance their operational efficiency, both of which may contribute to a reduction in non-performing loans. Utilising a dataset comprising 120 countries over the period from 2013 to 2020, the study provides empirical evidence supporting this hypothesis. The results remain robust even after addressing endogeneity concerns through the application of alternative regression techniques, including instrumental variables and system generalized method of moments models. Additionally, the study highlights that the impact of innovation on non-performing loans is more pronounced in countries with lower levels of corruption, whereas its effects may be diluted in high-corruption contexts. These findings offer significant policy implications, emphasising the importance of fostering innovation and reducing corruption to promote sustainable banking practices and economic growth.

Keywords: Bank, corruption, innovation, non-performing loans
JEL classification: G21, O33

1. Introduction

The stability of the banking sector is crucial for sustainable economic growth, and one of the key challenges facing financial institutions worldwide is the issue of non-performing loans (NPLs). High levels of NPLs can undermine the financial health of banks, reducing their ability to provide credit and support economic activities. Previous studies have extensively examined the macroeconomic and bank-specific factors contributing to NPLs, including GDP growth, unemployment rates, interest rates, bank profitability, capital adequacy, or bank management (i.e., Beck et al., 2015; Ghosh, 2015; Louzis et al., 2012; Makri et al., 2014; Radivojevic & Jovovic, 2017). However, the role of innovation in shaping the NPL dynamics remains largely unexplored. Understanding how innovation affects NPLs is essential for policymakers and banking institutions seeking to enhance financial stability and foster economic resilience.

Innovation has long been recognised as a driving force behind economic progress, improving efficiency, productivity and competitiveness across industries. In the financial sector, technological advancements have led to the emergence of new financial products, services and risk management tools. Previous studies indicate that

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innovation can affect financial stability (i.e., Bao et al., 2024; Merton, 1992; Piazza, 2015; Rajan, 2006; Yu, 2024), bank performance (i.e., Akhisar et al., 2015; Scott et al., 2017), and bank risk (i.e., Chen & Du, 2016; Guo et al., 2024; Li, C. et al., 2022). Despite the increasing significance of financial innovation, there is limited empirical research examining its direct impact on NPLs at the international level. This gap in the literature necessitates a comprehensive analysis of the relationship between innovation and NPLs.

This study aims to fill this research gap by investigating the impact of innovation on NPLs using a comprehensive dataset covering 120 countries from 2013 to 2020. This study conducts the analysis at the country-level instead of at the bank-level because we want to examine the macro-financial stability implications of innovation. Non-performing loans are not only a bank-specific outcome but also a reflection of aggregate economic resilience, business cycle dynamics, and structural transformation driven by innovation. By using country-level NPL ratios, we can assess whether innovation contributes to system-wide reductions in credit risk or, alternatively, amplifies risk. This perspective aligns with the policy-relevant objective of understanding how innovation affects the soundness of the banking system as a whole, which is of primary concern to regulators and central banks. Moreover, relying on country-level data can help mitigate several methodological limitations associated with bank-level analyses. Bank-level studies often face severe endogeneity arising from reverse causality and self-selection, as more efficient or less risky banks may be more likely to adopt innovative technologies. Country-level innovation indicators, which are typically exogenous to individual banks, reduce this concern and allow for a clearer identification of the innovation-NPL relationship. In addition, country-level data facilitate cross-country comparisons and improve external validity, enabling researchers to draw broader conclusions about how innovation influences credit risk across different institutional and developmental contexts.

We find that while Oceania demonstrates the highest innovation and the lowest NPLs, Africa displays the lowest innovation and highest NPLs. Furthermore, our regression analysis shows that increased innovation levels can lower NPLs in the banking system. Additionally, our results reveal that this impact of innovation exists in low-corruption environments and can diminish in highly corrupt settings. These findings are robust when we employ alternative regression methods, such as a pooled ordinary least squares (OLS) model, an instrumental variables approach, or a system generalized method of moments (SGMM) technique.

The contributions of this paper are threefold. First, this study adds to the existing body of literature on the determinants of NPLs. While prior research has thoroughly explored the macroeconomic and bank-specific determinants of NPLs, such as GDP growth, unemployment, interest rates, bank profitability, capital adequacy and bank management (e.g., Beck et al., 2015; Ghosh, 2015; Louzis et al., 2012; Makri et al., 2014; Radivojevic & Jovovic, 2017), this study introduces innovation as a novel determinant. The second contribution of this study is to expand the line of literature on the impact of innovation on bank risk. Previous studies highlight the positive effects of financial innovation on bank risk, such as enhancing financial stability (i.e., Li, G. et al., 2022; or Merton, 1992) or improving the risk management of banks (i.e., Bao et al., 2024). We address this gap by demonstrating that national innovation measured by a country capacity for and success in innovation also affect bank risk. Specifically, national innovation can reduce the level of NPLs in the banking system. Finally, we take into consideration this impact of innovation under the setting of high and low corruption. Existing relevant studies indicate that corruption can either hinder or support innovation (i.e., Bukari & Anaman, 2021; Cerdeira & Lourenco, 2022; Ellis et al., 2020; Xie et al., 2019). Our findings indicate that high levels of corruption negate the beneficial role of innovation in reducing NPLs. To the best of our knowledge, we believe we are one of the first to find this evidence.

The rest of this paper is structured as follows. Section 2 reviews the literature on non-performing loans and innovation, and explain theoretically how innovation can affect non-performing loans. Section 3 provides the data and methodology employed in this study. Section 4 reports the empirical results. Finally, Section 5 concludes and provides policy recommendations.

2. Literature Review

The issue of non-performing loans in banks has long been a topic of significant interest among scholars worldwide. Numerous studies have examined factors, including both macroeconomic factors and individual bank characteristics, that influence banks' non-performing loans. For example, Makri et al. (2014) found evidence indicating that a country's public debt ratio and unemployment rate have a positive impact on the non-performing loans of banks, while GDP growth has a negative impact on the non-performing loans. Beck et al. (2015) also pointed out an inverse relationship between GDP growth and non-performing loans of the banking system. Furthermore, Beck et al. (2015) also indicated that when a country's currency depreciates and lending interest rates rise, the bad debt of the banking system increases. Finally, this study highlights the negative impact of stock prices on non-performing loans of the banking system. Radivojedic and Jovovic (2017) also found similar results to the previous studies, showing that an increase in GDP can reduce the non-performing loans of the banking system, whereas currency depreciation and rising unemployment rates can increase bad debt. Additionally, this study also reports a positive relationship between the inflation rate and the bad debt ratio of the banking system and an inverse relationship between housing prices and non-performing loans.

Regarding the characteristics of banks, the findings of Makri et al. (2014) showed that the ratio of capital and reserves to total bank assets and bank profitability has a negative impact on banks' non-performing loans. The studies by Radivojedic and Jovovic (2017) and Dimitrios et al. (2016) also indicated an inverse relationship between bank profitability and bad debt ratio. Radivojedic and Jovovic (2017) provided evidence that the capital adequacy ratio, interest margin and risk provisioning ratio have a positive impact on non-performing loans of the banking system.

One of the shortcomings of the aforementioned studies is that they have overlooked the potential impact of innovation on non-performing loans across the entire banking system. Innovation has long been considered one of the crucial foundations for a country's long-term economic growth (Dosi, 1988; Nelson, 1993; Soete & Freeman, 2012). Several studies have shown that innovation is a significant driver of economic growth. For instance, Lee and Lee (2020) pointed out that innovation helps promote economic growth in the United States. Law et al. (2020) found evidence indicating that innovation enhances economic growth in Malaysia. Similarly, Gyedu et al. (2021) reported similar evidence when studying G7 and BRICS countries.

Innovation is also considered one of the key factors influencing the stability of financial markets. However, the impact of innovation on financial market stability remains unclear. On one hand, innovation is believed to contribute to better and more stable financial market performance. Merton (1992) argued that innovation has gradually transformed financial markets over time by introducing new financial products such as forward contracts, futures contracts, options and swaps. These new financial products help markets function more effectively, creating more opportunities for investors by better meeting their needs. In addition, Merton (1992) suggested that new financial products enable investors to diversify their investments more efficiently, allowing them to gain more from their portfolios. Innovation can also foster financial integration among countries, thereby helping to reduce investment risks and allocate capital more efficiently (Mendoza et al., 2009). Bao et al. (2024) found that financial technology innovation can enhance bank risk management, implying that financial technology innovation can improve financial market stability. Yu (2024) also found that financial technology innovation can lead to a reduction in bank risk.

On the other hand, innovation that leads to the creation of many high-risk financial products is also considered a cause of financial crises, such as the global financial crisis of 2009. Several studies suggest that the development of financial markets can pose threats to economic growth. For instance, Rajan (2006) argued that the growth of financial intermediaries can introduce risks to these very institutions, and if these risks materialise, they can have negative effects on the broader economy. Piazza (2015) pointed out that financial innovations reduce the incentives to gather internal information and degrade the quality of public information, leading to a tendency for the economy to invest more in overly risky technologies, which can endanger economic stability.

The aforementioned studies suggest that innovation has a significant impact on financial markets in general and financial intermediaries such as banks in particular. Numerous studies have explored the relationship between innovation and bank performance. Scott et al. (2017) suggested that innovation in the network links among banks enhances long-term profitability, especially for smaller banks. Additionally, Akhisar et al. (2015) provided evidence that innovation in electronic banking services helps banks improve their operational efficiency.

In addition to studying the impact of innovation on bank performance, several studies have examined the relationship between innovation and bank risk. Li, C. et al. (2022) provided evidence that innovation in financial technology helps reduce banks' risk-taking behaviour. Specifically, this study finds that innovation can reduce the asset-to-equity ratio of banks (indicating a reduction in lending), increases the Z-score (calculated as the sum of the return on assets ratio plus the capital adequacy ratio divided by the standard deviation of the return on assets ratio), and increases the deposit-to-loan ratio of banks.

Chen and Du (2016) have developed a model and found evidence of a U-shaped relationship between financial innovation and bank stability (measured by the volatility of bank returns from lending). Specifically, the study shows that when financial innovation begins, bank stability decreases (the volatility of bank returns increases). However, after financial innovation reaches a certain threshold, bank stability improves (the volatility of bank returns decreases). Guo et al. (2024) found the quantile-varying relationship between FinTech adoption and bank risk-taking. Their results indicate a risk-increasing effects of FinTech adoption for low and middle quantiles but a risk-reduction effects of Fintech adoption for high quantiles.

Gonzalez et al. (2016) mentioned that financial innovation increases risk, measured by bankruptcy risk and the Z-score, for European banks. Chen and Shen (2024) showed that FinTech can increase the systemic risk of Chinese banks. Therefore, the results regarding the impact of innovation on bank risk are mixed, with some studies indicating that innovation reduces bank risk (e.g., Li, C. et al., 2022; or Li, G. et al., 2022), while others suggest that it increases bank risk (e.g., Gonzalez et al., 2016).

Although some studies have investigated the impact of global innovation on bank performance measured by ROA (return on assets), ROE (return on equity), or stock returns (e.g., Albaity et al., 2025), few studies have yet investigated the impact of innovation on the non-performing loans of the banking system. Theoretically, the impact of innovation on the non-performing loans of the banking system can be explained by two arguments. First, innovation might lead banks to reduce lending (Li, C. et al., 2022). This reduction in lending can then lead to a decrease in the banks' non-performing loans (Keeton & Morris, 1987). Second, Lee et al. (2021) suggested that advancements in innovation could enhance the operational efficiency of banks. Increased operational efficiency, in turn, could reduce the banks' non-performing loans (Podpiera & Weill, 2008; Salas & Saurina, 2002). Thus, both arguments imply that an increase in innovation could reduce the non-performing loans of the banking system. Therefore, this study proposes the following research hypothesis:

Hypothesis 1: An increase in innovation can reduce the non-performing loans of the banking system.

3. Data and Methodology

3.1 Data

The sample consists of country-level banking data from 120 countries during the period from 2013 to 2020. We source the data from the World Bank database. In this study, we use an index measuring innovation from the World Intellectual Property Organization (WIPO) database. Our final data is an unbalanced panel consisting of 771 country-year observations.

3.2 Methodology

We employ the following model to estimate the impact of innovation on bank risk:

$$NPL_{it} = f(GII_{it}, \text{Control variables}_{it}) \quad (1)$$

where i and t indicate country i and year t, respectively. The dependent variable in our study is NPL, which captures the non-performing loans of a country's commercial banking system. It is computed as bank non-performing loans to the total gross loans of a country. The higher the value of this indicator, the higher the non-performing loans in the country's commercial banking system. The independent variable in the model is an index measuring the innovation of an economy. In this study, we employ the Global Innovation Index (GII) as the independent variable. The Global Innovation Index takes the pulse of innovation against a background of an economic and geopolitical environment fraught with uncertainty. This index ranges from 0 to 100 and a higher value of this index implies stronger innovation in the country.

In the model, we also include some control variables that can impact the non-performing loans of the banking system. We include bank profitability (ROE) to capture their effects on bank risk. We also capture the impact of regulatory capital on bank risk by containing the ratio of total regulatory capital to the asset in the model. We include the ratio of operating expenses over the sum of net-interest revenue and other operating income (COST_INCOME) to control the effects of cost management on bank risk. We include the ratio of the assets of three largest commercial banks over the total commercial banking assets (BANK_CONCENTRATION) to control the effects of bank concentration on bank risk. Finally, to capture the macroeconomic effects on bank risk, we include the inflation rate (INFLATION) in Equation (1). Definition of the variables employed in this study is provided in Table 1. When estimating Equation (1), we also include year dummy variables. The standard errors are adjusted for heteroskedasticity and clustered at the country level.

In this paper, we firstly use a pooled ordinary least squares (OLS) model to regress Equation (1). The pooled OLS model provides a baseline assessment of the relationship between innovation and nonperforming loans by exploiting both the cross-sectional and time-series variation in the panel dataset. By treating the data as a single pooled sample, the model assumes homogeneity in slope coefficients across countries and over time. Despite this restrictive assumption, pooled OLS is useful as a first-pass estimation strategy, offering intuitive and easily interpretable estimates of the average

Table 1. Variable definition

Variable	Definition
NPL	The ratio of defaulting loans (payments of interest and principal past due by 90 days or more) to total gross loans (total value of loan portfolio).
GII	Global Innovation Index.
ROE	Commercial banks' after-tax net income to yearly average equity.
REGULATORY_CAPITAL	The ratio of total regulatory capital to the assets held, weighted according to the risk of those assets.
COST_INCOME	Operating expenses of a bank as a share of the sum of net-interest revenue and other operating income.
BANK_CONCENTRATION	The assets of three largest commercial banks as a share of total commercial banking assets.
INFLATION	Inflation rate.

association between innovation and banks' nonperforming loans. However, because pooled OLS does not control for unobserved country characteristics, the estimated effect may be subject to omitted-variable bias. In addition, the pooled OLS framework does not explicitly address potential endogeneity concerns arising from reverse causality or simultaneity between innovation and nonperforming loans, leading to biased co-efficient estimates.

As a result, in the robustness tests, we employ alternative regression methods to deal with endogeneity problems. Specifically, we employ an instrumental variables (IV) model to estimate Equation (1). In the first step, the potentially endogenous explanatory variable, which is the innovation index in this paper, is regressed on the instrumental variables and all other exogenous control variables included in the structural model. This stage isolates the component of the endogenous variable that is driven solely by exogenous variation. We select the labour productivity and education index as instruments in this paper. In the second step, the dependent variable, which is the nonperforming loan in our paper, is regressed on the predicted values of the endogenous variable (innovation index) obtained from the first stage, along with the same set of control variables. Because the predicted component of innovation is constructed using only exogenous variation from the instruments, it is uncorrelated with the error term in the nonperforming loan equation. As a result, the second-stage coefficient captures the causal effect of innovation on nonperforming loans, free from biases arising from reverse causality or omitted variables.

We also apply a two-step system generalized method of moments (SGMM) to account for the dynamic nature of nonperforming loans and to address potential endo-geneity in the regression equation. Nonperforming loans are well known to exhibit strong persistence over time, reflecting the slow adjustment of credit risk and the accumulation of legacy problem loans. Including the lagged dependent variable in the regression captures this dynamic behaviour but renders conventional estimators such as pooled OLS and fixed effects biased and inconsistent. System GMM overcomes this issue by jointly estimating equations in first differences and in levels. The system GMM framework also effectively addresses endogeneity concerns arising from simultaneity, reverse causality, and omitted variables. System GMM exploits internal instruments, namely, lagged levels and lagged differences of the endogenous variables, to isolate exogenous variation.

4. Empirical Results

4.1 Current Situation of the Innovation and Non-performing Loans of the Banking System

Figure 1 reports the average value of the Global Innovation Index of the countries in our sample according to the continents. We divided our sample into 6 continents, which are Europe, Asia, North America, South America, Africa and Oceania in Figures 1A, 1B, 1C, 1D, 1E and 1F, respectively. Figure 1 provides some noticeable results. The first discussion will focus on the GII trend of each continent. For Europe, the figure shows a rising trend for this continent from 2013 to 2017 with a peak in 2017, followed by a steep drop in 2020. For Asia, the GII experienced an upward trend from 2013 to 2019.

Figure 1A: Europe

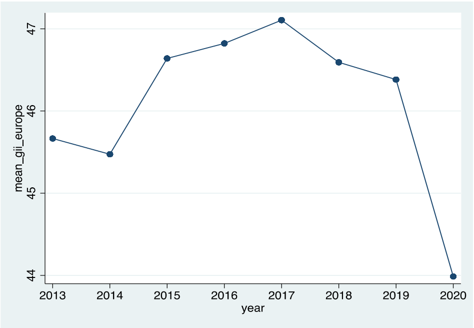

Figure 1B: Asia

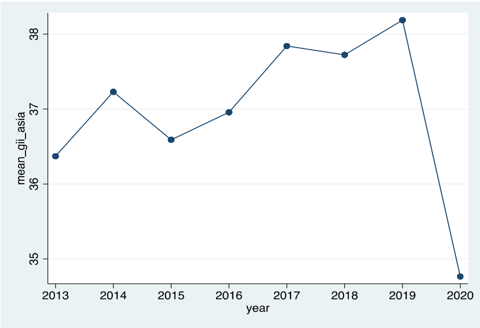

Figure 1C: North America

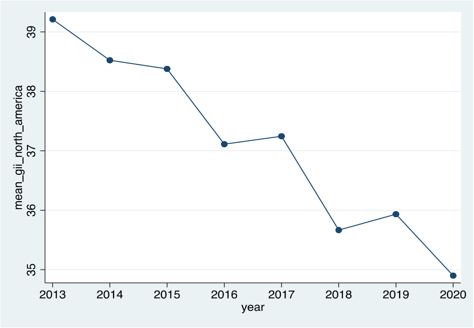

Figure 1D: South America

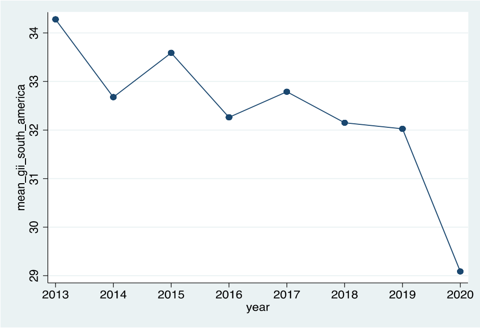

Figure 1E: Africa

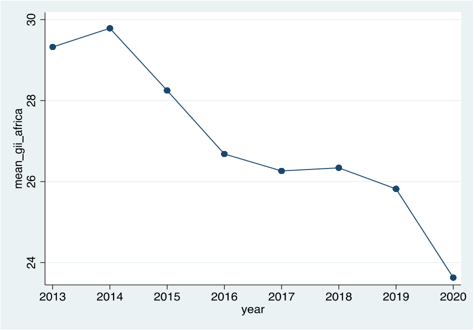

Figure 1F: Oceania

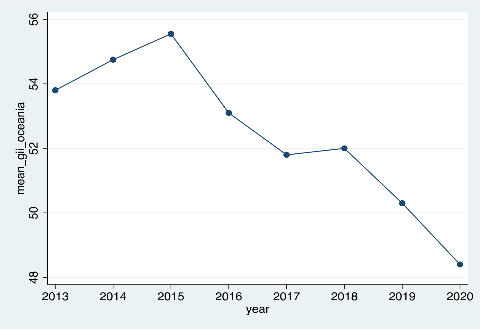

Figure 1. Global Innovation Index of countries according to continents

However, a sharp decline in the Asian GII occurred in 2020. For the four remaining continents, the patterns are similar when the GII of the countries in these continents on average reduced over the period from 2013 to 2020 with a big drop in 2020. Overall, Figure 1 suggests that the innovation capability of countries in our sample has weakened in 2020. This may be due to the negative impact of Covid-19 pandemic that affects all the countries worldwide detrimentally.

Figure 1 also displays there are significant variations in the Global Innovation Index between continents. Figure 1 illustrates that countries in Oceania have the highest GII with the value ranging from around 48 to 56, implying the innovation capability of the countries in this continent is the best. However, this may be because we have only two countries in our sample for this continent, which are Australia and New Zealand. Both of the two countries are very developed countries. European countries have the second highest GII index (varying from around 44 to 47), followed by Asian and North American countries (ranging from approximately 35 to 39). The fifth rank in GII belongs to countries in South America with the value of GII being from roughly 29 to 34. Countries in Africa have the lowest GII index, suggesting that these countries have the worst innovation capability.

Figure 2 reports the trends in the non-performing loans of the banking industry of countries according to the continents. Similar to Figure 1, we also divide the countries in our sample into six continents. For Europe, the non-performing loans in the banking systems of this continent experienced a clear downward trend from 2013 to 2020, with a significant reduction in NPLs in 2018. This may suggest that European banks have been steadily improving their management of non-performing loans, possibly due to regulatory reforms and improved banking practices following the 2008 financial crisis. For Asian banks, the non-performing loans had a big drop in 2014 and was followed by slight fluctuations from 2014 to 2020, with a small uptick in 2020. The non-performing loans of North American banks and South American banks show different trends. Whereas the NPLs of the former decreased in 2014 and 2015, followed by a relatively flat period with slight fluctuations until a rise toward 2020, the NPLs of the latter rose sharply from 2013 to 2018, peaking around 2019 before dropping in 2020. For Africa, the NPLs of African banks increased sharply from 2013 to 2016 and then fell from 2017 to 2019. They rose slightly in 2020. For Oceania banks, the graph illustrates a decrease in the NPLs from 2013 to 2015, followed by fluctuations in 2016 and 2017 before rising from 2018 to 2020.

With respect to variations in the NPLs between continents, Figure 2 reports that on average, the continent with the lowest NPLs is Oceania. The NPL ratio of this continent ranges from around 0.7% to 1.2% in our sample period. This may be because countries in Oceania have well-established and stringent regulatory systems. Central banks and financial regulators, such as the Reserve Bank of Australia (RBA) and the Reserve Bank of New Zealand (RBNZ), enforce strict capital requirements, risk management practices and loan monitoring processes. These measures help prevent excessive risk-taking by banks. Additionally, Oceania enjoys relatively stable economic conditions, characterised by steady growth, low unemployment rates and manageable inflation. Economic stability reduces the likelihood of businesses and individuals defaulting on their loans. Furthermore, banks in Oceania tend to focus on lending to creditworthy customers, which reduces the likelihood of defaults. The banking sector is generally cautious in lending, especially in terms of mortgage loans, which represent a significant portion of their loan portfolios. Banks in Oceania also typically maintain conservative lending practices, including thorough credit assessments and stress testing. This proactive approach allows banks to anticipate and mitigate potential risks that could lead to loan defaults.

The continents with the second and third highest NPL ratios are North America and South America, respectively. The NPL ratio of these two continents varies from roughly 1.7% to 3.2%. This can be expected because the banking system in North America, including US and Canadian banks, is highly regulated. For example, in the

Figure 2. Non-performing loans of the banking industry of countries according to the continents

US, banks are under the oversight of government bodies such as the Federal Reserve, Federal Deposit Insurance Corporation and the Office of the Comptroller of the Currency. After the 2008 financial crisis, significant reforms like the Dodd-Frank Act introduced more stringent capital requirements and stress tests for banks, helping to reduce risky lending practices. Canada's banking system is known for its conservative approach, with the Office of the Superintendent of Financial Institutions enforcing strict regulations. Canadian banks typically have higher capital buffers, which protect against loan defaults. Chile's banking system is one of the strongest in Latin America, with oversight from the Central Bank of Chile and the Superintendency of Banks and Financial Institutions. Banks in these countries are subject to strict capital and liquidity requirements, helping to maintain financial stability. Uruguay has a similar regulatory framework that ensures banks operate within prudent lending guidelines and maintain sound risk management practices.

Asian banks rank fourth in NPL ratio, followed by European banks. On average, the NPL ratio of Asian banks varies from around 3.5% to just above 5.0% and the corresponding figure for European banks ranges between approximately 5% and 10%. The continent that has the highest NPL ratio, on average, is Africa, with the NPL ratio being from 7% to just below 10%. African countries tend to have higher NPL ratio, which may be due to their political instability and conflict. Political instability, corruption and conflict in some African nations contribute to economic uncertainty. Instability can disrupt economic activities, leading to job losses, business closures and reduced government revenue, all of which increase the risk of loan defaults. In countries experiencing conflict or internal unrest, the banking sector is particularly vulnerable as economic activities decline sharply, leading to higher NPLs. Moreover, in some African countries, banking regulations and supervisory frameworks are underdeveloped or not strictly enforced. This leads to lax lending practices, poor credit assessment processes, and insufficient monitoring of loan performance, allowing banks to accumulate high-risk loans. In addition, many African countries have underdeveloped financial systems with limited access to credit bureaus and reliable credit information. This makes it difficult for banks to accurately assess the creditworthiness of borrowers, leading to higher-risk lending and an increased chance of defaults. Poor access to financial services in rural areas also hampers effective loan recovery, as many customers are beyond the reach of formal banking infrastructure. Finally, some African banks may lack sophisticated risk management tools and strategies, making it difficult to identify and mitigate risks before loans go bad. This is particularly true for smaller banks with limited resources for technology and analytics. The lack of credit information systems also hampers banks' ability to effectively monitor loans and take early corrective actions, contributing to higher default rates.

4.2 Descriptive Statistics

Table 2 provides the summary statistics of all variables employed in this study. The results show a big variation in NPL and GII variables. NPL has a mean value of 5.988% with the minimum and maximum values of 0.213% and 54.541%, respectively.

The average value of GII is 38.516 with a range from 17.2 and 68.4. For control variables, commercial banks in our sample on average have return on equity of 10.740% and a standard deviation of 7.610%. The regulatory capital on average accounts for 17.656% of the total assets. The average value for the ratio of operating expenses over bank income is around 55.673%. On average, the three largest commercial banks have assets that account for 61.466% of total commercial banking assets.

Table 3 reports the correlation matrix of all variables used in this study. The results indicate that the correlation coefficients of all variables are lower than 0.7, suggesting that our regression model does not have multi-collinearity problems.

Table 2. Summary statistics

Variable	N	Mean	Std. dev.	Min	Max
NPL (%)	771	5.988	7.084	0.213	54.541
GII	771	38.516	11.781	17.200	68.400
ROE (%)	771	10.740	7.610	-31.283	56.773
BANK_CAPITAL (%)	771	10.217	3.047	4.343	21.057
REGULATORY_CAPITAL (%)	771	17.656	3.624	8.200	35.653
COST_INCOME (%)	771	55.673	11.563	5.032	118.190
BANK_CONCENTRATION (%)	771	61.466	17.612	16.144	100.000
INFLATION (%)	771	3.932	6.154	-25.958	54.013

Table 3. Correlation matrix

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) NPL	1.000							
(2) GII	-0.203	1.000						
(3) ROE	-0.219	-0.363	1.000					
(4) BANK_CAPITAL	0.146	-0.405	0.147	1.000				
(5) REGULATORY_CAPITAL	-0.025	0.133	-0.037	0.405	1.000			
(6) COST_INCOME	0.015	0.161	-0.327	-0.225	-0.032	1.000		
(7) BANK_CONCENTRATION	0.002	0.231	-0.035	-0.054	0.227	0.058	1.000	
(8) INFLATION	0.097	-0.289	0.366	0.151	-0.035	-0.045	-0.184	1.000

4.3 Regression Results

Column 1 of Table 4 shows the estimated results of Equation (1) from a pooled OLS model. The coefficient of GII is negative and significant at the 1% level, suggesting a negative impact of innovation on non-performing loans. In other words, innovation can reduce banks' nonperforming loans. This result is consistent with previous studies indicating that innovation can reduce bank risk (i.e., Li, C. et al., 2022; Li, G. et al., 2022). The estimated coefficient implies an economically meaningful effect of innovation on nonperforming loans. Specifically, a one-standard deviation increase in the innovation index is associated with a decline of approximately 2.144% in the nonperforming loan ratio (= 11.781x0.182), holding other factors constant. When scaled by the dispersion of nonperforming loans, this corresponds to a reduction of about 0.303 standard deviations of NPLs (= 2.144/7.084). This magnitude suggests that cross-country differences in innovation capacity translate into substantial differences in banks' nonperforming loans. In column 2 of Table 4, we estimate Equation (1) with a one-year lag of all right-hand side variables. The estimated results of this column are similar to those in column 1.

With regard to the control variables, we find some noticeable results. First, the coefficient on ROE is negative and significant at the 1% level in both columns (1) and (2), suggesting that when firm profitability increases, the NPL can reduce. This can be

Table 4. Baseline regression

VARIABLES	Dependent variable: NPL	
	(1)	(2)
GII	-0.182***	-0.200***
	(0.041)	(0.038)
ROE	-0.403***	-0.502***
	(0.080)	(0.072)
BANK_CAPITAL	0.135	0.163
	(0.147)	(0.136)
REGULATORY_CAPITAL	-0.042	-0.094
	(0.139)	(0.145)
COST_INCOME	-0.040	-0.049*
	(0.024)	(0.025)
BANK_CONCENTRATION	0.040	0.046
	(0.041)	(0.042)
INFLATION	0.199**	0.242**
	(0.084)	(0.115)
Constant	15.322***	18.681***
	(2.758)	(2.406)
Observations	771	647
R-squared	0.192	0.264

Note: ***, **, * indicate significant levels at 1%, 5% and 10%, respectively.

explained because profitable banks tend to have better risk management practices and greater financial stability, which help in maintaining lower NPL ratios. High profitability enables banks to set aside more provisions for loan losses, thus mitigating the impact of non-performing loans. Previous studies such as Radivojevic and Jovovic (2017) also showed a negative relationship between profitability and NPLs. Second, the coefficient on INFLATION is significantly positive in two columns of Table 4, implying a positive relationship between inflation and NPLs. This may be because high and volatile inflation can erode real incomes and increase the cost of living, thereby diminishing borrowers' ability to service debt. Nkusu (2011) reported that in low-income countries, higher inflation was associated with an increase in NPLs, as inflationary pressures often reduce the disposable income available for debt repayment.

4.4 Robustness Tests

In this section, we perform two alternative methods to check the robustness of our results. First, we employ an instrumental variable regression method to estimate Equation (1) to deal with the endogeneity problems. To do this, we need to have instrumental variables for GII variables. The first instrument we select is the labour productivity index of a country, which is collected from the International Labour Organization. This index measures the total volume of output (measured in terms of gross domestic product) produced per unit of labour (measured in terms of the number of employed persons or hours worked) during a given time reference period. Labour productivity is a fundamental driver of innovation at the macroeconomic level. Higher labour productivity reflects more efficient production processes, better managerial practices, and greater adoption of advanced technologies, all of which create an enabling environment for innovation activities. Economies with higher productivity can allocate more resources to research and development, attract technologically sophisticated firms, and generate knowledge spillovers that foster innovation outputs such as patents and new technologies. In contrast, labour productivity does not directly determine the quality of banks' loan portfolios. While productivity may correlate with overall economic performance, its effect on NPLs is largely indirect and operates through structural channels, such as technological upgrading and innovation-led growth, rather than through banks' credit risk management or borrowers' repayment behaviour. Once macroeconomic conditions and banking-sector characteristics are controlled for, labour productivity has no independent theoretical link to NPLs other than via its influence on innovation.

The second instrument we choose is the educational index, which is sourced from the Global Data Lab. This index is constructed based on two indicators. The first one, mean years of schooling of adults aged 25+, reflects the current situation with regard to education in society. The second one, expected years of schooling (EYS), indicates the future level of education of the population. Expected years of schooling is defined as the number of years of schooling a child of school entrance age can expect to receive if prevailing patterns of age-specific enrolment rates persist throughout the child's schooling life. When computing the dimension index for education, the values of mean years of schooling and expected years of schooling are weighted equally. The education index captures the stock of human capital, which is a core input in the innovation process. Higher educational attainment enhances workers' cognitive skills, research capabilities and absorptive capacity, enabling economies to generate, adopt and diffuse new technologies more effectively. By contrast, education does not directly affect nonperforming loans. Banks' NPL ratios are primarily driven by borrowers' financial conditions, credit standards and macro-financial shocks, rather than by the average level of education in the economy. Any potential effect of education on loan performance is indirect, materialising through long-term improvements in productivity and innovation that enhance firms' competitiveness and income-generating capacity, rather than through immediate changes in credit risk.

Taken together, labour productivity and education satisfy the relevance condition by being strongly associated with country-level innovation, while also meeting the exclusion restriction in that they do not directly influence nonperforming loans. Their impact on NPLs, if any, is transmitted through innovation-induced structural transformation and economic upgrading, making them appropriate instruments for innovation in the analysis of bank credit risk. We expect a positive relationship between the global innovation index and the two instrumentals. The estimated results are reported in column (1) of Table 5. The results in column (1) show that the coefficient on GII remains negative and significant at the 1% level. The postestimation tests show that the Kleibergen-Paap rk LM statistic is significant, suggesting that our instruments are

Table 5. Alternative regression methods

VARIABLES	Dependent variable: NPL IV (1)	SGMM (2)
L.NPL		0.927***
		(0.040)
GII	-0.157***	-0.067**
	(0.060)	(0.030)
ROE	-0.393***	-0.219***
	(0.075)	(0.040)
BANK_CAPITAL	0.182	-0.029
	(0.190)	(0.157)
REGULATORY_CAPITAL	-0.067	-0.075
	(0.164)	(0.093)
COST_INCOME	-0.039	-0.060***
	(0.024)	(0.019)
BANK_CONCENTRATION	0.038	-0.010
	(0.040)	(0.022)
INFLATION	0.203**	0.096***
	(0.087)	(0.031)
Constant	12.344***	9.966***
	(3.035)	(2.441)
Observations	771	656
Kleibergen-Paap rk LM statistic	37.560***	
Kleibergen-Paap rk Wald F statistic	88.333	
Hansen J Statistics (p-value)	0.743	
AR(1) test (p-value)		0.088
AR(2) test (p-value)		0.766
Hansen test (p-value)		0.630
R-squared	0.191	0.916

Note: ***, **, * indicate significant levels at 1%, 5% and 10%, respectively.

relevant to GII. Moreover, the Kleibergen-Paap rk Wald F statistic is higher than 10, indicating that our instruments are not weak. Additionally, the p-value of the Hansen test is higher than 0.1, implying that our instruments are uncorrelated with the error term. These results confirm the validity of our instrument variables.

The second regression method we use to deal with the endogeneity problems of the model is a two-step System Generalized Method of Moments method. We add the one-year lag value of NPL in the model to capture the dynamic effects of the model. This method uses the lags of the endogenous variables as the instruments for the endogenous variables and the contemporary exogenous variables as the instruments for the exogenous variables. The results from this regression are reported in column (2) of Table 5. The results show that the postestimation tests confirm the validity of the regression method. First, a statistically significant AR(1) test (p-value < 0.1) is expected and desirable. In SGMM, the model is typically estimated in first differences to eliminate unobserved time-invariant effects. The statistically significant AR(1) test indicates that the differencing procedure is working as intended.

Second, a statistically insignificant AR(2) test (p-value > 0.1) is crucial for instrument validity. The null hypothesis of the AR(2) test is no second-order serial correlation in the differenced residuals, which corresponds to no first-order serial correlation in the level error term. This condition is essential because lagged levels of the endogenous variables are used as instruments for the differenced equation. If AR(2) is significant, these lagged levels would be correlated with the error term, violating the moment conditions and rendering the instruments invalid. Hence, a high p-value for AR(2) indicates that the exclusion restrictions underlying the instruments are satisfied. Finally, a statistically insignificant Hansen test (p-value > 0.1) supports the overall validity of the instrument set. The Hansen test examines the null hypothesis that the instruments are jointly exogenous. A high p-value implies that the overidentifying restrictions cannot be rejected, meaning that the instruments are not systematically correlated with the error term. Conversely, a low p-value would indicate instrument endogeneity or misspecification. At the same time, extremely high p-values (e.g., close to 1) may signal instrument proliferation, which weakens the power of the test. The estimation results from the SGMM show that the coefficient on GII continues to be negative and significant at the 5% level. In this analysis, we also find that the coefficient on the lag value of NPL is significantly positive at the 1% level, suggesting that the NPL in the previous year affects positively the NPL in the current year. Overall, our results indicate that the previous findings are robust and support our hypothesis 1.

4.5 Impact of Corruption on the Relationship between Innovation and Non-performing Loans

In this section, we examine whether corruption can affect the negative impact of innovation on nonperforming loans. Previous studies report that corruption can impact innovation. On the one hand, several studies have found that corruption impedes innovation. For instance, Ellis et al. (2020) examined US firms and discovered a significant negative relationship between local political corruption and both the quantity and quality of corporate innovation. Their findings suggested that corruption reduces social welfare by hindering innovation. Similarly, Bukari and Anaman (2021) analysed firms in 33 lower-middle and upper-middle-income economies and conclude that corruption generally has a negative and significant effect on firm innovativeness. This adverse impact is more pronounced in lower-middle-income countries and Africa.

On the other hand, some studies suggest that corruption may facilitate innovation. Xie et al. (2019) investigated firms in China and found that corruption can have a positive effect on new product innovation, especially under conditions of policy instability and competitive threats from the informal sector. They argued that in transition economies with inherent institutional weaknesses, firms might resort to corruption as a strategy to navigate bureaucratic hurdles and foster innovation. Additionally, Cerdeira and Lourenco (2022) analysed Portuguese firms and showed that corruption fosters innovation, particularly among domestic firms. They suggested that in environments with certain institutional settings, corruption might help firms overcome bureaucratic and regulatory obstacles, thereby enhancing their innovative activities.

To investigate the impact of corruption on the relationship between innovation and non-performing loans of the banking system, we will divide our sample into two subsamples based on an index capturing the level of corruption of a country, namely the Control of Corruption Index. This index captures perceptions of the extent to which public power is exercised for private gain, including both petty and grand forms of corruption, as well as "capture" of the state by elites and private interest. We source the information for this index from the World Bank Database. A higher value of the index indicates a lower level of corruption. We use the median value of the index to split the sample into two subsamples. Countries with index values at or below the median are classified as high-corruption countries, while those with values above the median are classified as low-corruption countries. Table 6 shows the estimation results of Equation (1) for each sub-sample.

Panel A contains observation corresponding to high level of corruption. Results show that the coefficient on the innovation index (GII) is insignificant in all three columns of this panel, suggesting that the negative impact of innovation on non-performing loans of the banking system is insignificant when the level of corruption is high. By contrast, for Panel B including the observations related to low level of corruption, the corresponding coefficient is significant in all three columns of this panel, suggesting that the negative effects of innovation on non-performing loans remain when the level of corruption is low. Since non-performing loans harm the economy, our findings highlight the negative impact of corruption, which undermines the potential benefits of innovation in reducing these loans.

5. Conclusions

The aim of this paper is to provide significant insights into the impact of innovation on non-performing loans of the banking system. By employing a comprehensive dataset spanning 120 countries from 2013 to 2020 and utilising robust econometric regression techniques, we find that higher levels of innovation can lower the level of non-performing loans. However, our results show that in countries with high levels of corruption, the beneficial effects of innovation on reducing non-performing loans are weakened. In contrast, in countries with lower levels of corruption, innovation maintains its strong negative impact on non-performing loans, reinforcing the notion that an effective institutional environment is crucial for maximising the benefits of innovation in the banking industry.

Our study offers valuable policy implications for governments. Given the detrimental impact of NPLs on economic stability, fostering innovation should be a priority for policymakers seeking to enhance financial sector resilience. Our findings also highlight the importance of addressing corruption to ensure that the benefits of innovation are fully realised. This study is not without limitations. It relies on country-level data, which may mask variations in the relationship between innovation and NPLs at the individual bank level.

Table 6. Impact of corruption on the relationship between innovation and non-performing loans of the banking system

	Panel A: High level of corruption		
	Pooled OLS	IV	SGMM
VARIABLES	(1)	(2)	(3)
L.NPL			0.954***
			(0.029)
GII	-0.057	-0.027	-0.039
	(0.156)	(0.217)	(0.093)
ROE	-0.280***	-0.273***	-0.144***
	(0.075)	(0.075)	(0.039)
BANK_CAPITAL	0.031	0.023	0.101
	(0.227)	(0.228)	(0.151)
REGULATORY CAPITAL	0.194	0.197	-0.143
	(0.171)	(0.167)	(0.182)
COST_INCOME	-0.033	-0.028	-0.002
	(0.046)	(0.051)	(0.084)
BANK_CONCENTRATION	0.012	0.013	-0.031
	(0.033)	(0.032)	(0.048)
INFLATION	0.256*	0.256*	0.102**
	(0.142)	(0.140)	(0.040)
Constant	6.776	5.572	6.197
	(6.397)	(8.394)	(5.824)
Observations	386	386	325
R-squared	0.121	0.120	0.894

	Panel B: Low level of corruption		
	Pooled OLS	IV	SGMM
VARIABLES	(1)	(2)	(3)
L.NPL			0.803***
			(0.049)
GII	-0.242***	-0.200**	-0.079*
	(0.056)	(0.079)	(0.046)
ROE	-0.562***	-0.550***	-0.289**
	(0.113)	(0.111)	(0.136)
BANK_CAPITAL	0.109	0.196	-0.215
	(0.177)	(0.290)	(0.196)
REGULATORY CAPITAL	-0.212	-0.256	-0.173**
	(0.195)	(0.255)	(0.084)
COST_INCOME	-0.055	-0.054	-0.065
	(0.034)	(0.035)	(0.045)
BANK_CONCENTRATION	0.076	0.076	0.011
	(0.057)	(0.057)	(0.026)
INFLATION	0.082	0.093	0.118**
	(0.105)	(0.089)	(0.056)
Constant	18.848***	16.885***	14.756***
	(4.103)	(5.971)	(5.604)
Observations	385	385	331
R-squared	0.315	0.313	0.933

Note: ***, **, * indicate significant levels at 1%, 5% and 10%, respectively.

Future research could further explore the mechanism through which innovation influences NPLs at the micro-level, focusing on specific banking practices. Additionally, examining the role of emerging financial technology such as artificial intelligence and blockchain in reducing NPLs could provide deeper insights into the evolving landscape of banking risk management. By continuing to explore these dynamics, scholars and practitioners can contribute to the development of more robust and sustainable financial systems worldwide.

References

Akhisar, I., Tunay, K.B., & Tunay, N. (2015). The effects of innovations on bank performance: The case of electronic banking services. *Procedia – Social and Behavioral Sciences, 195*, 369–375. https://doi.org/10.1016/j.sbspro.2015.06.336

Albaity, M., Mallek, R.S., Ur-Rehman, I., & Mustafa, H. (2025). Global innovation and uncertainty dynamics: Implications for bank performance. *Journal of Innovation & Knowledge, 10*(6), Article 100800. https://doi.org/10.1016/j.jik.2025.100800

Bao, W., Xiao, J., Deng, T., Bi, S., & Wang, J. (2024). The challenges and opportunities of financial technology innovation to bank financing business and risk management. *Financial Engineering and Risk Management, 7*(2), 82–88. https://doi.org/10.23977/ferm.2024.070212

Beck, R., Jakubik, P., & Piloiu, A. (2015). Key determinants of non-performing loans: New evidence from a global sample. *Open Economies Review, 26*, 525–550. https://doi.org/10.1007/s11079-015-9358-8

Bukari, C., & Anaman, E.A.A. (2021). Corruption and firm innovation: A grease or sand in the wheels of commerce? Evidence from lower-middle and upper-middle income economies. *Eurasian Business Review, 11*, 267–302. https://doi.org/10.1007/s40821-020-00164-8

Cerdeira, J., & Lourenco, D. (2022). Does corruption impact firm innovation? Evidence from Portugal. *Economies, 10*(7), Article 173. https://doi.org/10.3390/economies10070173

Chen, Q.A., & Du, F. (2016). Financial innovation, systematic risk and commercial banks' stability in China: Theory and evidence. *Applied Economics, 48*(41), 3887–3898. https://doi.org/10.1080/00036846.2016.1148255

Chen, Q., & Shen, C. (2024). How FinTech affects bank systemic risk: Evidence from China. *Journal of Financial Services Research, 65*, 77–101. https://doi.org/10.1007/s10693-023-00421-7

Dimitrios, A., Helen, L., & Mike, T. (2016). Determinants of non-performing loans: Evidence from Euro-area countries. *Finance Research Letters, 18*, 116–119. https://doi.org/10.1016/j.frl.2016.04.008

Dosi, G. (1988). Sources, procedures, and microeconomic effects of innovation. *Journal of Economic Literature, 26*(3), 1120–1171. https://www.jstor.org/stable/2726526

Ellis, J., Smith, J., & White, R. (2020). Corruption and corporate innovation. *Journal of Financial and Quantitative Analysis, 55*(7), 2124–2149. https://doi.org/10.1017/S0022109019000735

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. https://doi.org/10.1016/j.jfs.2015.08.004

Gonzalez, L.O., Gil, L.I.R., Cunill, O.M., & Lindahl, J.M.M. (2016). The effect of financial innovation on European banks' risk. *Journal of Business Research, 69*(11), 4781–4786. https://doi.org/10.1016/j.jbusres.2016.04.030

Guo, P., Cheng, M., & Shen, Y. (2024). FinTech adoption and bank risk-taking: evidence from China. *Applied Economics Letters, 31*(7), 594–602. https://doi.org/10.1080/13504851.2022.2140755

Gyedu, S., Heng, T., Ntarmah, A.H., He, Y., & Frimppong, E. (2021). The impact of innovation on economic growth among G7 and BRICS countries: A GMM style panel vector autoregressive approach. *Technological Forecasting and Social Change, 173*, Article 121169. https://doi.org/10.1016/j.techfore.2021.121169

Keeton, W.R., & Morris, C.S. (1987). Why do banks' loan losses differ? *Economic Review*, Federal Reserve Bank of Kansas City, 72(5), 3–21.

Law, S.H., Sarmidi, T., & Goh, L.T. (2020). Impact of innovation on economic growth: Evidence from Malaysia. *Malaysian Journal of Economic Studies, 57*(1), 113–132. https://doi.org/10.22452/MJES.vol57no1.6

Lee, C-C., Li, X., Yu, C-H., & Zhao, J. (2021). Does fintech innovation improve bank efficiency? Evidence from China's banking industry. *International Review of Economics & Finance, 74*, 468–483. https://doi.org/10.1016/j.iref.2021.03.009

Lee, K., & Lee, J. (2020). National innovation systems, economic complexity, and economic growth: Country panel analysis using the US patent data. *Journal of Evolutionary Economics, 30*, 897–928. https://doi.org/10.1007/s00191-019-00612-3

Li, C., He, S., Tian, Y., Sun, S., & Ning, L. (2022). Does the bank's FinTech innovation reduce its risk-taking? Evidence from China's banking industry. *Journal of Innovation & Knowledge, 7*(3), Article 100219. https://doi.org/10.1016/j.jik.2022.100219

Li, G., Elahi, E., & Zhao, L. (2022). Fintech, bank risk-taking, and risk-warning for commercial banks in the era of digital technology. *Frontiers in Psychology, 13*, Article 934053. https://doi.org/10.3389/fpsyg.2022.934053

Louzis, D.P., Vouldis, A.T. & Metaxas, V.L. (2012). Macroeconomic and bank-specific determinants of non-performing loans in Greece: A comparative study of mortgage, business and consumer loan portfolios. *Journal of Banking & Finance, 36*(4), 1012–1027. https://doi.org/10.1016/j.jbankfin.2011.10.012

Makri, V., Tsagkanos, A. & Bellas, A. (2014). Determinants of non-performing loans: The case of Eurozone. Panoeconomicus, 61(2), 193–206. https://doi.org/10.2298/PAN1402193M

Mendoza, E.G., Quadrini, V., & Rios-Rull, J-V. (2009). Financial integration, financial development, and global imbalances. *Journal of Political Economy, 117*(3), 371–416. https://doi.org/10.1086/599706

Merton, R.C. (1992). Financial innovation and economic performance. *Journal of Applied Corporate Finance, 4*(4), 12–22. https://doi.org/10.1111/j.1745-6622.1992.tb00214.x

Nelson, R.R. (1993). *National innovation systems: A comparative analysis*. Oxford University Press.

Nkusu, M.M. (2011). *Nonperforming loans and macrofinancial vulnerabilities in advanced economies* (IMF Working Paper No. WP/11/161). International Monetary Fund. https://www.imf.org/external/pubs/ft/wp/2011/wp11161.pdf

Piazza, R. (2015). Financial innovation and risk: The role of information. *Annals of Finance, 11*, 477–502. https://doi.org/10.1007/s10436-015-0267-z

Podpiera, J., & Weill, L. (2008). Bad luck or bad management? Emerging banking market experience. *Journal of Financial Stability, 4*(2), 135–148. https://doi.org/10.1016/j.jfs.2008.01.005

Radivojevic, N., & Jovovic, J. (2017). Examining of determinants of non-performing loans. *Prague Economic Papers, 26*(3), 300–316. https://doi.org/10.18267/j.pep.615

Rajan, R.G. (2006). Has finance made the world riskier? *European Financial Management, 12*(4), 499–533. https://doi.org/10.1111/j.1468-036X.2006.00330.x

Salas, V., & Saurina, J. (2002). Credit risk in two institutional regimes: Spanish commercial and savings banks. *Journal of Financial Services Research, 22*, 203–224. https://doi.org/10.1023/A:1019781109676

Scott, S.V., Van Reenen, J., & Zachariadis, M. (2017). The long-term effect of digital innovation on bank performance: An empirical study of SWIFT adoption in financial services. *Research Policy, 46*(5), 984–1004. https://doi.org/10.1016/j.respol.2017.03.010

Soete, L., & Freeman, C. (2012). *The economics of industrial innovation*. Routledge.

Xie, X., Qi, G., & Zhu, K.X. (2019). Corruption and new product innovation: Examining firms' ethical dilemmas in transition economies. *Journal of Business Ethics, 160*, 107–125. https://doi.org/10.1007/s10551-018-3804-7

Yu, J. (2024). Stabilizing leverage, financial technology innovation, and commercial bank risks: Evidence from China. *Economic Modelling, 131*, Article 106599. https://doi.org/10.1016/j.econmod.2023.106599