THE ECONOMETRIC MODELLING OF BANKS NON-PERFORMING LOANS AT THE COUNTRY-LEVEL AND THE BANK-LEVEL

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Dedication

To my amazing parents.

To my loving siblings.

This is for us.

Declaration

I declare that the contents of this thesis are original and have not been submitted in whole or in part for consideration for any other degree or qualification in this, or any other university. Except where stated otherwise in specific reference and acknowledgement, this work is original. This thesis contains fewer than 60,000 words including appendices, bibliography, footnotes, equations, and tables and has fewer than 150 figures.

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Abstract

There has been a lot of debate regarding the many determinants of banks' non-performing loans across several regions of the world. This debate between several researchers and policy makers has been ongoing since the 2008 global financial crisis and even intensified with the emergence of the sovereign debt crisis in the Eurozone in 2010. Due to the rapid increase of non-performing loans (NPLs) immediately after the global financial crisis that led to the folding up of a significant number of banks, several studies have been done to investigate the determinants of banks' non-performing loans. This thesis, amongst other determinants, focuses on the effect of banking competition on NPLs at the country-level and at the bank-level and also investigates the relationship between NPLs and banks credit ratings. In chapter 1, I provide a general introduction to the thesis.

In chapter 2, we identify banking competition as a key determinant of NPLs and investigate the relationship between them at the country level. Using a panel data set covering a total of 105 countries for the period 2004-2016 and employing different panel data models, focusing on the fixed-effects estimator which takes into account country-level unobserved heterogeneity, this chapter tests the two views in the literature, i.e. the "competition-fragility" hypothesis and the "competition-stability" hypothesis). Contrary to previous studies that find evidence that supports only one hypothesis, this study provides evidence that supports both hypotheses. The results show that overall, a U-shaped relationship exists between NPLs and banking competition, with negative relationship at low competition levels, while positive for higher levels of competition. We go further to test whether the country's level of development in which banks operate significantly influences the relationship between banking competition and NPLs. The results further show that, when the country's level of development is accounted for a U-shaped relationship still holds for low and medium developed countries while for highly developed countries, the result suggests a less quadratic relationship. Results

from this chapter contribute to the existing literature by using more recent data which covers a bigger sample size and by providing evidence that shows that overall, there is an optimal level of banking competition at which predicted NPLs are at their minimum. This chapter also contributes to the existing literature by investigating this relationship before and after the global financial crisis, employing different measures of banking competition and accounting for the potential issue of endogeneity of the banking competition variables through the application of the Instrumental Variable technique.

In chapter 3, using a combination of bank-level data and country-level data, we go further to test this relationship at the bank-level. Covering a total of 706 banks operating in 85 countries for the period 2004-2016, this chapter employs the use of a multi-level model approach due to the unique structure of our dataset which exhibits crossed random effects. The results suggest that a U-shaped relationship still holds for low and medium developed countries while for highly developed countries, the result suggests a less quadratic relationship as observed in low and medium developed countries. These results confirm that even at the bank-level, the country's level of development in which banks operate has an impact on the relationship between NPLs and banking competition.

In chapter 4, we investigate the relationship between NPLs and banks credit ratings. Using a total of 145 banks for the period 2004-2016, this chapter employs the use of the Panel Vector Autoregressive Model as well as the Panel Granger causality test to examine whether a two-way relationship exists between bank credit ratings and NPLs. The results reveal that, not only do NPLs affect banks credit ratings, but banks credit ratings also – through lending channels - affect NPLs.

Chapter 1

General Introduction

Several research studies have shown the importance of the banking system on the overall financial stability of an economy (Hoggarth et. Al., 2002; Uhde and Heimeshoff, 2009; Ben et. Al., 2018). Therefore, investigating those key factors that provide insight into the strength and financial soundness of the banking system is paramount. This thesis focuses on non-performing loans (NPLs), as existing studies show that NPL is one of those key factors that provide insight into the strength and financial soundness of the banking system (Balgova et. al., 2016; Anastasiou et. al., 2019). The 2008 global financial crisis proved beyond all doubt the importance of ensuring good loan performance in the banking system. Due to the rapid increase of NPLs right after the global financial crisis, a significant number of banks folded up which had a huge impact on the banking industry as well as the overall economy. This occurrence, as a result of high NPLs, raised a lot of concern within the banking industry and among regulatory authorities in several countries. This concern led to an increase in the interest in NPLs within the academia and sparked a lot of debate regarding the determinants that influence banks' NPLs.

Since the 2008 global financial crisis, several studies that have attempted to study the determinants of NPLs have identified banking competition as one of those key determinants (Lowe, 2009; Balgova et. al., 2016; Ozili, 2018). Before the 2008 global financial crisis, competition in the banking industry in many countries was not very encouraging as many believed that allowing for competition in the industry will lead to banking fragility (Beck et. Al., 2006; Allen and Gale, 2004). In response to the financial crisis, for example, the U.S. Congress passed the Dodd-Frank Act in 2010. This legislation aimed to reduce risks in the financial system by increasing transparency, improving accountability, and enhancing consumer protections. This measure was intended to curb excessive risk-taking and promote a more competitive and stable banking environment. Similarly, The European Union implemented several reforms to strengthen the banking sector's resilience and enhance competition. The Banking Union, which includes the Single Supervisory Mechanism (SSM) and the Single Resolution Mechanism (SRM), aimed to centralize the supervision and resolution of banks within the Eurozone. Additionally, the CRD IV package, which came into effect in 2014, introduced stricter capital requirements, improved risk management practices, and greater transparency. These regulations weredesigned to create a more level playing field among banks, reduce the likelihood of future crises, and ensure that banks could compete fairly while maintaining financial stability. However, some years after the 2008 global financial crisis, many regulatory authorities re-evaluated their existing policies and regulations regarding banking competition. This change brought about a more conducive environment for banking competition as many began to embrace the view that allowing for competition in the banking industry could lead to a more stable banking system.

In recent times, despite allowing for more banking competition, NPLs have been seen to be on the increase as different countries are recording high rates of NPLs. This has been a source of worry in the banking industry because, if not properly managed, could lead to a potential threat to the financial strength of the industry. Competition has always been a contentious issue in the banking system and the debate on its effect is still inconclusive nowadays. As a result of this, this thesis answers the question: what is the impact of banking competition on NPLs? In chapter 2, using country-level panel data that covers a total of 105 countries for the period 2004-2016, we approach this question by testing the two different banking competition views in literature, the competition-fragility view (Marcus, 1984 and Keeley, 1990) and the competition-stability view (Boyd and De Nicolò, 2005) while also controlling for the country's level of development in which the banks operate. We argue that the country's level of development in which the banks operate impacts the effect banking competition has on NPLs. Knowing the extent to which this relationship is impacted by the country's level of development is important to policy makers and regulatory authorities as this will help them in making more informed decisions when initiating and implementing certain banking policies. Applying fixed effects estimations and the Instrumental Variable Technique, which helps to address the potential issue of endogeneity of the competition variable, the results from this chapter provide evidence that shows that there is an optimal level of banking competition at which predicted NPLs are at their minimum. The results further reveal that the optimal level of competition in a country varies according to the country's level of development. The results reveal that in countries where the banking sector experiences low to moderate levels of competition, the relationship between competition and NPLs follows a U-shaped curve. This means that at very low levels of competition, banks may have little incentive to be efficient or stringent in their lending practices, leading to higher NPLs. As competition increases to a moderate level, banks become more efficient and careful with their lending, resulting in a decrease in NPLs. However, if competition increases beyond this optimal point, banks might take excessive risks to maintain their market share, causing NPLs to rise again, hence the U-shape.

In Chapter 3, we investigate the relationship between banking competition and non-performing loans (NPLs) by utilizing bank-level data while controlling for the level of development of the countries in which the banks operate. We contend that while aggregate-level data provides useful overviews, bank-level data offers a more granular perspective, enabling a precise understanding of patterns, outcomes, and impacts. This level of detail enhances the accuracy of insights, allowing researchers, policymakers, and banks to make more informed decisions and design more effective banking policies. By employing a multi-level model to account for the hierarchical nature of the dataset and analyzing data from 706 banks across 85 countries, our findings indicate that in low and medium developed countries, there exists an optimal level of banking competition where predicted NPLs are minimized. Conversely, in highly developed countries, a less competitive banking market tends to improve loan performance. These insights highlight the importance of tailoring banking competition policies to the specific developmental context of each country to optimize banking stability and performance.

In Chapter 4, we shift our focus to another critical factor that indicates the strength and financial soundness of the banking system: banks' credit ratings. Previous studies (Gray et al., 2006; Hassan, 2013; Klusak et al., 2017) have established that bank credit ratings provide crucial insights into the likelihood of a bank defaulting on its debt payments or going out of business. These studies also identify non-performing loans (NPLs) as a key determinant of banks' credit ratings. Thus, in this chapter, we investigate the relationship between banks' credit ratings and NPLs using data from 145 banks. Unlike previous research that primarily focuses on a unidirectional relationship between banks' credit ratings and NPLs, our study proposes that a bidirectional relationship is theoretically more appropriate. Empirical evidence supports this proposition. Utilizing the Panel Vector Autoregressive Model and the Panel Granger causality test, our main findings reveal that NPLs not only impact banks' credit ratings, but banks' credit ratings also influence NPLs through lending channels.

In summary, our study provides significant insights on the relationship between banking competition, non-performing loans (NPLs), and banks' credit ratings across different levels of economic development. Chapter 3 reveals that in low and medium developed countries, there is an optimal level of banking competition that minimizes NPLs, while in developed countries, less competitive banking markets enhance loan performance. These findings show the importance for policymakers and regulatory authorities to tailor banking policies to the specific developmental context of their country to optimize banking stability. Chapter 4 extends the analysis by examining the bidirectional relationship between banks' credit ratings and NPLs, showing that not only do NPLs influence credit ratings, but credit ratings also affect NPLs through lending channels. This two-way relationship highlights the need for a more comprehensive approach in assessing and managing banking risks.

Our contributions include providing a better understanding of how economic development influences the impact of banking competition on NPLs and establishing the bidirectional relationship between NPLs and banks' credit ratings. These insights are crucial for designing targeted regulatory frameworks that enhance financial stability. However, the study has certain limitations. The cross-sectional nature of the dataset may not fully capture the dynamic aspects of banking competition and credit ratings over time. Additionally, future research could investigate the impact of other macroeconomic variables and consider a broader range of financial institutions. Further longitudinal studies are recommended to validate and extend our findings so as to get deeper insights into the relationships between banking competition, NPLs, and credit ratings across various economic contexts.

Chapter 2

2.1 The Relationship between Non-Performing Loans and Level of Competition in the Banking Industry: Evidence from Panel Data

There has been a lot of debate regarding the several determinants of banks' non- performing loans across several regions of the world (Ahmad and Ariff, 2007; Skarica, 2014; Ghosh, 2015). This debate between several researchers and policy makers has been ongoing since the 2008 global financial crisis and even intensified with the emergence of the sovereign debt crisis in the Eurozone in 2010. Due to the rapid increase of non-performing loans (NPLs) right after the global financial crisis that led to the folding up of a significant number of banks, several studies have been done to investigate the determinants of banks' non-performing loans (Saba et. al., 2012; Messai and Jouini, 2013; Makri et. al., 2014; Tanaskovic and Jandric, 2015; Anastasiou et. al., 2019). According to World Bank Definition, loans can be classified as nonperforming when payments of principal and interest are 90 days or more past due or when future payments are not expected to be received in full. The higher the percentage of a bank's NPLs, the higher the threat to the bank's profitability. This is because when a loan is granted it is considered as an asset in the bank's balance sheet which the borrower is obligated to pay back with interest. However, if for any reason the borrower stops paying, the value of the assets begins to decline thereby making the loan asset become riskier and eventually become a loss.

A rising share of NPLs in the loan portfolio of banks signifies greater risks affecting the asset quality of the banks which represents a deteriorating balance sheet of banks. The deterioration of banks' asset quality is not only financially destabilizing for the banking system but may also impair social welfare, reduce economic efficiency, and decline economic activity. Several regulators and banks have linked NPLs to bank failures which is often an indicator to banking crises hence, making NPLs a good measure of banking stability (Ghosh, 2015). In fact, due to the adverse economic consequences of NPLs, many banking analysts have referred to NPLs as a “financial pollution” (Barseghyan, 2010; Renda, 1999; Zeng, 2012). The effect high rate of NPLs has on banks and the economy as a whole is the reason why high NPLs are considered a source of concern in several economies. This is because losses due to NPLs erode the bank’s profitability, reduce the bank’s capital/net worth by creating a pressing need for recapitalization, constrains credit provision to potentially profitable businesses and hence affects the productivity and growth of the economy (Balgova et. al., 2016; Anastasiou et. al., 2019). Also, when an economy experiences low growth due to the constraints of credit provision to potential profitable businesses as a result of high NPLs, there are less investments in the economy because individuals and businesses lack the incentive and capacity to invest which in turn will lead to banks being less profitable. As a result of the decrease in the profitability of banks, there is an increase in the need for banks to raise more capital but if this issue is not properly handled it might eventually begin to threaten the solvency of banks in the economy (Lu and Whidbee, 2013). High rate of NPLs could also be seen to be hurting the economy through the way it undermines the effect of a country’s monetary policies. That is, even if the Central Bank reduces the lending interest rate, banks will still not increase their lending as much because of the burdens associated with the already existing high rate of NPLs (European Commission, 2017). Despite the several studies that have been carried out to ascertain the various determinants of NPLs, more research questions in this area are still being asked as new factors that influence the behaviour of NPLs are being discovered over time.

The level of NPLs in several countries has become a major source of concern. For example, according to Fitch Rating 2019, NPLs in Sri Lanka rose by a worrisome 64% in 2018 and further increased in the first quarter of 2019. This has raised a lot of concern among policy makers and regulators as several banks in the country are under the greatest pressure due to the increased vulnerability as a result of higher loan impairment. In Nigeria, the Central Bank revealed that the total amount of banks’ NPLs at the end of 2018 had hit 4.9 billion US Dollars, which was validated by the National Bureau of Statistics (Leadership, 2019). This high rate of

NPLs in the country has become a matter of utmost concern as several policy makers and regulators believe that it may lead to yet another crisis in the banking industry and by extension, affect the economy. According to a report by Retail banker International (2018), the Tanzanian government lost 5 banks in 2018 as a result of low performance, which was attributed to the volume of the banks' NPLs. It was also reported by Retail Banker International (2018) that IMF discovered that, nearly half of the banks in Tanzania are at the risk of insolvency. It was advised that the issue of the high level of NPLs be addressed in the country. Other countries like Kenya, India, China, Bangladesh and some developed countries like Cyprus, Greece, Italy, Portugal just to mention a few, are also experiencing the level of NPLs that is threatening the solvency of the banking system in these countries.

Giving the consistent rise in non-performing loans, investigating the factors underlying NPLs is of significant importance for regulatory authorities who are seeking more financial stability of the banking sector and effective banks' management.

The literature also identifies the Z-score as a critical measure of banking stability. The Z-score takes into account capital adequacy and profitability, which are core financial soundness indicators. However, it has been criticized in the literature for not showing significant variability prior to a bank crisis, unlike asset quality (Cihak and Schaeck, 2007, 2010). The Z-score compares the buffer of a country's commercial banking system (capitalization and profitability/returns) with the volatility of those returns. Specifically, it relates a bank's capital level to the variability in its returns to determine how much fluctuation in returns can be absorbed by the bank's capital before it becomes insolvent (Hafeez et al., 2022). Consequently, the Z-score captures the probability of default within a country's commercial banking system and serves as a measure of bank risk.

Despite the Z-Score being used in some literature, this study focuses mainly on NPLs as a measure of banking stability because of its relationship with the asset quality of a bank. Cihak and Schaeck (2007, 2010) identify asset quality as the main financial soundness indicator that shows significant variability prior to a bank crisis with NPLs increasing prior to the crisis deteriorating the overall asset quality of the financial institution. Studies show that banks' non-performing loan reflects on asset quality, credit risk and efficiency in the allocation of resources to productive sectors (Rajan and Dhal 2003, Lu and Whidbee 2013, Maggi and Guida 2009, Cucinelli 2015).

NPLs are considered as a major proxy of credit risk since the entire banking system is directly impacted by NPLs. A rising NPLs indicates a susceptible financial system, while a lower rate of NPLs is a signal of financial soundness. NPLs reduce the investment opportunities, restraint interest revenues and boost the liquidity crisis that is initially responsible for bankruptcy in a financial system (Anjom and Karim, 2016). High NPLs tend to affect commercial banks of countries by exposing commercial banks to significant credit risk which jeopardizes the entire financial system and thereby, the country's economy. The minimization of banks' NPLs is a necessary condition for improving the performance and financial soundness of the banking sector and by extension, increase the rate of economic growth. This can only be effectively achieved when policy makers are adequately well informed and have a clear understanding of all the factors that might affect the behavior of non-performing loans.

2.1.1 Competition in Banking

The global financial crisis rekindled the interest of policy makers and academics in banking competition and the role of the state in competition policies (that is, policies and laws that affect the extent to which banks compete). Some believe that increases in competition and financial innovation in markets such as subprime lending contributed to the financial crisis and for this reason competition has been traditionally seen with suspicion in the financial sector (Simkovic, 2013).

Others worry that the crisis and government support of the largest banks increased banking concentration, reducing competition and access to finance, and potentially contributing to future instability as a result of moral hazard problems associated with too-big-to-fail institutions (Blinder, 2013). Too-big-to-fail institutions are institutions that are so interlinked with other market participants and the overall economy that their failure would be very catastrophic to the economy. That is, these institutions are very large and complex that a failure could pose a risk to overall financial stability and lead to a worldwide economic collapse. Before the 2008 global financial crisis, too-big-to-fail concept/institutions, which happened to be mostly financial institutions, was encouraged by the banking industry and the government due to the several advantages that were attributed to having large institutions thereby allowing for less competition in the banking industry. However, after the global financial crisis and having experienced the risks that were associated with the too-big-to-fail institutions, it became more evident that the too-big-to-fail concept needed to be properly addressed as its failure could have a catastrophic impact on financial stability. This led to several solutions being proposed by economists, legislators and regulators with increased banking competition being one of the solutions (Kashkari, 2016; Morrison, 2011; Kaufman, 2014).

Competition has always been a contentious issue in the banking sector and the debate on its effect is still inconclusive till date. This is because despite the trends in competition over the years, two opposing views exist regarding the effect banking competition has on banks' NPLs. According to the traditional "competition-fragility" hypothesis (Marcus, 1984 and Keeley 1990), which is also known as the franchise value hypothesis, it states that an increase in competition leads to an increase in fragility in the banking system. It assumes that more competition is associated with a higher risk loan portfolio, increasing the incentives to take risks on the side of the bank and therefore leading to a rise in failure probabilities. This is because more rivalry may reduce the banks' incentive to properly screen borrowers (Allen and Gale, 2004). This view also assumes that more bank competition erodes market power, decreases profit margins, and results in a reduced franchise value or market value of the banks beyond their book values (Berger et al., 2009). According to Vives (2001), the traditional “competition-fragility” view can be associated to the reason why in the 1990’s, policy makers and regulators in some countries traditionally tried to restrict competition in the banking sector with aim of avoiding excessive risk taking.

The "competition-stability" hypothesis, proposed by Boyd and De Nicolò (2005), is built on the assumption that increased competition leads to greater stability in the banking system, which may be true when competition is relatively high. This hypothesis stands in direct contrast to the "competition-fragility" hypothesis. According to the "competition-stability" hypothesis, higher competition reduces market power in the loan market, which in turn may lower bank risk. This is because higher interest rates, resulting from lower competition, make it harder for borrowers to repay loans and exacerbate moral hazard incentives, pushing borrowers towards riskier projects. Additionally, higher interest rates may lead to a riskier pool of borrowers due to adverse selection processes, thereby suggesting that less competitive markets are less stable (Boyd and De Nicolò, 2005). This hypothesis is then tested using empirical data to evaluate the validity of the assumptions and the resulting theory. The “competition-stability” view opposes the notion that banks are too big to fail. According to this view, due to limited competition in the banking sector, extreme risk taking led to the bankruptcy of many banks during 2008 global financial crisis.

Despite the controversy surrounding banking competition and its role in the global financial crisis, the economic principle that competition leads to increased efficiency holds true for the banking sector as well. In banking, competition drives the efficient allocation of financial resources, encourages the development and adoption of new technologies, and stimulates innovation in financial products and services. This competition results in a broader array of banking products and services, improved quality, lower costs for consumers, and increased productivity within the banking industry. Over time, these enhancements contribute to overall economic growth by facilitating better financial intermediation, increasing access to credit, and supporting entrepreneurial activities and investments (Lowe, 2009). Therefore, while the specific dynamics of competition in banking may differ from other sectors, the underlying economic principles remain applicable.

The relationship between competition and stability has been investigated in several papers and the empirical evidence in support of the competition-fragility and the competition-stability views is rather mixed. As a result of these opposing views, it is in this context that this study will undertake an empirical analysis for evaluating the effect competition in banking has on banks' loan performance by testing the two opposing hypotheses in the existing literature. This study argues that perhaps, it could also be possible that there is a "risk-shifting" effect of competition. That is, this effect might be seen if the market structure in which the banking industry operates is considered. Starting from monopoly, an increase in competition might be good for the banking industry because higher bank risk that is associated with the higher interest rates charged to loan customers might be reduced due to a decrease in market power. In other words, the probability that a loan customer will default in payment due to higher interest rates charged as a result of high market power is reduced. Going further, as competition continues to increase, its positive effect it has on loan performance might begin to wear off and the bank's loan portfolio begins to become risky again. This could be linked to the competitive reaction of banks who try to keep their customers by reducing the standards and regulations regarding loan applications, thereby leading to a higher risk loan portfolio. Hence, there is a probability that a U-shaped relationship, which supports the two existing opposing views in the literature, actually exists between competition and loan performance in the banking industry.

The main objective of this paper is to provide new evidence on this relationship using a data sample of 105 countries over the period 2004-2016, which covers the pre and post era of the global financial crisis. Exploiting cross-country variation in banking non-performing loan trends is likely to yield more robust results than an analysis of individual countries as mostly seen in the literature. In contrast to many studies in literature that only tests one of the competition views, this study will provide empirical evidence testing both the competition-stability and competition-fragility views. This study will investigate whether an optimum level of competition exists in the banking industry and will further provide estimates of this level if an optimum level of competition is observed.

In addition, this study will also contribute to existing literature by providing new evidence on this relationship by further taking into account the country’s level of development in which the banks operate. That is, it investigates whether it varies across the level of development of countries. The reason for the interest in investigating this relationship across different levels of development is because less developed countries as opposed to more developed countries, have a relatively less developed banking industry and therefore any form of shock in the banking industry either through competition or otherwise might have a slightly different effect in the industry. On the other hand, more developed countries as opposed to less developed countries are known to experience more competition and better access to credit facilities due to good governance, better structure, better economic policies, and less corruption.

Therefore, the level of financial development in a country is crucial because it shapes the country's ability to withstand and respond to financial or economic crises. In more financially developed countries, robust financial institutions, diversified financial markets, and comprehensive regulatory frameworks provide a buffer against economic shocks. These countries typically have better access to capital, more efficient financial intermediation, and more sophisticated financial instruments, which help mitigate the impact of crises. Additionally, developed financial systems enhance the domestic mobilization of resources, enabling quicker and more effective responses to economic downturns (Ozili, 2019). Consequently, when there is a shock in competition, such as increased banking competition, the effect is likely to be less significant in more developed countries. Their advanced financial infrastructure and regulatory mechanisms can absorb and adapt to competitive pressures more effectively, maintaining stability and continuity in financial services. This resilience contrasts with less developed countries, where financial systems may be more fragile and less capable of managing and mitigating the adverse effects of competitive shocks.

Finally, this study will investigate the relationship between banking competition and its impact on the banking industry by examining periods before and after the global financial crisis. By comparing the results between these two distinct periods, the analysis aims to provide deeper insights into the changes that have occurred in the banking sector due to the crisis. This comparative analysis is of particular interest because the global financial crisis significantly altered the financial environment, affecting regulatory frameworks, market structures, and competitive dynamics within the banking industry. Understanding how competition influenced banking stability and performance before and after the crisis can help identify the long-term effects of regulatory changes and market adaptations. Moreover, this analysis can inform policymakers and regulators about the efficacy of measures implemented post-crisis and guide future policy decisions to enhance banking sector resilience and stability. Thus, the study contributes to a better understanding of the evolving nature of banking competition and its broader economic implications.

2.1.2 The Conception of Competition

Even though the concept of competition has always been central to economic thinking, it is a concept that has taken on several interpretations and meanings. Smith (1776), in *The Wealth of Nations* originated the concept of competition. In his analysis he argues that free competition is an ordering force towards equilibrium. That is, in the long run, free competition results in the market prices being equal to the cost of production. However, he further argues that competition is not a static state but a race between competitors to gain higher market share. It is this race between competitors that forces the market price towards the equilibrium of demand and supply, with individual freedom being an essential condition for free competition.

Smith inspired subsequent works on the conception of competition in economics but over time this has been developed into two major views of competition (McNulty, 1967; Vickers, 1995; Blaug, 2001). Standard theory views competition as a static equilibrium outcome. That is, it refers to competition as a static state in which firms cannot charge overprice and then earn abnormal profit. On the other hand, other economists, especially the Austrian School, have criticized this static view and have held on to the key role played by rivalry to define competition.

Cournot (1838) defined competition as the equilibrium condition itself and not the process that tends towards a certain equilibrium position in the long run. He argues that competition is that condition where prices equal the cost of production while highlighting several assumptions required to obtain a competitive condition which were never mentioned by Smith. The assumptions are a considerable number of rivals, free entry and exit and possessing common knowledge about market opportunities. This assumption by Cournot plays a key role in Cournot oligopoly analysis. According to Cournot, as the number of producers in the market increases, the excess of the price of cost approaches zero.

Perfect competition is the antipode of monopoly. This is because contrary to perfect competition, there is no one to compete with in monopoly hence, making it possible for a monopolist to extract abnormal profits even though it is limited by elasticity of demand.

Chamberlin (1938) and Robinson (1969) contributed to Cournot oligopoly theory by proposing reconciling perfect competition and reality by developing a theory of workable competition as what often plays out in the business world is a mixture of competition and monopoly. The Cournot oligopoly theory allows scholars to derive testable hypothesis, recognize different possible forms of market structure (perfect competition, imperfect competition, and monopoly) and also measure the degree of competition. Therefore, both structural and most of the non-structural measures of competition are based on Cournot oligopoly theory.

2.1.3 Measuring Bank Competition

Several approaches have been used to measure bank competition. These measures fall under one of these two categories. Firstly, we have the so-called "structure-conduct-performance" (SCP) paradigm (Bain, 1959), which focuses on measures of bank concentration and the decomposition of interest spread. Secondly, we have the "non- structural approach" (Lerner, 1934; Panzar and Rosse, 1982), which is based on the new empirical industrial organization and focuses on direct measures of bank pricing behavior or market power. This approach consists of the Lerner Index, Panzar-Rosse model and the Boone Indicator. The non-structural approach was developed based on the deficiencies found in the structural approach.

According to the so-called "structure-conduct-performance paradigm", a stable and causal relationship exists between the structure of the banking industry, firm conduct, and performance. This approach assumes that larger and fewer firms are more likely to engage in anticompetitive behaviour thereby suggesting that competition is negatively related to the level of concentration in the banking sector. This approach argues that competitive features of an industry are inferred from the structural characteristics. The measures in this approach seek to explain aspects of the conduct and performance of firms in terms of the structural characteristics of the markets in which they operate. They are used to explain the competitive performance in the banking industry as the result of market structure. They can reflect changes in concentration as a result of the entry of a bank into the market or its exit from it or caused by a merger. Concentration ratios take both the distribution in firm size (inequality) and the number of firms into account in a given market. Empirical work focuses on the number of firms and their relative size in order to gauge market concentration. The structural characteristics of a market cover the number of firms and their absolute and relative size as well as the entry and exit conditions and the extent of product differentiation. The most important insight into the Structural approach is that the more concentrated an industry is, the easier it is for firms to operate in an uncompetitive manner. One of the major weaknesses of this approach is that it focuses and assigns substantial weight only to the biggest banks while completely ignoring the smaller banks. Another weakness is that the accuracy prediction on measure of banking competition is challenged by the concept of market contestability. Market contestability assumes that the behaviour of banks in contestable markets is dependent on the freedom of entry and exit in the banking sector. Hence, in an industry with low entry restrictions on new banks and easy exit conditions, banks are assumed to behave competitively even if the market is concentrated.

Therefore, for the purpose of this study, as also seen in recent literature (Beck et. al. 2013, Soedarmono et. al. 2013, Love and Martínez, 2014), the “non-structural approach” will be employed. This is because the non-structural approach corrects for the deficiencies found in the structural approach and directly assesses the competitive conduct of firms. It considers the entry requirements for domestic and foreign banks, capital requirements and the regulations a acting bank activities (Leon, 2015).

To effectively investigate the relationship between banking competition and banking financial stability as measured by NPLs, this study employs the Lerner index as one of the measures of banking competition.

The Lerner Index is a popular measure of market power in empirical research. The market power of a firm is identified by the divergence between the firm’s price and its marginal cost. The price and marginal cost should be equal in perfect competition but will diverge in less competitive environments. A bigger wedge between price and marginal cost signals greater monopoly power. The Lerner index identifies the extent to which the price charged by a firm in a market diverges from the price that would emerge in case of perfect competition. This explains why it is calculated as the difference between actual price and marginal cost, divided by price.

The theoretical and historical foundations of the Lerner index have been extensively discussed in the literature (Lerner, 1995; Landes et. Al., 1997; Amoroso et. Al., 2012; Giocoli, 2012). Its theoretical foundation is rooted in Cournot static oligopoly theory. Under standard assumptions, the Lerner index should converge to zero as competition increases, while it rises (up to the theoretical limit of one) as firms' market power becomes greater. It measures the kind of competition that exists in the market in which the banking industry operates. The Lerner Index ranges from 0 to 1 and an increase in the Lerner index indicates a deterioration of the competitive conduct of financial intermediaries. For a perfectly competitive market, the Lerner index is equal to zero and as the Lerner index tends towards 1, the market begins to tend towards a monopoly market. That is, the banking market is in perfect competition when the Lerner index is equal to zero. However, as the Lerner index increases, competition in the banking market decreases.

Demirguc-Kunt and Martinez Peria (2010) defined the Lerner index as a proxy for profits that accrue to a bank as a result of its pricing power (P) in the market. They calculated P as the total bank revenue over assets and calculated MC by taking the derivative from a translog cost function as specified in the equation below:

$$
\begin{aligned}
Ln(C_{it}) = {} & a_{0i} + b_0 \ln(Q_{it}) + b_1 0.5[\ln(Q_{it})]^2 + a_1 \ln(W_{1it}) + a_2 \ln(W_{2it}) \\
& + a_3 \ln(W_{3it}) + b_2 0.5 \ln(Q_{it}) * \ln(W_{it}) + b_3 0.5 \ln(Q_{it}) * \ln(W_{2it}) \\
& + b_4 0.5 \ln(Q_{it}) * \ln(W_{3it}) + a_4 \ln(W_{1it}) * \ln(W_{2it}) + a_5 \ln(W_{1it}) * \ln(W_{3it}) \\
& + a_6 \ln(W_{1it}) * \ln(W_{3it}) + a_7 0.5[\ln(W_{1it})]^2 + a_8 0.5[\ln(W_{2it})]^2 \\
& + a_9 0.5[\ln(W_{3it})]^2 + d_1 Trend + d_2 Trend^2 + d_3 Trend \\
& * \ln(Q_{it}) + d_4 Trend * \ln(W_{1it}) + d_5 Trend \\
& * \ln(W_{2it}) + d_6 Trend * \ln(W_{3it}) + u_{it}
\end{aligned}
$$

Where, i denotes banks and t denotes years. C is total operating plus financial costs, Q is total assets, w_1 is the ratio of interest expenses to total deposits and money market funding (proxy for input price of deposits), w_2 is the ratio of personnel expenses to total assets (proxy for input price of labor) and w_3 is the ratio of other operating and administrative expenses to total assets (proxy for input price of equipment/fixed capital).

Demirguc-Kunt and Martinez Peria (2010) also included a trend to capture the influence of technical change leading to shifts in the cost function over time and performed the estimation under the restrictions of symmetry and degree one homogeneity in the price of inputs. However, the results do not change when the constraints were dropped as noted by Demirguc-Kunt and Martinez Peria (2010).

Therefore, the Lerner Index is then computed as;

$$Lerner\ Index_{it} = (P_{it} - MC_{it})/P_{it}$$

P_{it} is the price of assets and is equal to the ratio of total revenue to total assets and MC_{it} is the marginal cost.

The biggest limitation of this method is the difficulty associated with marginal cost computation. As shown above, the translog cost function requires a great number of parameters that must be estimated in order to make operational the concept of "translog cost function" thereby imposing hard constraints on the result feasibility due to the occurrence of an extended collinearity. In fact, the number of the parameters practically "explodes" as the number of production factors which are taken into account increases. Even though they argue that the difficulties generated by collinearity could be surpassed through the application of the ridge regression, the ridge regression has been known to also have its shortcoming. Klacek and Vopravil (2008) show that the ridge (correction) parameter used to diminish the collinearity impact is in fact subjectively chosen. Also, the deviation of the results obtained in the context of ridge regression tends to be greater and greater as the number of production factors is higher and higher.

The Lerner Index as a measure of banking competition has its unique advantages. One of such advantages is that it does not assume the market is in equilibrium, which is very important because equilibrium is quite rare in the banking market. The Lerner Index is a flexible indicator and does not require defining the structure of the relevant market. It also takes into consideration the differences between banks, such as size, product, and geographic differentiation and in addition, it captures the mark-up that banks charge to their customers by calculating the difference between loan interest rates and marginal costs and expressing it as a proportion of the former. Hence making it a direct measure of competition in the banking industry. Finally, the Lerner Index can be calculated with a limited number of observations. This advantage is very unique as competitive concerns occur mainly when the number of firms is limited. Despite these advantages of the Lerner Index, this index still has its limitations as a measure of banking competition. The Lerner Index could over-estimate market power when banks' risk taking is not accounted for and it does not appropriately capture the degree of product substitutability in the market.

In addition to the Lerner Index, this study also uses the Boone indicator as an additional measure of banking competition. The Boone Indicator approach is based on the notion that competition rewards efficiency. That is, efficient firms are more highly rewarded in more competitive markets. The Boone Indicator assesses the impact of efficiency on performance, specifically in terms of profits. This approach argues that as competition increases in an industry, firms in the industry that operate inefficiently tend to be punished more harshly than more efficient firms. Thus, the Boone Indicator uses the relative profit differences based on the efficiency of firms as a measure of the level of competition within that industry. Therefore, the more competitive the industry is, the stronger the proposed relationship between efficiency differences and performance differences. Its calculation involves determining the elasticity of profits concerning marginal costs. That is, it is calculated by estimating the elasticity of profits with respect to marginal costs. This relationship is often expressed in the form of a regression:

$$\ln(\Pi_i) = \alpha + \beta \ln(MC_i) + \epsilon_i$$

where:
(Π_i) is the profit of firm i.

MC_i is the marginal cost of firm i.

α is a constant.

β is the Boone Indicator. ϵ_i is the error term

This elasticity is derived from regressing the logarithm of a profit measure against the logarithm of marginal costs. The core concept underlying the Boone indicator is that banks with higher efficiency tend to achieve greater profits. A more negative Boone indicator suggests a higher level of market competition, indicating a stronger influence on reallocation from inefficient to efficient firms in a competitive market. Although, unlike the Lerner Index, the Boone Indicator does not take into consideration the differences between firms such as product, size and geographical location. Notwithstanding, the crucial benefit of the Boone Indicator is that it depicts the level of competition correctly when competition becomes more intense through more aggressive interaction between firms and when entry barriers are reduced. That is, the Boone Indicator captures market dynamics and can also be implemented for a limited number of observations.

Finally, this study employs CR5 as part of our robustness checks which is a measure that falls under the Structural approach. The CR5, which is a concentration ratio, measures the market share of 5 of the largest banks in the banking market. One of the major limitations of the concentration ratio is that it focuses only on a fraction of the largest banks in the market and neglects the many small banks in the market. Summing only over the market shares of the 5 largest banks in the market, it takes the form:

$$CR_k = \sum_{i=1}^{k} s_i$$

Where k is 5 largest banks in the market and s is the cumulative market share of i number of banks.

For this study, we use the computation of the Lerner index, Boone Indicator and the CR5 provided by Bank Scope Database.

2.2 Literature Review

In recent years, the literature on NPLs has occupied the interest of several scholars and researchers particularly the interest in understanding the variables liable to the financial vulnerability. This interest is because of the strong relationship that exists between non-performing loans and crises in the banking sector (Messai and Jouini, 2013). The assessment of credit risk is a critical part of the macro-prudential analysis, with the banking NPLs ratio, aggregated at the country level, serving as a proxy for the economy-wide probability of default of the banking sector's overall loan exposure.

Among factors cited by the literature as significant determinants of loan performance are both country level variables, such as the annual GDP growth, the annual inflation rate, the real exchange rate, the unemployment rate and bank level variables, such as return on equity, capital adequacy ratio and size of the bank. Among these studies, to the best of my knowledge, only a handful examined the relationship between banking competition and loan performance and even so, they all focused on individual countries or countries within a particular region.

Skarica (2014), analyzed the determinants of changes in the NPLs ratio across seven Central and Eastern Europe countries between the third quarter of 2007 and the third quarter of 2012. This study, using a fixed effect estimator, revealed that the primary cause of high level of NPLs is the economic slowdown, which was evident from the statistically significant coefficient of the macro-economic variables (GDP, unemployment and inflation rate). The result of this study is also in line with (Salas and Saurina 2002; Fofack, 2005; Jimenez and Saurina, 2006; Khemraj and Pasha, 2009; Dash and Kabra, 2010; and Saba et al., 2012) as they all argued that that higher positive level of real GDP growth translates to a higher level of income which by extensions improves the capacity of the borrower to pay its debts and also contributes to reduce bad debts in the banking industry. Therefore, when there is a downturn in the economy, that is either slowed or negative growth of GDP, the level of bad debts experienced will increase.

Skarica's use of fixed effects allows a more robust control for cross-country variation than OLS models (Dash and Kabra, 2010; Saba et al., 2012), but lacks the dynamic adjustment found in GMM approaches like Salas and Saurina (2002) and Jimenez and Saurina (2006). While the fixed-effect approach is appropriate for isolating country-specific effects, it might miss dynamic relationships over time that are captured by GMM. However, compared to the dynamic models used by Salas and Saurina (2002) and Jimenez and Saurina (2006), the fixed-effect model lacks the ability to capture the lagged effects of macroeconomic variables, potentially overlooking delayed responses to economic downturns.

Using data from US states and the District of Columbia from 1984 to 2013, Ghosh (2015) examined state level banking industry specific as well as region economic determinant of NPLs for all commercial banks and savings institutions. The result of the study using both fixed effect and dynamic GMM estimations revealed that, greater capitalization, liquidity risks, poor credit quality, greater cost efficiency and banking industry size to significantly increase NPLs while greater profitability lowers NPLs. The study also revealed that real GDP, real personal income growth rates and changes in house price index reduce NPL while inflation, unemployment and public debts significantly increase NPL.

Previous studies in different contexts such as Salas and Saurina (2002) and Jimenez and Saurina (2006) also utilized dynamic GMM in their analysis of Spanish banks, finding that lagged NPLs and macroeconomic factors such as GDP and interest rates have a persistent impact on loan quality. These studies similarly underscored the need to account for endogeneity, particularly the potential reverse causality between bank-specific variables and NPLs. Klein (2013), in his analysis of NPL determinants in Central, Eastern, and Southeastern Europe, used fixed effects models but did not implement a dynamic GMM approach. While Klein controlled for country-specific factors, his failure to account for the dynamic interaction between macroeconomic variables and NPLs may limit the robustness of his findings compared to Ghosh's use of both static and dynamic models.

The paper adds to the literature by studying bank size, credit terms, and macroeconomic shocks as influencing factors of NPLs within a financial institution through the use of both fixed and random effects models, an approach that is not fully captured in the available literature. It considers variations within banks (fixed effects) and between banks (random effects). Hence, this provides a profound insight into the drivers of NPLs more than Rajan and Dhal's (2003) approach did without highlighting a comparison between both fixed and random effects. The use of different measures of bank size brings out the varying impacts on NPLs, as opposed to works such as those by Louzis et al. (2012) and Makri et al. (2014), who have used only one measure of bank size. This goes beyond more basic models, such as that developed by Khemraj and Pasha (2009), in an effort to study the interaction of credit terms with size-induced risk preferences. While it does not capture dynamic feedback effects over time, as in Jimenez and Saurina (2006), they provide a fixed/random effect model offering a good influence from different-size banks to respond to credit terms and macroeconomic shocks.

Godlewski (2004) using both 2SLS (Two-Stage Least Squares) and 3SLS (Three-Stage Least Squares) techniques implored the return on assets (ROA) as one of his major bank specific variables while studying the relationship between bank capital and credit risk taking in 30 emerging market economies. He showed that the impact of banks' profitability, using the ROA as a performance indicator, has a negative impact on the level of non-performing loans ratio.

However, using a Generalized Method of Moments (GMM) proposed by Arellano and Bond on a panel of 129 banks applied in Spain between the period of 1993-2000, Garciya-Marco and Robles-Fernandez (2008) analyzed the determinants of risk-taking in Spanish financial intermediaries with special emphasis on the ownership structure and size of the different entities. Their study revealed that high levels of return on equity (ROE) are followed by a greater future risk. They argue that the policy of profit maximization is accompanied by high levels of risk and that the degree of shareholder concentration in Commercial banks has a negative impact on the level of risk-taking. The main findings reported by Garciya-Marco and Robles-Fernandez are compared with other literature evidence that, while GMM is widely applied in studying bank risk and ownership, different contexts (crisis versus a non-crisis period) and firm characteristics (family versus commercial banks) may provide a very different picture of the outcomes. Methodologically, GMM remains central to such a study, but robustness and instrument validity are areas given due attention.

Using a dynamic panel model, Louzis et al. (2012) followed methodologies also put into work by other research, such as Chaibi and Ftiti (2015), who based their work on France and Germany. Both studies implement the Generalized Method of Moments in order to control for endogeneity, but each adds greater specificity to the comparison by making it between a bank-based economy, such as Germany, and one more market-based, such as France. Although these findings focus on GDP and inflation, they provide evidence that French NPLs react more with regard to bank-specific variables compared to German ones. Xuelan (2012), on the other hand, whereas examining the NPLs that burst forth from the Chinese banking system, spotted sensitivity of business loans to a negative macroeconomic shock. Although the use of dynamic panel methods parallels that of Louzis et al., he brought in the importance of cost efficiency as a variable which determines the variation of NPLs between loan types, so interaction of macroeconomic and bank-specific factors is more nuanced.

In regard to competition, the impact it has on the banking industry is still inconclusive with opposing views existing in the literature. Casu and Girardone (2009), tested the relationship between competition and efficiency in banking using the Lerner index as a measure of competition. Their study focused on the 5 largest EU banking markets (France, Germany, Italy, Spain and the UK) within the period of 2000-2005. Using a panel data analysis, results of their study revealed that a decrease in competition, that is, an increase in the Lerner index would lead to a positive effect on efficiency. Beck et. al., (2013), using a cross-country variation from 1994-2009 also studied the relationship between bank competition and bank stability using the Z-score as a measure of stability. Result of their study revealed that, there is a positive relationship between the Lerner index and the Z-score. That is, an increase in competition will have an impact on banks' fragility.

Studies including that of Ahi and Laidroo (2019) adopted a non-linear approach to competition stability. They employed both the Boone Indicator and the Lerner Index over a wider period across EU banks, revealing a U-shaped relationship between competition and stability. This non-linear approach certainly goes against Casu and Girardone's linear approach. It means the effect of competition on stability changes with different levels of competition. For instance, whereas bank stability rises at an optimal level of competition, too little or too much of it will then raise instability (Ahi & Laidroo, 2019). In their own paper on the relationship between Europe as it relates to competition and efficiency, Bolt and Humphrey utilized what is called frontier efficiency analysis. Unlike the more direct approach Casu and Girardone used of panel data, the frontier efficiency method shows greater depth in how a bank operating closer to a "competition frontier" can ensure maximum efficiency. They say that various payment and cost options can explain a significant variation in loan-deposit rate spreads, therefore amplifying the efficiency analysis more than the traditional method of analysis does.

Jimenez et al. (2013) tested the relationship between competition and NPLs from the year 1988 to 2003. They estimated their model in the first difference form using the GMM estimation technique. They tested if the franchise value paradigm (Competition-fragility hypothesis) or the MMR model applied to the Spanish banking system. Although a quadratic term was added in their model, the results from their study were more supportive of the “competition –fragility” hypothesis. The result of the study suggests that more competition is associated with a higher risk loan portfolio in the Spanish banking system.

Berger et al. (2009), used data from several banks across 23 developed countries (1999- 2005) to test the determinants of NPLs before the 2008 global financial crisis. They included measures of market power in their model while controlling for indicators of the business environment. Since the dataset is large, involving countries and years, its results may be given preference over others for cross-country comparisons. Examples include Karadima & Louri (2020), which examines the relationship between the Lerner Index and NPLs in Euro-area banks. By using a penalized quantile regression to control for the presence of skewed distributions of NPL, they discovered that increased competition stabilizes with NPL growth, but concentration accelerates the decline of NPLs in periphery economies.

Although the study of Berger et al. (2009) focused on bank-level relationship, the result from their study revealed that the relationship between the degree of market power (Lerner index) and loan portfolio risk is significantly positive. They further suggest that even though the riskiness of banks’ loan portfolio increases as a result of an increase in their market power, the need for these banks to protect their higher franchise value, which arises from an increase in market power, makes them employ other risk management methods to reduce the overall bank risk. Berger et al. (2009), also revealed that GDP has a negative significant effect on the rate of NPLs which is in line with Ghosh, 2015; Messai and Jouini, 2013; Rajan and Dhal, 2003). The ambiguity regarding the effect of banking competition on loan performance is reflected in the empirical literature that has, to date, not formed a consensus as to the direction in which NPLs are affected.

Mamonov (2012) also analyzed Russian banks but employed both structural and non-structural measures of market power. The result of a greater degree of market power was the rise in the quality of the portfolio, since it filtered the unsavory borrowers, in that respect, more market power lowered credit risk in those markets. That dynamic approach can apply the threshold, since market power and competition-stability depend on macroeconomic conditions. Other than that, the study by Spierdijk & Zaouras (2018) accounted for scale economies in the Lerner Index and identified that the lack of consideration of the two states in calculating the Lerner Index overestimated the level of market power. Applied to the U.S. banking system, this relatively subtle approach found massive underestimation of market power relative to traditional applications of the Lerner Index—an indication that Berger et al.'s results might be biased.

2.3 Data Description

To investigate the relationship between bank competition and NPLs, we consider an unbalanced panel data set that consists of 105 countries covering the period from 2004 to 2016. The data was compiled by combining data from the IMF, Bank Scope, and the World Bank (see Table 2.2 for an overview of all data sources used for our empirical analysis). Data on bank level variables such as Percentage of foreign banks among total banks, Return on Assets, Bank Size and Loan Deposit were obtained from Bankscope database and were estimated for only the banking sector. These variables were derived by estimating their average across all banks in each country for each year under study. Data on country level variables such as Gross Domestic Product Per Capital, Unemployment and HDI were obtained from the World Bank Database and were estimated for the whole country (not just the banking sector) for the period under study.

The data on NPLs at the country level (for the banking sector) was obtained from the World Bank Database. The database estimated the aggregate NPLs for each country by taking the average of NPLs across all banks in each country for each year under study. Data on the Lerner Index and other competition measures were obtained from Bankscope, which is a database compiled by Bureau Van Dijk (BVD). BVD uses Demirguc-Kunt and Martinez Peria (2010) methodology for the Lerner Index as discussed in section 2.1.3. The competition measures obtained only capture competition in the banking sector in each country for each year under study. In this study, it should be noted that the Lerner Index is used as the main measure of competition while the other measures are used as for robustness checks.

Table 2.1: List of Countries

Afghanistan	China	Honduras	Moldova	Swaziland	Cameroon
Albania	Colombia	India	Morocco	South Africa	Singapore
Algeria	Costa Rica	Indonesia	Mozambique	Turkey	New Zealand
Angola	Croatia	Kuwait	Switzerland	Sri Lanka	Spain
Argentina	Dominican Republic	Jordan	Namibia	Tajikistan	Norway
Armenia	Ecuador	Kazakhstan	Nigeria	Tanzania	Sweden
Azerbaijan	Egypt	Kenya	Pakistan	Thailand	Poland
Bangladesh	El Salvador	Korea, Rep.	Panama	Togo	United Arab Emirates
Belarus	Gabon	Kyrgyz Republic	Paraguay	Tonga	Portugal
Australia	Gambia	Lebanon	Peru	Tunisia	United Kingdom United States
Benin	Georgia	Lesotho	Philippines	Turkey	
Bhutan	Ghana	Macedonia	Romania	Uganda	
Bolivia	Belgium	Madagascar	Russia	Ukraine	
Bosnia and Herzegovina	Canada	Mauritania	Rwanda	Uzbekistan	
Botswana	Cyprus	Mauritius	Japan	Vanuatu	
Brazil	Denmark	Mexico	Senegal	Venezuela, RB	
Bulgaria	France	Greece	Serbia	Vietnam	
Burundi	Germany	Hungary	Sierra Leone	Yemen, Rep.	
Cambodia	Ireland	Italy	Netherlands	Zambia	

Table 2.2: Variables Used in the Study, Definition, Sources and Expected Sign

Variable	Definition	Source	Expected Sign
Non-performing Loans (NPL)%	The percentage of defaulting loans (payments of interest and principal past due by 90 days or more) to total gross loans (total value of loan portfolio).	World Bank National Accounts Data Base, and OECD National Accounts Data Files.	
Z-Score	It is a measure of the probability of default of a country's banking system.	Bankscope, Bureau van Dijk (BvD)	
Lerner Index	A measure of market power in the banking market. An increase in the Lerner index indicates a deterioration of the competitive conduct of financial intermediaries.	Bankscope, Bureau van Dijk (BvD)	**(+)** supports competition stability view. **(-)** supports competition fragility view. Jimenez et al. (2013).
Boone Indicator	It measures the effect of efficiency on performance in terms of profits. It is calculated as the elasticity of profits to marginal costs.	Bankscope, Bureau van Dijk (BvD)	**(+)** supports competition stability view. **(-)** supports competition fragility view.
CR5	CR5 is the share of assets held by the 5 largest banks in a given economy.	Bankscope, Bureau van Dijk (BvD)	**(+)** supports competition stability view. **(-)** supports competition fragility view.
Foreign Banks among Total Banks (%)	Percentage of the number of foreign owned banks to the number of the total banks in an Economy.	World Bank National Accounts Data Base, and OECD National Accounts Data Files.	**(+)/(-)** An increase in foreign ownership could be associated with a decrease in non-performing loans Lin and Zhang (2009). This is linked to the high level of efficiency that exists among foreign owed banks. It could also be associated with a higher NPL due to lack of adequate information and understanding of the environment they operate it thereby leading to decision taking that might increase the riskiness of the loan portfolio Rokhim and Susanto (2011).
Return on Assets (ROA)	It is a measure of the profitability of a commercial bank in relation to its total assets.	Bankscope, Bureau van Dijk (BvD)	**(-)** This is because high profitability and good financial leverage should lead to lower NPL Garciya-Marco and Robles-Fernandez (2008).
Bank Size (Total Assets)	This is the sum of the total earning assets, foreclosed real estate, fixed assets, goodwill, current assets and other assets.	Bankscope, Bureau van Dijk (BvD)	**(-)** An increase in bank size could be associated with a decrease in non-performing loans Yulianti et. al., (2018). This is linked to the low interest rates that are facilitated by big banks.
Loan Deposit Ratio (LDR)	This is the measure of the liquidity of a bank in paying back withdrawals made by depositors.	Bankscope, Bureau van Dijk (BvD)	**(+)** This is because the higher the amount of credit extended, the less NPL at commercial banks will be reduced (Riyadi et. Al., 2014; Mentari, 2017; Harutiyansari, 2018)
Unemployment	Unemployment refers to the share of the labor force that is without work but available for and seeking employment.	World Bank National Accounts Data Base, and OECD National Accounts Data Files.	**(+)** An increase in unemployment will make it difficult for borrowers to meet their debt obligations hence leading to an increase in NPL (Salas and Saurina, 2002; Fofack, 2005; Skarica, 2014).
Gross Domestic Product per Capital (GDP)	GDP is the sum of gross value added by all resident producers in the economy plus any product taxes and minus any subsidies not included in the value of the products.	World Bank National Accounts Data Base, and OECD National Accounts Data Files.	**(-)** A downturn in the economy, that is a negative growth in GDP, will affect the ability of borrowers to repay their loans which will therefore lead to an increase in the level of bad debts experienced (Ghosh, 2015).
Human Development Index (HDI)	The HDI is a measure of the level of development within a country taking into consideration both economic and social indicators.	World Bank National Accounts Data Base, and OECD National Accounts Data Files.	For developed countries, we expect a less significant effect because they are known to experience more competition and better access to credit facilities due to good governance, better structure, better economic policies, and less corruption. Hence a shock in competition might have a less significant effect in the countries while we expect a more significant result for developing countries due to their relatively less developed banking industry.

In this study our dependent variable is the percentage of non-performing loans to total (gross) loans (NPL) while as explanatory variables we use the Lerner Index alongside country- specific macroeconomic and financial indicators, which are commonly used in reference literature. For macroeconomic factors affecting the level of NPLs we used data on GDP per capital, Unemployment and Human Development Index while for bank specific indicators we used Return on Assets (after Tax), Bank Size, Loan Deposit ratio and Ratio of shares owned by foreign banks. These variables have been found to affect the vulnerability of banks' non-performing loans as highlighted in the several literatures discussed above and therefore will enhance the explanatory power of the empirical model.

The descriptive statistics of the variables used in the study are presented in Table 2.3.

Table 2.3: Descriptive statistics of variables used in model

Variable	Observations	Mean	Standard Deviation	Minimum Value	Maximum Value
Non-Performing Loans (NPL)	1,546	6.2789	4.8134	0.0818	45.3
Lerner Index	1,546	0.8986	0.6094	0.0003	0.9386
Log_GDP	1,451	7.7602	1.0720	5.3661	10.1458
Unemployment (UNEM)	1,536	8.1469	6.3121	0.14	38.04
Return on Assets (ROA)	1,348	2.2460	1.9765	-24.1168	16.8422
Loan Deposit Ratio (LDR)	1,546	29.9841	46.9719	10	179.971
Log_Bank Size	1,546	4.4002	0.2914	1.3942	4.6051
Foreign Banks among Total Banks	1,427	5.4360	7.5158	0	35
Human Development Index (HDI)	1,531	0.6177	0.1352	0.286	0.912
Regulatory barriers	1,493	6.1589	2.0638	1	10
Freedom to enter banking market	1,546	6.2660	1.8161	0.56	9.94

From Table 2.3, it can be observed that the overall value of NPL ranges from 0.08% to 45.30%, showing that, the percentage of bad loans recorded by commercial banks in certain countries were quite high compared to those recorded in other countries within the same time period. The Lerner Index has a minimum of 0.003 and a maximum of 93.87, indicating that some countries' banking market were tending towards monopoly between the year 2004 and 2016 while some were highly competitive. Variables log_GDP present a minimum of 5.37 and a maximum of

10.15, indicating that over the period of 2004 to 2016, some countries experienced a better business economy than others. Unemployment shows a minimum of 0.14% and a maximum of 38.04%, indicating that the level of unemployment in some countries was as low as 0.14% and relatively high in some countries. Return on Assets also recorded a minimum of – 24.12% and 16.84% indicating some countries experienced more banking profitability and more financial leverage between the year 2004 and 2016. Loan Deposit ratio recorded a minimum of 10% and a maximum of 180%, indicating that some commercial banks in some countries observe more liquidity and have a higher chance of being able to pay back withdrawals made by depositors. Log_Bank Size has a minimum of 1.39 and a maximum of 4.6, indicating that commercial banks in some countries have more assets and are bigger in size than some commercial banks in other countries. Foreign Banks among total banks shows a minimum of 0% and a maximum of 35%, indicating that the Percentage of the number of foreign owned banks to the number of the total banks in some countries was zero. That is, in some countries foreigners did not own any shares in commercial banks. Finally, the Human Development Index shows a minimum of 0.29 and a maximum of 0.91, indicating that over the period of 2004 to 2016, some commercial banks operated in countries with a higher level of development than others.

2.4 Empirical Methodology

In this section, we examine the possible determinants of NPLs. More importantly, we investigate the effect of competition in banking on NPLs while controlling for various macroeconomic and bank-specific variables aggregated at the country level. To capture the relationship between banking competition and NPLs, we allow for a quadratic effect by including the Lerner index in quadratic form. This approach enables us to identify the non-linear impact of competition on NPLs and to pinpoint the optimal level of competition. Specifically, we aim to determine the threshold at which increasing competition begins to pose a threat to NPLs, providing a more comprehensive understanding of how competition influences banking stability.

The motivation for this methodology arises from the need to explore how competition in the banking sector affects bank stability, with particular attention to how it may affect NPLs. NPLs are one of the significant indicators of a bank's health, something that may be brought about either through general macroeconomic factors or via internal policies adopted by a bank. This, therefore, calls for an in-depth analysis of the determinants of NPLs emanating from banking competition pertinent both from the regulatory authorities' perspective and that of bank management. In this way, by conditioning for both country-level macroeconomic and bank-specific variables, the study identifies the effect of competition on NPLs and hence offers a more focused analysis on how competition shapes banking outcomes.

This study uses the Lerner index in measuring competition in the banking sector. The theoretical consideration herein is that competition influences banks' risks along manifold lines. Stronger competition, for instance, may bring slender margins that could compel banks towards riskier loans in striving to keep profitability alive. Competition, on the other extreme, may prompt banks for efficiency gains, that lower operational risks. This implies that the relationship between competition and NPLs is nonlinear; thus, it requires a more advanced model to capture this dynamic properly.

In this regard therefore, the study introduces a quadratic term of the Lerner index into the model. This allows for identifying a nonlinear relationship between competition and NPLs, capturing how competition initially lowers risks up to a given threshold but beyond this level leads to greater risk-taking and rising NPLs when competition is excessive (Martinez-Miera & Repullo, 2010). This paper allows for such non-linearity in assessing and trying to isolate the optimal level of competition beyond which higher levels start to hurt banking stability by leading to higher NPLs. This is a very important policy consideration because identifying such a tipping point will help regulators balance the trade-off between promoting competition and ensuring financial stability.

For our analysis, we used a panel dataset. Panel data, which consists of observations on multiple entities (such as countries) over time, is known to be particularly informative. This type of data allows for more accurate predictions because it combines cross-sectional and time-series data, capturing both the individual differences between countries and changes over time (Hsiao et al., 1993). Additionally, panel data provides more degrees of freedom and reduces collinearity among explanatory variables, enhancing the reliability of the statistical estimates (Hsiao et al., 1995). Moreover, panel data enables us to investigate country-level heterogeneity in adjustment dynamics, meaning we can explore how different countries uniquely respond to changes in banking competition and other factors over time (Bond, 2002). This approach helps us understand the diverse impacts of competition on NPLs across various countries, accounting for their unique economic and financial environments.

This study exploits the panel structure of our dataset by running fixed effects (FE) estimations. The benefit of using fixed effects over random effects (RE) lies in the ability of fixed effects to control for unobserved heterogeneity that could bias the results. Specifically, fixed effects estimations account for time-invariant characteristics of the entities (such as countries) being studied, which could influence the dependent variable in this case, NPLs. By controlling for these individual-specific characteristics, fixed effects models provide more accurate estimates of the impact of the variables of interest, such as banking competition, on NPLs. This is particularly useful when these unobserved characteristics are correlated with the explanatory variables, as it prevents omitted variable bias and enhances the robustness of the findings.

In contrast, random effects models assume that these individual-specific characteristics are uncorrelated with the explanatory variables, which might not be a valid assumption in this context. Therefore, fixed effects estimations are preferred for obtaining reliable and consistent

results in the presence of potential correlation between unobserved heterogeneity and the independent variables. An important feature of our approach is that we control for possible endogeneity of the measures of competition. Endogeneity can arise when there is a reverse causality between competition and NPLs at the country level. Specifically, changes in country-level NPLs can influence the measures of competition, such as the Lerner index. If a country's banks experience an increase in NPLs, indicating higher loan portfolio risk and overall bank risk, these banks may seek to compensate for the increased risk by striving for higher expected returns. To achieve this, banks might attempt to gain a higher degree of market power, which would be reflected in an increased Lerner index. Therefore, the relationship between NPLs and competition is bidirectional: not only can competition influence NPLs, but NPLs can also impact the level of competition. This reverse causality complicates the analysis and necessitates the use of appropriate econometric techniques to address the potential endogeneity and obtain unbiased estimates.

To address this potential endogeneity, this study uses instrumental variable (IV) techniques estimations. We employ freedom to enter the banking market and regulatory barriers as instruments to explain measures of banking competition.

A further issue in testing the views on banking competition is the effect of the country's level of development. For example, banks operating in countries that are less developed tend to have a weak business environment and may find it difficult to expand their loan portfolios to take on additional risks. We include data on an index of development, which measures the country's level of development in our analysis.

We compute and consider separately several alternative measures of bank competition, including the Lerner index, which is based on the deviation between price and marginal costs. As discussed in section 2.1.3, we prefer the Lerner index, but we also include in our analysis other measures of competition and bank risk such the Boone Indicator and CR5 to check for robustness.

We considered the below panel data model:

$$NPL_{it} = a_0 + a_1 L_{it} + a_2 X_{it} + a_3 M_{it} + c_i + e_{it} \quad (1)$$

Where NPL_{it} is the aggregate non-performing loans to total gross loans L denotes banking competition, X denotes the macroeconomic factors, M denotes the bank specific variables as presented in Table 2.2, i corresponds to the examined countries of the sample, t denotes the year, a_0 is the intercept, a_1 is the vector of slope coefficients, representing the effects of the Lerner index on NPLs, a_2 is the vector of slope coefficients, representing the effects of the Macroeconomic variables on NPLs, a_3 is the vector of slope coefficients, representing the effects of the bank specific variables on NPLs , c_i is the country specific effect (that is, the country level time invariant factors explaining NPLs) and e_i is the remainder components (a "traditional" error term). In this model, all variables are aggregated at the country level, meaning that reflect the average or total values for each country over time. This aggregation allows us to analyze the impact of banking competition, macroeconomic factors, and bank-specific variables on the overall level of non-performing loans within each country. By considering country-level aggregates, we can capture broader economic and financial trends that influence banking stability across different countries.

First, we estimate the model using the Random Effect (RE) regression and Fixed Effect (FE) regression. The RE estimation assumes that the country's specific effects are uncorrelated with the independent variables while the FE estimation assumes that the individual specific effects are correlated with the independent variables. This might be the case because country time-invariant characteristics such as culture and institutional and legal framework might be correlated with our independent variables. Secondly, to test whether the coefficients of the RE model are statistically different from the coefficients of the FE model, the Durbin-Wu-Hausman test with the sigmamore option was used. Based on the result of this test as seen in appendix 2.7.1, the Hausman test gives us evidence to reject the null hypothesis.

Therefore, in this study only the fixed effect (FE) estimations were discussed and reported as seen in Appendix 2.7.4, 2.7.5 and 2.7.6. The fixed effect model helped to control for the average differences across countries in any observable or unobservable predictors and also helped to entirely capture the time constant omitted variables thereby greatly reducing omitted variable bias. Using this model, we assume that unobservable factors that might simultaneously affect our regression are time-invariant. Under FE, consistency does not require that the individual intercepts and e_{it} are uncorrelated. Only $(X_{it}e_{it})$ = 0 must hold.

Before applying panel regression, we check for the stationarity of the variables and also check for multicollinearity by using the correlation matrix. The result suggests that there is not much correlation between any of the explanatory variables as seen in Appendix 2.7.2. For example, the correlation between NPLs and Lerner index is -0.0093, indicating a very weak negative correlation. The correlation between NPLs and Bank Size is -0.0227, indicating a very weak negative correlation, while the correlation between NPLs and unemployment is 0.0397, indicating a very weak positive correlation. Note that for our regression, all standard errors are clustered at the country level to account for the within-country correlation that may exist between banks in the same country.

Furthermore, with the purpose of extending our investigation we include a quadratic term to capture a potential non-linear relationship between competition (L_{it}) and non-performing loans (NPL_{it}) as seen in equation 2. Additionally, to capture the dynamics of the economic cycle and its influence on loan performance, we use one lag for the GDP variable. Lagged GDP can have a significant impact on NPLs by reflecting past economic conditions and influencing borrowers' ability to repay loans. This is because economic cycles are reflected in GDP changes. That is, during economic expansion there is typically high GDP growth and low GDP growth during economic recession. Also, banks and financial institutions often adjust their lending practices in response to economic conditions. During periods of economic expansion (high lagged GDP), banks may be more willing to extend credit, potentially leading to a rise in loan issuance and, if not managed prudently, an increase in NPLs. Conversely, during economic downturns (low lagged GDP), banks may tighten lending standards to mitigate risks, potentially reducing the likelihood of new NPLs but possibly exacerbating existing NPLs due to reduced borrower capacity to service debts. Therefore, including the lagged GDP helps to check the influence of economic cycle on NPLs. The inclusion of time lags is commonly used in literature e.g. Jimenez and Saurina (2006), Louzis, Vouldis, and Metaxas (2010). Therefore, our second econometric model is expressed as follows:

$$NPL_{it} = a_0 + a_1 L_{it} + a_2 L_{it}^2 + a_3 X_{it} + a_4 M_{it} + a_5 \mathrm{GDP}_{it} + a_6 \mathrm{GDP}_{it-1} + c_i + e_{it} \quad (2)$$

Where,

GDP_{it} is the vector of the GDP variable for country i at time t.

GDP_{it-1} is the vector of the GDP variable for country i at time t-1.

a_5 is the vector of slope coefficient, representing the effects of GDP on NPLs.

a_6 is the vector of slope coefficient, representing the effects of GDP in the previous time period on NPLs in the current time period.

To compare the effect of competition on non-performing loans across different levels of economic development, we further modified model 2 by interacting the Lerner index with the Human Development Index (HDI) as seen in equation 3.

Therefore, the final model for this study is:

$$NPL_{it} = a_{0it} + a_1 L_{it} + a_2 L^2_{it} + a_3 X_{it} + a_4 M_{it} + a_5 \mathrm{GDP}_{it} + a_6 \mathrm{GDP}_{it-1} + a_7 \mathrm{H}_{it} + \theta_1 (L_{it} \times H_{it}) + \theta_2 (L^2 \times H_{it}) + c_i + e_{it} \quad (3)$$

Where,

H_{it} is the vector of the HDI variable for country i at time t.

a_7 is the vector of slope coefficient, representing the effects of HDI on NPLs.

θ_1 Measures the difference in the effect of banking competition when the country's level of development is considered.

θ_2 Measures the difference in the effect of the square of banking competition when the country's level of development is considered.

Finally, to address the likely endogeneity of the measures of banking competition, we employ the use of instrumental variables (IV) estimations as seen in Appendix 2.7.7 and 2.7.8. Schaeck and Cihak (2012) and Berger et. al., (2017) also employ the use of instrumental variables using the 2SLS technique and the GMM estimator respectively. The instrumental variables we use in this study are freedom to enter the banking market and regulatory barriers. Regulatory barriers are a key determinant for the scope of operations of banks and are likely to affect the level of competitiveness. This index provides information as to whether banks can engage in securities, insurance, and real estate activities, and whether they can hold stakes in nonfinancial institutions. This variable takes on values between (1) and (10) and varies over time, with higher values indicating greater restrictions on bank activities and nonfinancial ownership and control. Freedom to enter the banking market represents a broad indicator for the openness of a banking system, capturing whether foreign banks are allowed to operate freely, whether difficulties are faced when setting up domestic banks, and whether the government influences the allocation of credit. This variable takes on values between (0) and (10) and varies over time, where higher values indicate lower entry restrictions.

We argue that the instrumental variables meet the three assumptions needed for an instrumental variable, which are:

(1) The instrument Z and the banking competition variable, L are associated either because the instrument has a causal effect on L, or because L and the instrument have a common cause.

Both instruments of banking competition are likely to have a causal effect on banking competition.

(2) The instrument affects the outcome NPLs only through L (holding other control variables constant). It is unlikely that freedom to enter the banking market alone affects NPLs. To explain this, consider that regulatory barriers to entering the banking market are strongly correlated with the institutional quality in a country. These institutions, in turn, are correlated with NPLs. However, by using fixed effects (FE) estimations, we control for these country-specific institutions and other cultural factors, which are constant over time. This means that while regulatory barriers might be linked to broader institutional contexts, our FE model isolates the variation within countries over time, effectively controlling for these time-invariant institutional characteristics.

As a result, although the exclusion restriction condition might not hold perfectly in a standard cross-sectional instrumental variable (IV) analysis, it is more likely to hold in the FE IV context. This is because the fixed effects approach mitigates the influence of time-invariant confounders, allowing us to argue more convincingly that any remaining variation in freedom to enter the banking market affects NPLs primarily through changes in banking competition, rather than through direct effects of the regulatory barriers themselves. Instead, we would argue that freedom to enter the banking market acts primarily through banking competition. We also acknowledge that regulatory barriers may be another pathway through which banking competition affects NPLs, and thus adjust for this measured confounding in our analysis.

(3) The instrument is not associated with uncontrolled factors that cause NPLs.

Employing our instrumental variables to address the possible issue of endogeneity for our measure of competition, model 2 and model 3 can be written as model 4 and model 5 respectively (which are our preferred model).

$$NPL_{it} = a_0 + a_1 \acute{L}_{it} + a_2 \acute{L}^2_{it} + a_3 X_{it} + a_4 M_{it} + a_5 \mathrm{GDP}_{it} + a_6 \mathrm{GDP}_{it-1} + c_i + e_{it} \quad (4)$$

$$NPL_{it} = a_0 + a_1 \acute{L}_{it} + a_2 \acute{L}^2_{it} + a_3 X_{it} + a_4 M_{it} + a_5 \mathrm{GDP}_{it+} a_6 \mathrm{GDP}_{it-1} + a_7 \mathrm{H}_{it} + \theta_1 (L_{it} \times H_{it}) + \theta_2 (L^2 \times H_{it})_{it} + c_i + e_{it} \quad (5)$$

Where $\acute{L}_{it}$ is the predicted value after we regress L_{it} on the constant, our valid instruments and all other explanatory variables while $\acute{L}^2_{it}$ is the predicted value after we regress L^2_{it} on the constant, the squared of our valid instruments and all other explanatory variables.

2.5 Models Estimation

The results of all our estimations are presented in Table 2.4 and in appendix 2.7. We present the coefficients of the independent variables and the corresponding p-values, which are based on clustered (at the country level) standard errors. Via the examination of the coefficients of the regressors, statistically significant correlations with nonperforming loans were demonstrated.

Table 2.4: Regression Results of Model 1, 2, 3, 4 & 5

Variables	Model 1	Model 2	Model 3	Model 4 (IV Estimation)	Model 5 (IV Estimation)
Lerner Index	-0.0334** (0.0139)	-0.0685*** (0.0253)	-0.1873*** (0.0642)	-0.0583** (0.0262)	-0.1675** (0.0656)
Lerner Index^2		0.0004*** (0.0001)	0.0011*** (0.0004)	0.0336** (0.0149)	0.0989*** (0.0375)
Log_GDP	-0.7926*** (0.1575)	-0.7823*** (0.1577)	-0.7740*** (0.1780)	-0.7696*** (0.1611)	-0.7606*** (0.1807)
Log_GDPit-1	0.6735*** (0.1494)	0.6876*** (0.1496)	0.3930*** (0.1594)	0.6989*** (0.1530)	0.3112*** (0.1664)
Unemployment (UNEM)	0.8926** (0.3752)	0.8864** (0.3755)	0.6719* (0.4241)	0.9554** (0.3854)	0.7176* (0.4350)
Return on Assets (ROA)	-0.2749*** (0.0718)	-0.2654*** (0.0721)	-0.1788** (0.0849)	-0.2667*** (0.0737)	-0.1869** (0.0908)
Loan Deposit Ratio (LDR)	0.0049* (0.0035)	0.0049* (0.0035)	0.0055* (0.0034)	0.0051* (0.0035)	0.0059* (0.0034)
Foreign Banks among Total Banks	-0.0290** (0.0122)	-0.0305** (0.0123)	-0.0308** (0.0127)	-0.0291** (0.0129)	-0.0293** (0.0132)
Bank Size	-0.0436* (0.0230)	-0.0430* (0.0229)	-0.0313* (0.0195)	-0.0482** (0.0238)	-0.0350** (0.0201)
Human Development Index (HDI)			-0.2209*** (0.0569)		-0.2010*** (0.0605)
Lerner Index#HDI			-0.00218* (0.0011)		-0.0022** (0.0011)
Lerner Index^2#HDI			0.0001** (0.0000)		0.0014** (0.0007)
Constant	33.7109**	29.4555**	47.7048***	24.4817**	29.33316**
Observation	1,212	1,212	1,212	1,165	1,165
R-Squared	0.0624	0.0640	0.0859	0.0467	0.1036
Under-identification Test	-	-	-	0.0003	0.0002
Over-identification Test				0.4082	0.1689

Note: Table shows the coefficient estimates and p-values of the regression models. * Significance at the 10% level, ** significance at the 5% level, * significance at the 1% level. Also note that for the regressions all standard errors are clustered.**

2.5.1 Discussion of Main Results

Taking into consideration the basic aim of this study and from the results presented in table 2.4, we observe a negative linear relationship between the Lerner index and NPLs when we do not allow for a quadratic term. However, when we allow for a quadratic term to help investigate whether there is a non-linear relationship between banking competition and NPLs, we observe a statistically significant negative relationship exists between the Lerner Index and NPLs while a positive and significant relationship exists between the quadratic term and NPLs. This implies that a U-shaped relationship exists between the Lerner index and the performance of loans which is contrary to the inverted U-shaped relationship revealed by Berger et. al., (2009).

Model 4, which addresses the potential endogeneity problem in model 2, does not control for the country's level of development. We test for the validity of our instruments using the under-identification LM test and Sargan Statistic over-identification test. The results from these tests show that the instruments are valid as the p-value from the under-identification test requires a value lower than 0.05 to reject the null hypothesis at 5% while the p-value from the over-identification test requires a value higher than 0.05 to reject the null hypothesis at 5%. Also, the results of the first-stage regressions of banking competition on the instruments are presented in Appendix 2.7.3. The results show that while regulatory trade barriers decrease banking competition, freedom to enter the banking market and compete increases banking competition. The result from model 4 reveals similar results to model 2. It shows that, although at low levels of the Lerner index (i.e, very high competition), an increase in the Lerner index (meaning less competition) corresponds to decreasing NPLs. However, the rate at which NPLs decreases with the Lerner index decreases as competition becomes lower. At some point, NPLs reach a minimum and then increase with the Lerner index. This can be clearly seen in Figure 2.1. These results from model 4 show that there is an optimal level of competition at which NPLs are at their minimum. This implies that too much and too little competition in the banking industry is detrimental to the performance of loans. That is, high competition and high market power are both associated with riskier loan portfolios in the banking industry. Appendix 2.7.9 shows the overall turning point (optimal level of competition) when the country's level of development is not controlled for.

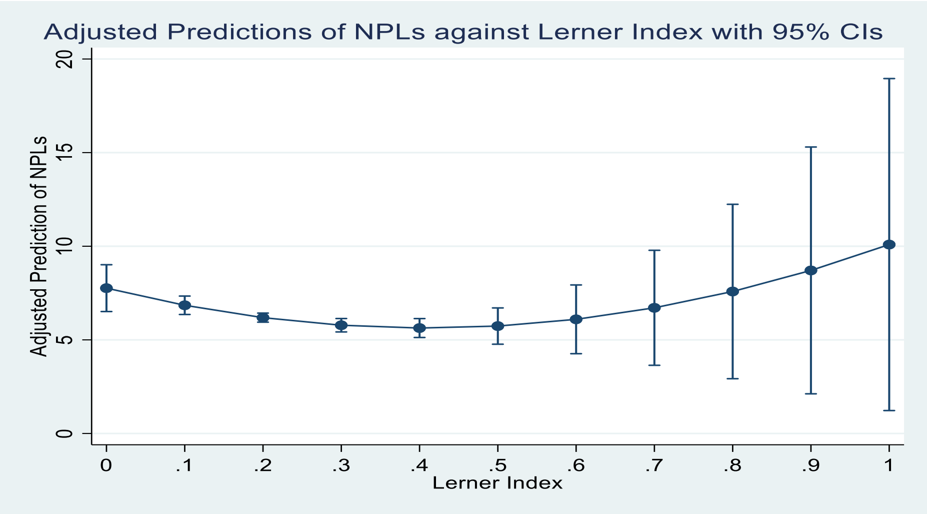


Figure 2.1: Adjusted Prediction of NPL against Lerner Index

Figure 2.2 shows the distribution of the Lerner index across countries. From the distribution, there are not many countries with the Lerner index greater than 0.5. This explains the difference in confidence interval we see in figure 2.1 as the Lerner index becomes greater than 0.5.

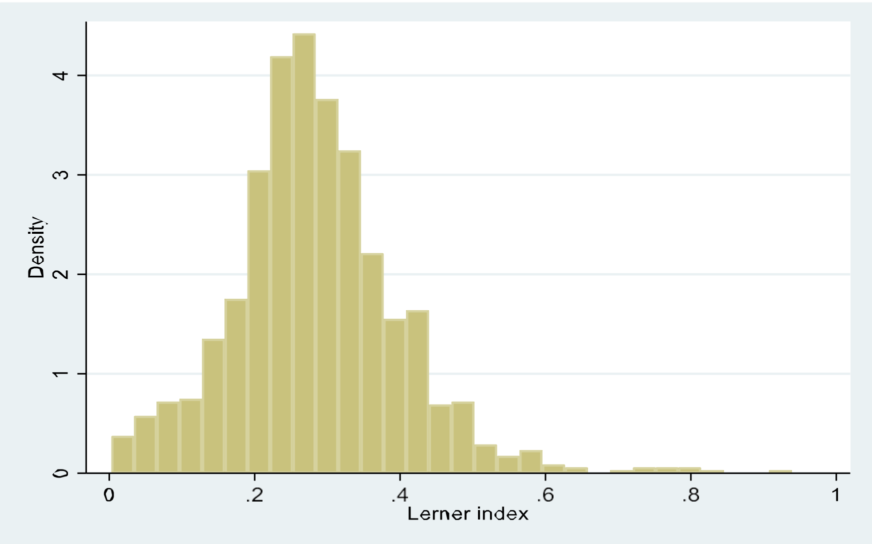


Figure 2.2: Histogram Showing the Distribution of the Lerner Index across Countries

Model 3 gives more insight into the relationship between banking competition and financial stability when the country's level of development in which the banks operate is taken into consideration. The results from this model show that the relationship between banking competition and non-performing loans is more quadratic for low developed and medium developed countries. That is, a U-shaped relationship seems to hold only for low and medium developed countries. This difference in the relationship that exists across the different levels of development could be associated with the fact that countries that are more developed tend to experience better access to credit facilities due to good governance, better structure, better economic policies, and less corruption. Hence a shock in competition might have a different effect in high developed countries than in medium and low developed countries as seen in figure 2.3.

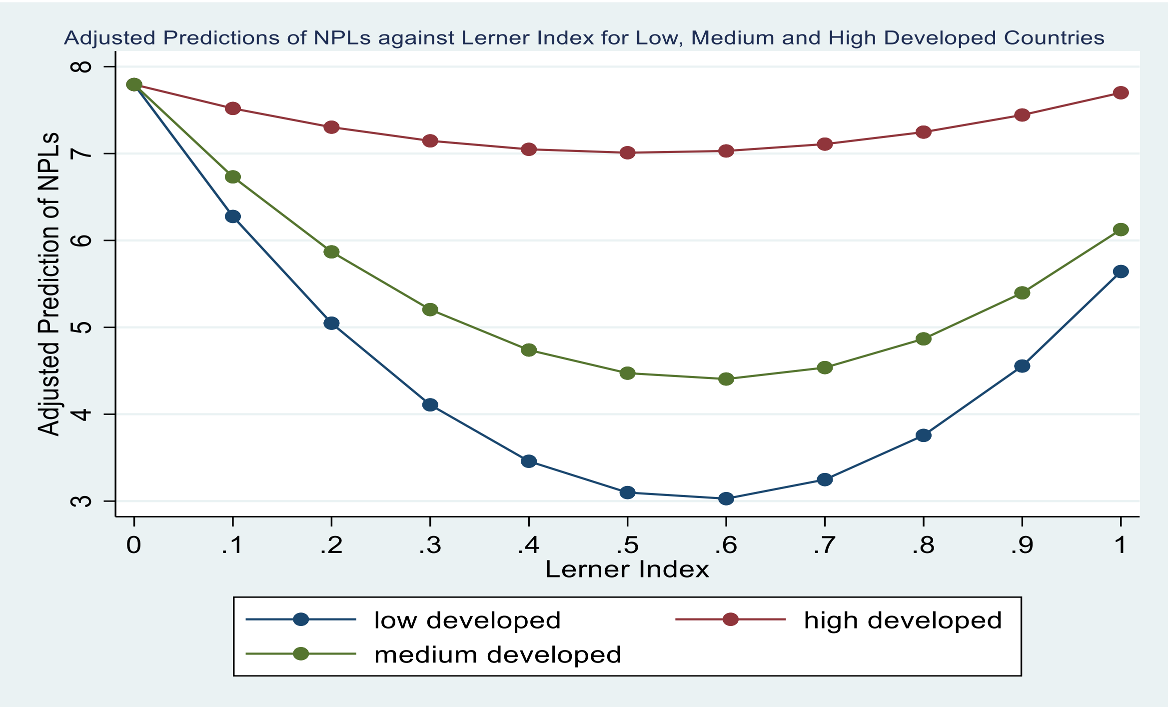


Figure 2.3: Adjusted Prediction of NPL against Lerner Index for Low, Medium and High Developed Countries

Results from this study provide evidence for both the "competition-fragility" hypothesis and "competition-stability" hypothesis. However, this seems to be more evident in low developed and medium developed countries as seen in Figure 2.3. This implies that, the optimal level of competition varies according to a country's level of development. This evidence in support of both the "competition-fragility" hypothesis and "competition-stability" hypothesis as observed in low and medium developed countries could be linked to the fact that in a very competitive environment, banks lose borrowers and earn less informational rent from their relationship with their borrowers due to the increase in rivalry that exists as a result of more competition. This in turn will result in a decrease in the banks' incentives to properly screen borrowers and thereby lead to a riskier loan portfolio. It could also be associated with the fact that very high competition erodes market power, decreases profit margins, and results in a reduced franchise value that encourages bank risk taking. On the other hand, very high market power could be associated to a riskier loan portfolio because more market power as a result lower competition in the loan market, may result in higher bank risk as the higher interest rates charged to loan customers make it harder to repay loans and worsen moral hazard incentives of borrowers to shift into riskier projects. Also, the higher interest rate could lead to a riskier set of borrowers due to an adverse set of selection procedures and scrutiny. When we address the potential endogeneity problem in model 3, model 5 gives us similar results as observed in model 3. Model 5 provides evidence showing that the level of development in which the banks operate influences the relationship between banking competition and NPLs.

With regards to the control variable, we find that GDP has a negative contemporaneous effect (i.e. decreasing NPLs) in the current year, but a positive effect the year after (i.e. increasing NPLs). That is, when the economy performs, the rise in income enables borrowers to repay their loans that are due to the banks in stipulated time therefore, recognizing the loan as standard loan and not a bad loan. This finding was corroborated with Salas and Saurina (2002), Louzis, Vouldis, and Metaxas (2010), Nkusu (2011), and De Bock and Demyanets (2012). The Lagged

GDP growth also significantly affects NPL but with a positive sign. This finding lends support to the notion that during the boom period, banks' credit standards become quite loose thereby leading to the deterioration of banks' assets.

Also, in line with Garciya-Marco and Robles-Fernandez (2008), we record a significant negative relationship between NPL and ROA. This result, as expected, indicates that a decrease in the profitability ratios will lead to an increase in non-performing loans, confirming the risk-taking behaviour of banks. This negative relationship is also in line with the argument that low profitability and bad financial leverage lead to riskier activities and riskier loan portfolios (Cotugno et. al. (2010), Louzis et. al. (2012).

Based on our estimations, we found a strong positive correlation between loan quality and unemployment, revealing that lack of employment weakens borrowers' ability to pay their loan installments thereby leading to an increase in bad loans.

Additionally, from our results, we observed that Percentage of the number of banks where 50% or more of its shares are owned by foreigners has a significant negative relationship with non-Performing loans. This evidence might be explained by the nature of foreign banks. That is, foreign banks can be described as having more capital, more experience, better efficiency, and better technological know-how which therefore leads to better loan screening and management skills and thereby leads to a decrease in non- performing loans.

Finally, we observed that Bank Size has a significant negative relationship with the ratio of non-performing loans. That is, it supports the theory that bigger banks tend to be less involved in high-risk activities or creating risky loan portfolios, thereby leading to lower non-performing loans (Yulianti et. al., 2018).

2.5.2 Robustness Checks

To establish the robustness of our findings, we present results from estimating various alternative specifications in appendix 2.8. First, we introduce alternative measures to banking competition (the Boone indicator and the concentration index CR5) and re-run our models. We present the results for these specifications in tables 2.5 and 2.6 respectively.

Table 2.5: Boone Indicator as a Measure of Competition

Variables	Model 1	Model 2	Model 3	Model 4 (IV Estimation)	Model 5 (IV Estimation)
Boone Indicator	-0.0153** (0.010)	-0.0478** (0.054)	-0.0506** (0.050)	-0.2181** (0.052)	-0.1150** (0.004)
Boone Indicator ^{2}		0.0081*** (0.009)	0.0127** (0.002)	0.1608*** (0.011)	0.1890** (0.069)
Log_GDP	-0.6484** (0.382)	-0.6461*** (0.480)	-0.6511*** (0.491)	-0.5396*** (0.4222)	-0.6894*** (0.180)
Log_GDPit-1	0.4769** (0.292)	0.3769** (0.221)	0.3808*** (0.426)	0.3482*** (0.281)	0.4599*** (0.164)
Unemployment (UNEM)	0.3294*** (0.089)	0.3198* (0.089)	0.3625** (0.087)	0.6328** (0.0851)	0.2205*** (0.052)
Return on Assets (ROA)	-0.4088*** (0.092)	-0.4076*** (0.092)	-0.4000*** (0.090)	-0.5423** (0.093)	-0.4669*** (0.086)
Loan Deposit Ratio (LDR)	0.0054* (0.003)	0.0053** (0.003)	0.0052** (0.003)	0.0068** (0.008)	0.0041** (0.004)
Foreign Banks among Total Banks	-0.0292*** (0.014)	-0.0291** (0.014)	-0.0286*** (0.014)	-0.0348** (0.023)	-0.0206** (0.013)
Bank Size	-0.0193** (0.038)	-0.0186** (0.038)	-0.0203** (0.003)	-0.0563** (0.074)	-0.0368** (0.021)
Human Development Index (HDI)			-0.1253** (0.043)		-0.1241** (0.051)
Boone Indicator#HDI			0.1207** (0.081)		-0.1255** (0.065)
Boone Indicator ^{2}#HDI			0.0037** (0.002)		0.0024** (0.001)
Constant	31.0721**	30.8862***	31.3703***	16.4170***	36.3193**
Observations	1,112	1,112	1,212	1,165	1,165
R-Squared	0.0786	0.0792	0.0866	0.0335	0.2515
Under-identification Test Over-identification Test	-	-	-	0.0070 0.4390	0.0030 0.4302

Note: Table shows the coefficient estimates and p-values of the regression models. * Significance at the 10% level, ** significance at the 5% level, * significance at the 1% level. Also note that for the regressions all standard errors are clustered.**

2.6: CR5 as a Measure of Competition

Variables	Model 1	Model 2	Model 3	Model 4 (IV Estimation)	Model 5 (IV Estimation)
CR5	-0.0486*** (0.025)	-0.1138*** (0.011)	-0.0842*** (0.027)	-0.1362*** (0.012)	-0.1186*** (0.018)
CR5 ²		0.0114*** (0.009)	0.0162*** (0.002)	0.0217*** (0.005)	0.0109** (0.011)
Log_GDP	-0.7899*** (0.052)	-0.7880*** (0.051)	-0.8988*** (0.140)	-0.8080*** (0.1515)	-0.7790** (0.189)
Log_GDPit-1	0.6000** (0.044)	0.5917** (0.044)	0.4858*** (0.038)	0.5637** (0.035)	0.5431** (0.065)
Unemployment (UNEM)	0.7520** (0.236)	0.4511** (0.154)	0.2672** (0.170)	0.1823** (0.014)	0.1531** (0.066)
Return on Assets (ROA)	-0.2840** (0.116)	-0.2830** (0.012)	-0.2741** (0.111)	-0.2815*** (0.213)	-0.4828** (0.033)
Loan Deposit Ratio (LDR)	0.0050* (0.0030)	0.0049** (0.003)	0.0049** (0.003)	0.0052* (0.003)	0.0104* (0.013)
Foreign Banks among Total Banks	-0.0240** (0.013)	-0.0242** (0.013)	-0.0206** (0.013)	-0.0254** (0.022)	-0.0094* (0.029)
Bank Size	-0.0125** (0.030)	-0.0134** (0.028)	-0.0071* (0.002)	-0.0139** (0.027)	-0.0881** (0.024)
Human Development Index (HDI)			-0.1237*** (0.037)		-0.1140** (0.052)
CR5**#HDI**			-0.2520** (0.035)		-0.2857** (0.012)
CR5 ²**#HDI**			0.0106** (0.004)		0.0069** (0.011)
Constant	26.3230***	19.5579***	19.3273***	16.1575***	25.5493**
Observation	1,112	1,112	1,112	1,165	1,165
R-Squared	0.0512	0.0566	0.0779	0.06384	0.6121
Under-identification Test	-	-	-	0.0044	0.0032
Over-identification Test				0.3259	0.2974

Note: Table shows the coefficient estimates and p-values of the regression models. * Significance at the 10% level, ** significance at the 5% level, * significance at the 1% level. Also note that for the regressions all standard errors are clustered.**

The results from tables 2.5 and 2.6 generally show our findings to be robust to these alternative measures of competition with similar results to our main specification. These results provide evidence for both the competition-stability and competition-fragility hypotheses. They show the presence of a significant non-linear relationship between banking competition and non-performing loans with this relationship being more evident in low developed and medium developed countries as seen in appendix 2.8.11.

Specifically, the robustness checks in tables 2.5 and 2.6 contribute to a better understanding of the consistency and reliability of the results of the model across different specifications. The table presents results from the fixed effects estimations (Models 1, 2 & 3) and from the instrumental variable estimations (Models 4 & 5). These models are crucial in explaining how the relationship among the variables is affected by the inclusion of a number of factors and the application of instrumental variables.

Similar to our main results, results from Model 1in tables 2.5 and 2.6 show that a negative linear relationship exists between banking competition and NPLs when we do not allow for a quadratic term. Models 2 and 4 in both tables show that, when we allow for a quadratic term to help investigate whether there is a non-linear relationship between banking competition and NPLs, a statistically significant negative relationship exists between the banking competition variable and NPLs while a positive and significant relationship exists between the quadratic term and NPLs. This implies that a U-shaped relationship exists between banking competition and loan performance, which is in line with the findings in our main results. Similarly, the results from Models 3 and 5, which take into account the country's level of development in which the banks operate, show that the relationship between banking competition and non-performing loans is more quadratic for low developed and medium developed countries. That is, a U-shaped relationship seems to hold only for low and medium developed countries. Overall, the robustness checks featuring the Boone Indicator (table 2.5) and CR5 (table 2.6) as alternative measures of competition provide evidence in support of our main results across different models' specifications.

Furthermore, to establish the robustness of our findings in our main results, we introduce the Z-Score as an alternative measure of financial stability and re-run our main model (Model 5). Model 5 does not only account for the country's level of development in which the banks operate but also addresses the potential problem of endogeneity using Instrumental variable technique. The results from our estimation are presented in table 2.7.

Table 2.7: Further Robustness Checks for Model 5

Variables	Z-Score as a Measure of Financial Stability	Before the Global Financial Crisis (NPL as the dependent Variable)	After the Global Financial Crisis (NPL as the dependent Variable)
Lerner Index	0.0613** (0.029)	0.7038** (0.069)	-0.0921** (0.056)
Lerner Index^2	-0.1220** (0.051)	0.0717* (0.020)	0.5717** (0.033)
Log_GDP	0.8829*** (0.141)	-0.2130** (0.063)	-0.5012** (0.081)
Log_GDPit-1	0.5301*** (0.130)	0.6539** (0.046)	0.8772** (0.076)
Unemployment (UNEM)	-0.2783** (0.338)	0.5771** (0.062)	0.1794* (0.033)
Return on Assets (ROA)	0.4009*** (0.071)	-0.8342** (0.084)	-0.6134*** (0.0226)
Loan Deposit Ratio (LDR)	-0.0039* (0.0035)	0.0542* (0.006)	0.0124** (0.024)
Foreign Banks among Total Banks	0.020** (0.010)	-0.0641** (0.0122)	-0.0534 (0.038)
Bank Size	0.0408*** (0.016)	-0.0109* (0.0230)	-0.1614** (0.0109)
Human Development Index (HDI)	0.435** (0.047)	-0.2010** (0.0605)	-0.2010*** (0.0605)
Lerner Index*HDI	0.0024*** (0.001)	-0.5034* (0.073)	-0.0342** (0.008)
Lerner Index^2*HDI	-0.0012** (0.001)	0.1602* (0.044)	0.0532** (0.005)
Constant	22.6070***	34.38**	43.08**
Observation	1,165	323	744
R-Squared	0.5808	0.6153	0.6725
Under-identification Test	0.0002	0.0114	0.0365
Over-identification Test	0.9729	0.8237	0.5723

Note: Table shows the coefficient estimates and p-values of the regression models. * Significance at the 10% level, ** significance at the 5% level, * significance at the 1% level. Also note that for the regressions all standard errors are clustered.**

The findings in the second column in table 2.7 provide similar results in support of both the competition-stability and competition-fragility hypotheses. The results show that a statistically significant positive relationship exists between banking competition and the Z-Score while a negative and significant relationship exists between the quadratic term and the Z-Score. However unlike in the case of NPLs, we observe an inverted U-shaped relationship for only low and medium developed countries as seen in figure 2.4. This difference in observation is attributed to how the Z-Score measures financial stability. That is, a higher Z-score indicates more stability in the banking industry while a higher NPL indicates less stability in the banking industry.

In the context of development, low, medium, and high development can be defined based on the Human Development Index (HDI), which is a composite measure of a country's development status (UNDP, 2021). The HDI takes into account factors such as life expectancy, education (mean years of schooling and expected years of schooling), and per capita income. Low development typically refers to countries with HDI values below 0.550, while medium development usually includes countries with HDI values ranging from 0.550 to 0.699. Then, high development encompasses countries with HDI values of 0.700 and above. These classifications are based on the United Nations Development Program’s (UNDP) categorization of countries according to their HDI scores. Therefore, when referring to low and medium developed countries in the context of the statement, we would be considering countries with HDI values below 0.700 but above 0.550, and high development would refer to countries with HDI values of 0.700 and above.

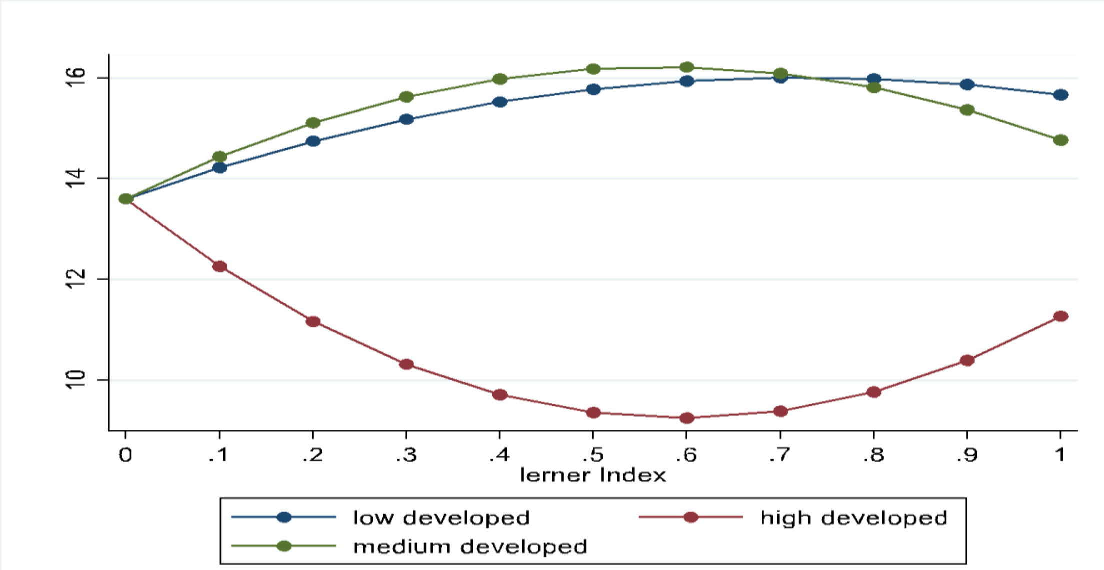


Figure 2.4: Adjusted Prediction of the Z-Score for Low, Medium and High Developed Countries

Finally, we investigate the periods before and after the global financial crisis and then re-run our final model 5 regression. The results which are also reported in table 2.7 (columns 3 and 4) sprovide different evidence. The result for the period before the global financial crisis provides evidence in support of only competition-fragility hypothesis as seen in figure 2.5. That is, the result indicates that before the global financial crisis, banking competition was not very encouraged within the industry as it was believed to lead to more fragility in the banking industry.

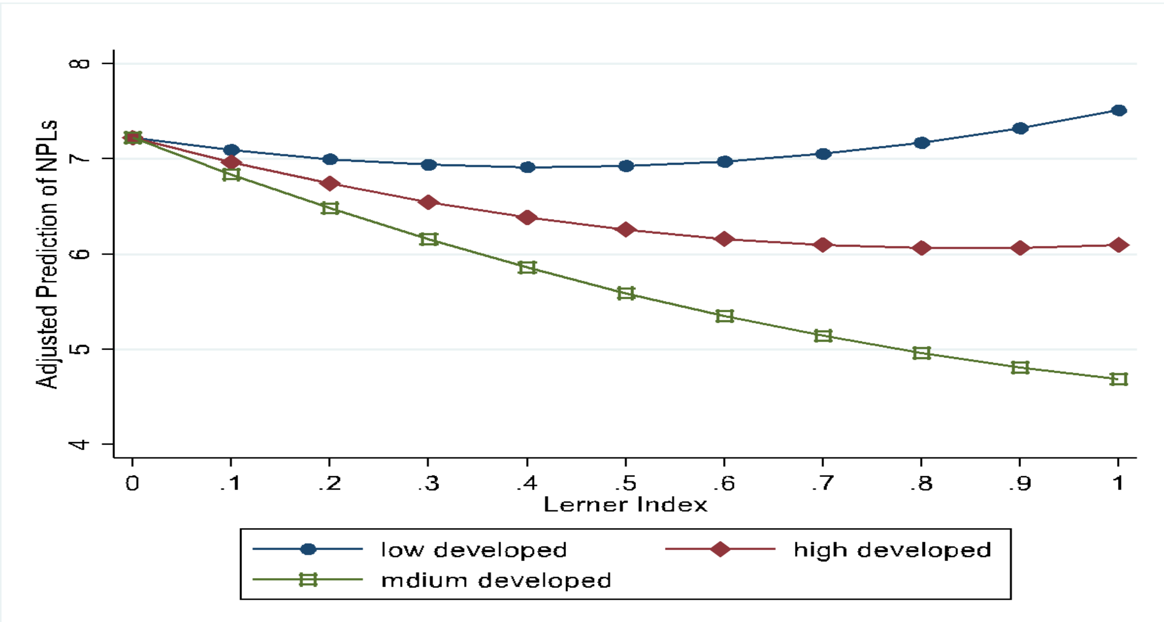


Figure 2.5: Adjusted Prediction of the NPLs for Low, Medium and High Developed Countries before the Global Financial Crisis

However, the results for the period after the global financial crisis provide evidence in support of both competition-fragility and competition-stability hypotheses as seen in figure 2.6. That is, for the period after the global financial crisis, the results show that a non-linear relationship exists between banking competition and financial stability, which is similar to our findings in our main specification. These results provide evidence suggesting that the banking industry was more receptive to competition in the banking industry after the global financial crisis.

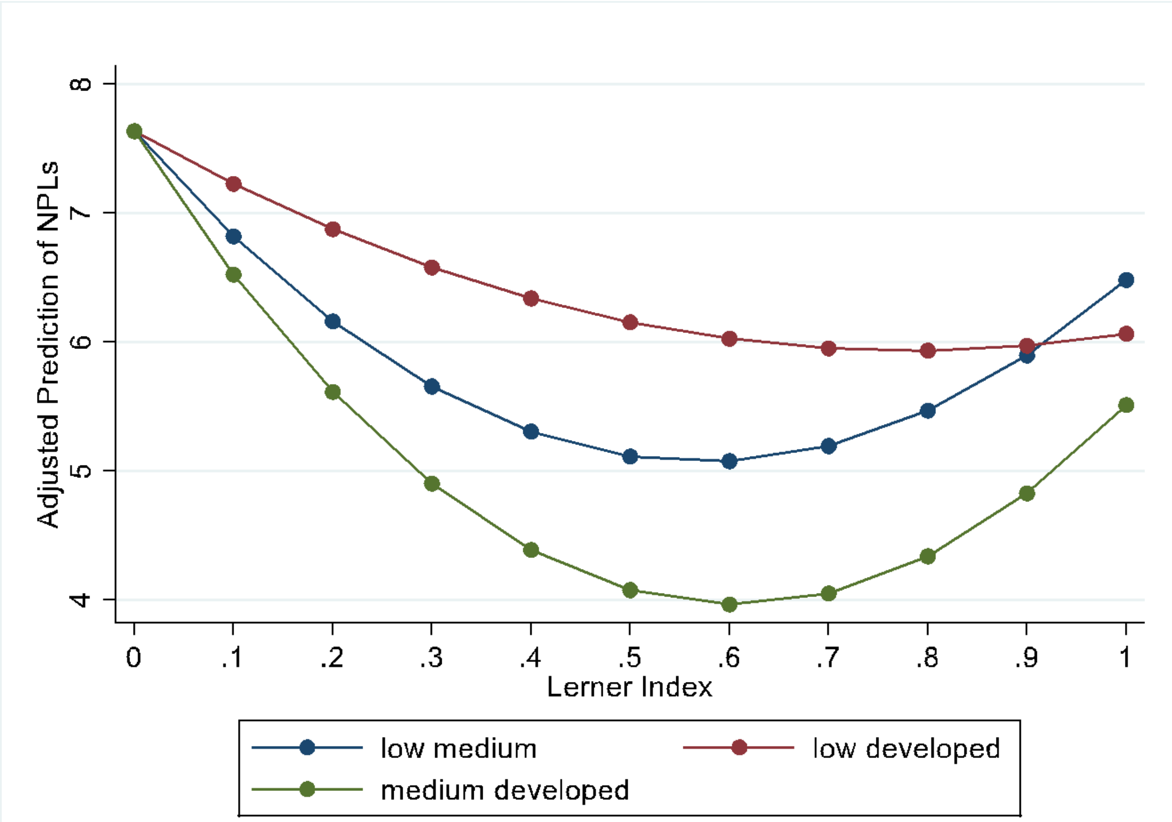


Figure 2.6: Adjusted Prediction of the NPLs for Low, Medium and High Developed Countries after the Global Financial Crisis

2.6 Conclusions and Recommendations

This study has analyzed the relationship between competition in the banking industry and financial stability using NPLs as a measure of financial stability. By investigating this relationship across countries at different levels of development, we are able to observe how this relationship differs across low developed, medium developed and high developed countries.

Our IV regression analysis provides evidence for the effect of banking competition on NPLs. We show that within our preferred model specification which incorporates the country's level of development, a U-shaped relationship seems to hold only for low and medium developed countries while we observe a weak non-linear relationship for high developed countries. This finding highlights the importance of controlling for the country's level of development when examining the relationship between banking competition and NPLs. When we compare to the literature on banking competition and financial stability, our findings are not particularly uncommon, as few studies like Kasman and Kasman (2015), Noman et al. (2017), and Jiménez et al. (2013) have shown similar findings on banking competition. It is important to note, however, that some of these studies are not directly comparable due to differences in study indicators such banking competition variable measures, financial stability variable measures or group of country. Nevertheless, they are relevant in giving vital insights into the general impact of banking competition on financial stability.

Among the three studies listed, the most relevant to our study is Jiménez et al. (2013), who undertaking an empirical procedure similar to our model 2 and only focusing on the Spanish banking system, shows the presence of a non-linear relationship between banking competition and NPLs. Although our study differs from this study given that we account for endogeneity using instrumental variables, use over 100 countries in our study and also control for the country's level of development.

One of the major limitations in this study is our unbalanced sample size across low, medium and high developed countries. Having a relatively unbalanced sample size for each group of countries, as in the case of our study, comes at the cost of much more limited variation in our data, particularly in our results. Given this, future research that estimates the relationship between banking competition and financial stability may need to use a balanced sample size for each group of countries when controlling for the country's level of development in their study.

Therefore, we cannot conclude that a non-linear relationship only exists for low and medium developed countries due to the limitations present. Our findings call for further research, particularly within the context where equal data on all groups of countries is scarce. The implementation of higher quality datasets for low, medium and high developed countries will help to give further insight into the true nature of the relationship between banking competition and financial stability.

Overall, our results indicate that the country's level of development in which the bank operates has an impact on the relationship between banking competition and loan performance. Hence, policies to address competition in the banking industry in response to high rates of NPLs need to take into consideration the country's level of development while also ensuring that competition remains at its optimal level in the banking industry.

2.7 Appendix

2.7.1 Hausman Test

2.7.1a `hausman fixed random`

```
                 ---- Coefficients ----
             |      (b)          (B)            (b-B)     sqrt(diag(V_b-V_B))
             |     fixed        random       Difference          S.E.
-------------
 lernerindex | -.0333822     -.0235412       -.009841            .0059825
        gdp  |
        --.  | -.7926114     -.7607598      -.0318517            .0526322
        L1.  |  .6734607      .7031168      -.0296561            .0237174
 foreignban~ | -.0290276     -.0275648      -.0014628            .0017819
        roa  | -.2749396     -.2838568       .0089172            .0223196
 loandeposit~|  .0048724      .0051185      -.0002461             .000412
    banksize | -.0435599     -.0401286      -.0083688            .0048531
       unem  |  .8926179       .355638       .5369798            .2579184
------------------------------------------------------------------------------

b = consistent under Ho and Ha; obtained from xtreg
            B = inconsistent under Ha, efficient under Ho; obtained from xtreg

    Test:  Ho:  difference in coefficients not systematic

                 chi2(12) = (b-B)'[(V_b-V_B)^(-1)](b-B)

                             =  17.05
                   Prob>chi2 =  0.0406

                 (V_b-V_B is not positive definite)
```

2.7.1b `hausman fixed random, sigmamore`

```
                 ---- Coefficients ----
             |      (b)          (B)            (b-B)     sqrt(diag(V_b-V_B))
             |     fixed        random       Difference          S.E.
-------------
 lernerindex | -.0333822     -.0235412       -.009841            .0058146
        gdp  |
        --.  | -.7926114     -.7607598      -.0318517            .0519645
        L1.  |  .6734607      .7031168      -.0296561            .0230401
 foreignban~ | -.0290276     -.0275648      -.0014628            .0014531
        roa  | -.2749396     -.2838568       .0089172            .0197677
 loandeposit~|  .0048724      .0051185      -.0002461             .000244
    banksize | -.0435599     -.0401286      -.0083688            .0030841
       unem  |  .8926179       .355638       .5369798            .2557958
------------------------------------------------------------------------------

b = consistent under Ho and Ha; obtained from xtreg
            B = inconsistent under Ha, efficient under Ho; obtained from xtreg

    Test:  Ho:  difference in coefficients not systematic

                 chi2(12) = (b-B)'[(V_b-V_B)^(-1)](b-B)

                             =  21.91
                   Prob>chi2 =  0.0385
```

2.7.1c The Hausman Test Statistic

The Hausman test is a commonly used statistical method for assessing the suitability of fixed effects (FE) versus random effects (RE) models in panel data analysis. The main idea behind the Hausman test is to determine whether the random effects estimator is consistent, which depends on the assumption that the individual effects are uncorrelated with the explanatory variables. The null hypothesis of the Hausman test is that the random effects model is appropriate, implying that the random effects estimator is both consistent and efficient. If the test statistic significantly rejects this null hypothesis, it suggests that the fixed effects model is more appropriate because the random effects estimator is inconsistent under the alternative hypothesis (Hausman, 1978). The Hausman test statistic is calculated as:

$$\chi^2=(b-B)'[\mathrm{Var}(b-B)]^{-1}(b-B)$$

where b represents the fixed effects estimator, B is the random effects estimator, and Var(b−B) is the variance-covariance matrix of the differences between the estimators.

The Hausman test is based on comparing the difference between the fixed and random effects estimates. Under the null hypothesis, both the fixed and random effects estimators are consistent, but the random effects estimator is more efficient (i.e., it has smaller standard errors). The Hausman test assesses whether this efficiency advantage is outweighed by the potential inconsistency of the random effects estimator. One of the key properties of the Hausman test is that it requires the variance-covariance matrix of the difference between the estimators to be positive definite. When this matrix is not positive definite, the test cannot proceed as usual because it cannot be inverted, leading to a non-invertible matrix problem as seen in appendix 2.7.1a. This issue makes the estimation of the variance-covariance matrix problematic (Wooldridge, 2010).

To address the issue of a non-invertible variance-covariance matrix in the Hausman test, Stata offers the sigmamore option as applied in appendix 2.7.1b. This option adjusts the way the variance-covariance matrix is calculated by applying a more robust estimation method. In particular, sigmamore enables the use of a more generalized version of the variance-covariance matrix that can handle cases where the matrix is not positive definite. The main advantage of this adjustment is that it can prevent the problem of a non-invertible matrix from invalidating the Hausman test. Specifically, the sigmamore option applies a modified estimator for the variance of the difference between the fixed and random effects estimators, which is useful in cases where the typical method of calculating the variance fails (Arellano, 1987). This option improves the robustness of the Hausman test, allowing researchers to continue their analysis. In simple terms, the sigmamore option helps to ensure that the weighting matrix is well-conditioned and reduces the chances of encountering a non-invertible matrix as seen in our stata output in appendix 2.7.1b.

2.7.2 Test for Multicollinearity

```
              |    NPLs   lernerindex gdp    foreigbank~ roa  loandep~ banksize     unem
-------------------------------
         NPLs~ |  1.0000
   lernerindex | -0.0093    1.0000
           gdp | -0.1410   -0.0585  1.0000
  foreignbank~ | -0.0468    0.0170  0.0191    1.0000
           roa | -0.1097    0.1439 -0.1986   -0.0088   1.0000
     loanratio |  0.0265   -0.0202 -0.0124   -0.0200  -0.0076   1.0000
      banksize | -0.0227    0.0223 -0.1393    0.0703   0.0675  -0.0380  1.0000
          unem |  0.0397    0.0798 -0.1721    0.0031   0.1060  -0.0326  0.0421   1.0000
```

2.7.3 First Stage Regression of Banking Competition on the Instruments

```
Fixed-effects (within) regression               Number of obs       =   1,212
Group variable: country                         Number of groups    =     105

R-sq:                                           Obs per group:
     within  = 0.0379                                          min =       1
     between = 0.0095                                          avg =    12.8
     overall = 0.0011                                          max =      13

                                                F(2,1374)           =   27.09
corr(u_i, Xb)  = -0.2108                        Prob > F            =  0.0000

                                                Std. Err. adjusted for 105 clusters in
                                                country)
----------------------------------------------------------------------------------------------
---

                              l3|       Coef.  Std. Err.        t  P>|t|     [95% Conf. Interval]
 -------------------------------
          regulatorytradebarriers |   .7308631  .2554977      2.86  0.004      .2296553   1.232071
   freedomtoentermarketsandcompete |  -1.451715  .2135749     -6.80  0.000     -1.870683  -1.032746
                            _cons |   26.62433  2.080082     12.80  0.000      22.54385   30.70481
 -------------------------------
                          sigma_u |  8.0609929
                          sigma_e |  7.4169901
                              rho |  .54153576  (fraction of variance due to u_i)
----------------------------------------------------------------------------------------------
---
F test that all u_i=0: F(116, 1374) = 14.52             Prob > F = 0.0000
```

2.7.4 Model 1

```
Fixed-effects (within) regression               Number of obs       =   1,212
Group variable: country                         Number of groups    =     105

R-sq:                                           Obs per group:
     within  = 0.0624                                         min =       1
     between = 0.0197                                         avg =    11.0
     overall = 0.0342                                         max =      12

                                                F(8,1094)           =    9.11
corr(u_i, Xb)  = -0.2846                        Prob > F            =  0.0000

                                              (Std. Err. adjusted for 105 clusters in country)

-----------------------------------------------------------------------------------------
                             |                 Robust
                        NPLs |      Coef.  Std. Err.          t  P>|t|     [95% Conf. Interval]
-----------------------------
                lernerindex|    -.0333822      .013858   -2.41  0.016      -.0605734   -.006191
                             |
               log_gdp     |
                       --. |    -.7926114     .1575098   -5.03  0.000      -1.101667   -.483556
                        L1. |     .6734607     .1494385    4.51  0.000       .3802421   .9666792
                             |
foreignbanksamongtotalbanks  |    -.0290276     .0122116   -2.38  0.018      -.0529883  -.0050668
                      roa    |    -.2749396     .0718018   -3.83  0.000      -.4158245  -.1340548
              loandepositratio |   .0048724     .0034867    1.40  0.053        .001169   .0117138
                    banksize |  -.0435599     .0229545   -1.90  0.058      -.0014798   .0885996
                       unem|     .8926179     .3752458    2.38  0.018        .128901    .156335
                      _cons |    33.71085     13.10344    2.57  0.010       28.00014   39.42156
-----------------------------
                    sigma_u |   3.6502275
                    sigma_e |   3.3123159
                        rho |   .54841873  (fraction of variance due to u_i)

-----------------------------------------------------------------------------------------

F test that all u_i=0: F(109, 1094) = 11.82                  Prob > F = 0.0000
```

2.7.5 Model 2

```
Fixed-effects (within) regression               Number of obs      =    1,212
Group variable: country                         Number of groups   =      105

R-sq:                                           Obs per group:
     within  = 0.0640                                          min =        1
     between = 0.0197                                          avg =     11.0
     overall = 0.0372                                          max =       12

                                                F(9,1093)          =     8.30
corr(u_i, Xb)  = -0.2103                        Prob > F           =   0.0000

                                              (Std. Err. adjusted for 105 clusters in country)

------------------------------------------------------------------------------------------

                             |                Robust
                        NPLs |      Coef.  Std. Err.         t  P>|t|      [95% Conf. Interval]
 -----------------------------------------------------
                 lenerindex |  -.0685064    .0252747    -2.71  0.007      -.1180988    .038914
                             |
   c.lernerindex#c.lernerindex |   .0003952    .0001437     2.75  0.006       .0001132   .0006773
                             |
                     log_gdp|   -.7823335     .774418    -4.96  0.000       -.823816   .8658185
                             |
                     log_gdp|
                         L1.|    .6875873    .1496473     4.59  0.000       .3939589   .9812157
                             |
  Foreignbanksamongtotalbanks|   -.0305159    .0122868    -2.48  0.013      -.0546243   .0364076
                         roa |  -.2654065    .0721216    -3.68  0.000       -.406919    .123894
             loandepositratio|    .0049041    .0034854     1.41  0.056       .0019348   .0077429
                     banksize|   -.0430189     .022948    -1.87  0.051      -.0880461  -.0020082
                         unem|    .8864352    .3754703     2.36  0.018       .1497111   1.623159
                       _cons |   29.45554    13.57229     2.17  0.030      24.824847   36.08624
 -----------------------------------------------------
                     sigma_u |  3.5576118
                     sigma_e |  3.3110686
                         rho |  .53584763  (fraction of variance due to u_i)

------------------------------------------------------------------------------------------

F test that all u_i=0: F(109, 1093) = 11.76                Prob > F = 0.0000
```

2.7.6 Model 3

```
Fixed-effects (within) regression               Number of obs      =    1212
Group variable: country                         Number of groups   =     105

R-sq:                                           Obs per group:
     within  = 0.0859                                          min =       1
     between = 0.0197                                          avg =     9.0
     overall = 0.0282                                          max =      10

                                                F(14,827)          =    5.55
corr(u_i, Xb)  = -0.5290                        Prob > F           =  0.0000

                                              (Std. Err. adjusted for 105 clusters in country)

------------------------------------------------------------------------------------------

                             |                 Robust
                        NPLs |      Coef.   Std. Err.       t  P>|t|     [95% Conf. Interval]
-----------------------------
                         hdi |  -.2208921    .0569497   -3.88  0.000       -3326752   .9102234
                 lernerindex |  -.1873258    .0641925   -2.92  0.004       -.3133251   .0713264
                             |
         c.lernerindex#c.hdi |  -.0021791    .0011106   -1.96  0.050       -.004359   0.015494
   c.lernerindex#c.lernerindex |    .001108     .000367    3.02  0.003       .0003876   .0018284
           c.lernerindex#
         c.lernerindex#c.hdi |   .0000135    6.39e-06    2.11  0.035       9.43e-07    .000026
                     gdp     |
                         --. |  -.7739583    .1779715   -4.35  0.000       -1.123287   .4246294
                         L1. |   .3930267    .1594474    2.46  0.004       .0800575   .7059958
                             |
Foreignbanksamongtotalbanks  |  -.0308544    .0126923   -2.43  0.015       -.0557674   .0259415
                         roa |  -.1787775    .0848732   -2.11  0.035       -.3453698   1.012185
           loandepositratio  |   .0054716    .0033918    1.61  0.053       -.0011859   .0121291
                    banksize |  -.0312804    .0194769   -1.61  0.055       -.0695104   .0069497
                     unem    |   .6718657    .4240886    1.58  0.051         .504282   .7105509
                       _cons |   24.48173    10.26903    3.67  0.000        20.50083    31.5501
-----------------------------
                     sigma_u |  4.3338618
                     sigma_e |  3.1448453
                         rho |  .65506729       (fraction of variance due to u_i)

------------------------------------------------------------------------------------------

F test that all u_i=0: F(104, 827) = 11.15                   Prob > F = 0.0000
```

2.7.7 Model 4

```
IV (2SLS) estimation
--------------------

Estimates efficient for homoskedasticity only
Statistics robust to heteroskedasticity and clustering on country
                                                      Number of obs =     1165
                                                      F( 10,  1154) =     8.02
                                                      Prob > F      =  0.0000
Total (centered) SS      =             14213.5529     Centered R2   =  0.0467
Total (uncentered) SS    =            37551.02298     Uncentered R2 =   0.6391
Residual SS              =            13550.41964     Root MSE      =   4.612

------------------------------------------------------------------------------------------

                               |             Robust
                          NPLs |    Coef.     Std. Err.    t     P>|t|      [95% Conf. Interval]
-----------------------------
                  lernerindex  |-.0582558      .026235    -2.22 0.026      -.1096755 1.0068362

c.lernerindex#c.lernerindex    |  .033641     .0149164     2.26 0.024       .0044054  .0628765
                          gdp  |
                          --. |  -.7695847     .1610856    -4.78 0.000      -1.085307 1.4538626
                           L1. | .6989444     .1529628     4.57 0.000       .3991427   .998746
Foreignbanksamongtotalbanks    |-.0290582     .0128673    -2.26 0.024      -.0542776 1.0038388
                          roa  |-.2666435     .0736972    -3.62 0.000      -.4110872 1.1221997
         loandepositratio      | .0050665     .0035499     1.43 0.054      -.0018913  .0120242
                  banksize     |-.0482365     .0237516    -2.03 0.022      -.0947889  .9016842
                      unem     | .9554149     .3854081    -2.48 0.013        .800029  1.010801
                         _cons | 24.48168     13.99495     1.75 0.030      22.947926  32.91128
-----------------------------
Underidentification test (Anderson canon. corr. LM statistic):          18.579
                                                Chi-sq(3) P-val =     0.0003
  ------------------------------------------------------------------------------
Weak identification test (Cragg-Donald Wald F statistic):                4.687
Stock-Yogo weak ID test critical values:  5% maximal IV relative bias    11.04
                                         10% maximal IV relative bias     7.56
                                         20% maximal IV relative bias     5.57
                                         30% maximal IV relative bias     4.73
                                         10% maximal IV size             16.87
                                         15% maximal IV size              9.93
                                         20% maximal IV size              7.54
                                         25% maximal IV size              6.28
Source: Stock-Yogo (2005).  Reproduced by permission.
  ------------------------------------------------------------------------------
Sargan statistic (overidentification test of all instruments):          1.792
                                                Chi-sq(2) P-val =     0.4082
  ------------------------------------------------------------------------------
Instrumented:           lernerindex c.lernerindex#c.lernerindex
Included instruments: gdp L.gdp foreignbanksamongtotalbanks

                      roa loandepositratio banksize unem
Excluded instruments: regulatorytradebarriers

                      c.regulatorytradebarriers#c.regulatorytradebarriers
                      freedomtoentermarketsandcompete

                      c.freedomtoentermarketsandcompete#c.freedomtoentermarketsandcompete
------------------------------------------------------------------------------
```

2.7.8 Model 5

```
IV (2SLS) estimation

--------------------

Estimates efficient for homoskedasticity only
Statistics robust to heteroskedasticity and clustering on country
                                                      Number of obs =      1165
                                                      F( 12,  1152 )=      6.99
                                                      Prob > F       =  0.0000
Total (centered) SS      =            14213.5529      Centered R2    =  0.1036
Total (uncentered) SS    =            37551.02298     Uncentered R2 =   0.6607
Residual SS              =            12741.71919     Root MSE       =   4.472

---------------------------------------------------------------------------------------------
                                 |                     Robust
                             NPLs |      Coef.    Std. Err.       tP>|t|     [95% Conf. Interval]
--------------------------------
                      lernerindex |    -.1674832      .065639   -2.550.011      -.2961334  1.0388331
                              hdi |    -.2010121     .0605129   -3.320.001      -.3196153    .082409
              c.lernerindex#c.hdi |    -.0021767     .0011499   -1.890.028      -.0044304    1.00077
      c.lernerindex#c.lernerindex |      .098887     .0375293    2.630.008        .025331    .172443
c.lernerindex#c.lernerindex#c.hdi |     .0013529     .0006614    2.050.024       .0000565   .0026493
                              gdp |
                              --. |  -.7605869       .1807653   -4.210.000       -1.11488  1.4062934
                              L1. |     .3111635     .1663874    1.870.001      -.0149497   .6372767
     Foreignbanksamongtotalbanks |    -.0293391     .0131625   -2.230.026      -.0551372   .0235411
                              roa |    -.1868591     .0908171   -2.060.040      -.3648573  -.0088608
                loandepositratio |     .0058828     .0034325    1.710.057      -.0008447   .0126103
                        banksize |    -.0350329     .0200964   -1.740.021      -.0744211   .0043553
                             unem |     .7176778     .4349725    1.650.052       .1348526   1.570208
                            _cons |   29.33316      29.28741     3.790.030       25.64151   35.44615
--------------------------------
Underidentification test (Anderson canon. corr. LM statistic):                    19.479
                                                   Chi-sq(3) P-val =              0.0002
          --------------------------------------------------------------------------
Weak identification test (Cragg-Donald Wald F statistic):                          3.270
Stock-Yogo weak ID test critical values:                           <not available>
          --------------------------------------------------------------------------
Sargan statistic (overidentification test of all instruments):                     3.557
                                                   Chi-sq(2) P-val =              0.1689
          --------------------------------------------------------------------------
Instrumented:         lernerindex c.lernerindex#c.lernerindex
                      c.lernerindex#c.hdi c.lernerindex#c.lernerindex#c.hdi
Included instruments: gdp L.gdp foreignbanksamongtotalbanks

                      roa loandepositratio banksize unem
Excluded instruments: regulatorytradebarriers

                      c.regulatorytradebarriers#c.regulatorytradebarriers
                      freedomtoentermarketsandcompete

                      c.freedomtoentermarketsandcompete#c.freedomtoentermarketsandcompete
                      c.regulatorytradebarriers#c.lernerindex

                      c.freedomtoentermarketsandcompete#c.lernerindex
```

2.7.9 Turning point using model 4

```
       lernerindex_LD:  -_b[lerneindex]/(2*_b[c.lernerindex#c.lernerindex])

       ------------------------------------------------------------------------------

               NPLs |      Coef.   Std. Err.       z    P>|z|     [95% Conf. Interval]
       --------------+-------------------------------------------------------

      lernerindex_LD |   .4088147   .1041045     3.93   0.000     .2047737    .6128557
      ------------------------------------------------------------------------------
```

2.8 Robustness Checks

Boone Indicator as a Measure of Competition

2.8.1 Model 1

```
Fixed-effects (within) regression               Number of obs     =      1,112
Group variable: country                         Number of groups  =        105

R-squared:                                      Obs per group:
     Within  = 0.0786                                         min =          3
     Between = 0.0588                                         avg =       11.0
     Overall = 0.0476                                         max =         12

                                                F(10, 104)        =       3.93
corr(u_i, Xb) = -0.4814                         Prob > F          =     0.0000

                               (Std. err. adjusted for 105 clusters in country)
-------------------------------------------------------------------------------
              |               Robust
         NPLs | Coefficient  std. err.      t    P>|t|     [95% conf. interval]
--------------+----------------------------------------------------------------
booneindicator|  -.0153376   .0103118    -1.65   0.012    -.0227633    .0302386
              |
       loggdp |
          --. |  -.6484303   .3818222    -1.35   0.022    -.8204968   -.4081078
          L1. |   .4769624   .2219481     0.89   0.014     .3607105    .8414635
oreignbanksamongtotalbank|  -.0291682   .0144471    -2.02   0.006    -.0578494   -.0004871
          roa |  -.4088169   .0922799    -4.43   0.000    -.5920157   -.2256182
 loandepositratio |   .0053682   .0027277     1.97   0.023    -.000047    .0107835
     banksize |  -.0192595   .0377436    -0.51   0.041    -.0941901     .055671
         unem |   .329367    .0891864     1.49   0.009     .1079866     .641132
        _cons |   31.07205   18.45792     1.68   0.010    25.571559    37.71567
--------------+----------------------------------------------------------------
      sigma_u |  4.1733722
      sigma_e |  3.0932374
          rho |  .64543031   (fraction of variance due to u_i)
------------------------------------------------------------------------------
```

2.8.2 Model 2

```
Fixed-effects (within) regression               Number of obs     =      1,112
Group variable: country                         Number of groups  =        105

R-squared:                                      Obs per group:
     Within  = 0.0792                                         min =          3
     Between = 0.0587                                         avg =       11.0
     Overall = 0.0478                                         max =         12

                                                F(10, 104)        =       6.14
corr(u_i, Xb) = -0.4768                         Prob > F          =     0.0000

                               (Std. err. adjusted for 105 clusters in country)
-------------------------------------------------------------------------------
              |               Robust
          NPLs| Coefficient  std. err.      t    P>|t|     [95% conf. interval]
--------------+----------------------------------------------------------------
booneindicator|   -.047825   .0544025    -1.48   0.031    -.0917682    .6558274
           c. |
booneindicator# |
           c. |
booneindicator  |   .0081161   .0094628     0.86   0.003      -.01067    .0269022
       loggdp |
          --. |  -.6461401   .4801788    -1.35   0.012    -.9957416   -.5071353
          L1. |   .3769196   .2211473     0.89   0.023     .1591635    .6713003
reignbanksamongtotalbank |   -.029122   .0144403    -2.02    0.047    -.0577896   -.0004545
          roa |  -.4075856   .0916896    -4.45   0.000    -.5896126   -.2255586
loandepositratio |   .0053509   .0027245     1.96   0.032    -.0000579    .0107597
     banksize |  -.0185928   .0378413    -0.49   0.024    -.0937173    .0565317
        unem  |    .319779   .0892044     1.48   0.042      .09071     1.511524
        _cons |   30.88617   18.45928     1.67   0.000    25.760146    47.53248
--------------+----------------------------------------------------------------
      sigma_u |  4.1618225
      sigma_e |  3.0942841
          rho |  .64400574   (fraction of variance due to u_i)
```

2.8.3 Model 3

```
Fixed-effects (within) regression               Number of obs     =      1,212
Group variable: country                         Number of groups  =        105

R-squared:                                      Obs per group:
     Within  = 0.0866                                         min =          3
     Between = 0.0622                                         avg =       11.0
     Overall = 0.0504                                         max =         12

                                                F(10, 104)        =       5.77
corr(u_i, Xb) = -0.5236                         Prob > F          =     0.0000

                               (Std. err. adjusted for 105 clusters in country)
------------------------------------------------------------------------------
             |               Robust
        NPLs | Coefficient  std. err.      t    P>|t|     [95% conf. interval]
-------------+----------------------------------------------------------------
booneindicator |   -.050159   .050438    -1.21   0.019    -.0808668    .2083497
          c. |
booneindicator#|
          c. |
booneindicator |    .0127388   .0024616     1.49   0.025    .0050855    .1573254
          c. |
booneindicator#|
       c.hdi |   -.1206922   .081452   -1.45   0.020    -.3356063   -.1049451
          c. |
booneindicator#|
          c. |
booneindicator#|
       c.hdi |   .0036741   .0020622    1.78   0.028     -.041983    .7768209
             |
      loggdp |
         --. |  -.6511258   .4906844    -1.33   0.008    -.9525257   -.3230058
         L1. |   .3807967   .4260592     0.89   0.004     .1650379    .6226631
             |
reignbanksamongtotalbank |  -.0285867   .0144813    -1.97   0.001    -.0573358    .0001623
         roa |  -.3999751   .0903439    -4.43   0.000    -.5793305   -.2206198
loandepositratio |   .0052037   .0027241     1.91   0.039    -.0002044    .0106118
    banksize |  -.0202514   .0375843    -0.54   0.041    -.0948658    .0543629
        unem |    .362536   .0867493     1.57   0.020     .8085633    1.560561
       _cons |   31.37026   18.62372     1.68   0.005    25.602498    48.34302
-------------+----------------------------------------------------------------
     sigma_u |  4.2853705
     sigma_e |  3.0857393
         rho |  .65854826   (fraction of variance due to u_i)
```

2.8.4 Model 4

```
IV (2SLS) estimation
--------------------

Estimates efficient for homoskedasticity only
Statistics robust to heteroskedasticity and clustering on country

                                                      Number of obs =     1165
                                                      F( 10,   104) =     1.88
                                                      Prob > F      =   0.0050
Total (centered) SS     =  21879.61982                Centered R2   =   0.0493
Total (uncentered) SS   =  56593.54991                Uncentered R2 =   0.0335
Residual SS             =  75469.33347                Root MSE      =    9.147

------------------------------------------------------------------------------
             |               Robust
        NPLs | Coefficient  std. err.      t    P>|t|     [95% conf. interval]
-------------+----------------------------------------------------------------
booneindicator   |  -.2180558   .0523952    -0.73   0.014    -.4259508   -.1543395
              c. |
booneindicator # |
booneindicator   |   .1608408   .0112852     0.75   0.005     .1201581    .4847642
          loggdp |
             --. |  -.5396186   .4222205    -0.84   0.000    -.8362657   -.3591285
             L1. |   .3482379   .2810117     0.78   0.003     .2435273    .8954111
                 |
reignbanksamongtotalbank |  -.0348178    .023242    -1.50   0.034    -.0803714    .0107357
             roa |  -.5423058    .092706    -2.14   0.032    -1.611995   -.0426163
loandepositratio |   .0068396   .0078072     0.88   0.041    -.0084623    .0221415
        banksize |  -.0562892   .0739658    -0.76   0.047    -.2012594     .088681
            unem |    .632758    .085078     0.63   0.028    -3.433901    6.699418
           _cons |   16.41702   7.658478     2.14   0.002     10.40667    21.42736
------------------------------------------------------------------------------
Underidentification test (Kleibergen-Paap rk LM statistic):              0.641
                                                   Chi-sq(3) P-val =    0.0070
------------------------------------------------------------------------------
Weak identification test (Cragg-Donald Wald F statistic):               12.472
                         (Kleibergen-Paap rk Wald F statistic):         11.172
Stock-Yogo weak ID test critical values:  5% maximal IV relative bias    11.04
                                         10% maximal IV relative bias     7.56
                                         20% maximal IV relative bias     5.57
                                         30% maximal IV relative bias     4.73
                                         10% maximal IV size             16.87
                                         15% maximal IV size              9.93
                                         20% maximal IV size              7.54
                                         25% maximal IV size              6.28
Source: Stock-Yogo (2005).  Reproduced by permission.
NB: Critical values are for Cragg-Donald F statistic and i.i.d. errors.
------------------------------------------------------------------------------
Hansen J statistic (overidentification test of all instruments):         0.351
                                                   Chi-sq(2) P-val =    0.4390
------------------------------------------------------------------------------
Instrumented:         booneindicator c.booneindicator#c.booneindicator
Included instruments: loggdp L.loggdp Foreignbanksamongtotalbank roa
                      loandepositratio banksize unem
Excluded instruments: regulatorytradebarriers
                      c.regulatorytradebarriers#c.regulatorytradebarriers
                      freedomtoentermarketsandcompete
                      c.freedomtoentermarketsandcompete#c.freedomtoentermarketsandcompete
```

2.8.5 **Model 5**

```
IV (2SLS) estimation

--------------------

Estimates efficient for homoskedasticity only

Statistics robust to heteroskedasticity and clustering on country

                                                  Number of obs =     1165
                                                  F( 12,  104)  =     3.09
                                                  Prob > F       =  0.0003
Total (centered) SS      =         12247.51699    Centered R2    =  0.1148
Total (uncentered) SS    =         31383.02727    Uncentered R2 =   0.2515
Residual SS              =         23490.68677    Root MSE       =   6.728

-------------------------------------------------------------------------------------------------

                             |               Robust
                        NPLs |      Coef. Std. Err.          t P>|t|      [95% Conf. Interval]
 ----------------------------
              booneindicator |   -.114988 .0039604      -2.52 0.012      -.2346958   .0452666
                         hdi |  -.1240938 .0513504      -2.42 0.016      -.2502349   .0924738
     c.booneindicator#c.hdi |  -.1255207 .0653551      -1.92 0.035      -.3425729 1.0536143
                             |
          c.booneindicator# |
           c.booneindicator |   .1890374 .0686196       2.75 0.006       .0545454   .3235294
                             |
          c.booneindicator# |
     c.booneindicator#c.hdi |   .0023788 .0010027       2.37 0.018       .0004136    .004344
                             |
                      loggdp |
                        --. |  -.6893763 .1800865      -3.83 0.000      -1.042339 1.3364133
                        L1.|     .4598577 .1642124       2.80 0.005       .1380073   .7817081
                             |
 foreignbanksamongtotalbanks |  -.0206125 .0130688      -1.58 0.015      -.0462269    .005002
                         roa |  -.4669179 .0863492      -5.41 0.000      -.6361592 1.2976765
            loandepositratio |   .0040723 .0035669       1.14 0.044      -.0029187   .0110633
                    banksize |  -.0368153 .0209004      -1.76 0.038      -.0777793   1.004148
                        unem |    .220527 .0517207       2.70 0.007       .9105884    2.33509
                       _cons |   36.31927 26.63954       2.49 0.013       24.10673   38.53718
 ----------------------------

Underidentification test (Anderson canon. corr. LM statistic):           1.158
                                               Chi-sq(3) P-val =    0.0030
 ------------------------------------------------------------------------------
Weak identification test (Cragg-Donald Wald F statistic):             11.188
 ------------------------------------------------------------------------------
Hansen J statistic (overidentification test of all
instruments:                                                             1.687
                                               Chi-sq(2) P-val =    0.4302

-------------------------------------------------------------------------------
Instrumented:          booneindicator c.booneindicator#c.booneindicator c.booneidicator#c.hdi
                       c.booneindicator#c.booneindicator#c.hdi

Included instruments:  loggdp L.loggdp foreignbanksamongtotalbanks roa loandepositratio
                       banksize unem
Excluded instruments: regulatorytradebarriers
                   c.regulatorytradebarriers#c.regulatorytradebarriers
                   freedomtoentermarketsandcompete
                  c.freedomtoentermarketsandcompete#c.freedomtoentermarketsandcompete
                       c.regulatorytradebarriers#c.booneindicator
                       c.freedomtoentermarketsandcompete#c.booneindicator
```

CR5 as a Measure of Competition

2.8.6 Model 1

```
Fixed-effects (within) regression               Number of obs     =      1,112
Group variable: country                         Number of groups  =        105

R-squared:                                      Obs per group:
     Within  = 0.0513                                         min =          3
     Between = 0.0129                                         avg =         11
     Overall = 0.0231                                         max =         12

                                                F(9, 104)         =       5.32
corr(u_i, Xb) = -0.3857                         Prob > F          =     0.0000

                               (Std. err. adjusted for 105 clusters in country)
-------------------------------------------------------------------------------
             |               Robust
        NPLs | Coefficient  std. err.      t    P>|t|     [95% conf. interval]
-------------+-----------------------------------------------------------------
         cr5 |   -.048633   .0247793    -1.96   0.002    -.0977659    .0004998
             |
      loggdp |
         --. |  -.7899102   .0515177    -1.53   0.008    -1.811411    .2315909
         L1. |   .5998697   .0444874     1.35   0.010    -.2822345    1.481974
             |
reignbanksamongtotalbank |  -.0239251   .0134149    -1.78   0.017    -.0505244    .0026742
         roa |  -.2839994    .115937    -2.45   0.016     -.513881   -.0541179
loandepositratio |    .0050102    .002551     1.96  0.042    -.0000479    .0100683
    banksize |  -.0125138   .0276995    -0.09   0.028    -.0524091   -.0074367
        unem |   .7519910    .235878     0.61   0.016     .5222714    1.182894
       _cons |   26.32256   12.44413     2.12   0.000     18.64813    32.99697
-------------+-----------------------------------------------------------------
     sigma_u |   3.995941
     sigma_e |  3.3355319
         rho |  .58935361   (fraction of variance due to u_i)
```

2.8.7 Model 2

```
Fixed-effects (within) regression               Number of obs     =      1,112
Group variable: country                         Number of groups  =        105

R-squared:                                      Obs per group:
     Within  = 0.0566                                         min =          3
     Between = 0.0131                                         avg =       10.3
     Overall = 0.0262                                         max =         12

                                                F(9, 104)         =       2.35
corr(u_i, Xb) = -0.3978                         Prob > F          =     0.0006

                               (Std. err. adjusted for 105 clusters in country)
-------------------------------------------------------------------------------
              |               Robust
         NPLs | Coefficient  std. err.      t    P>|t|     [95% conf. interval]
--------------+----------------------------------------------------------------
          cr5 |  -.1138388   .0106379    -1.13   0.002    -.4165769   -.0242545
              |
  c.cr5#c.cr5 |   .0113755   .0088563     1.55   0.003     .0061315    .0213804
              |
       loggdp |
          --. |  -.7880011   .0508727   -1.55   0.000    -1.796713    .2207108
          L1. |   .5917225    .0436791    1.35   0.008    -.2743533    1.457798
reignbanksamongtotalbank |  -.0242113   .013415    -1.80   0.024    -.0508108    .0023881
          roa |  -.2828927   .0115263    -2.45   0.016    -.5114391   -.0543463
     loandepositratio |    .004914   .0026183     1.88   0.033    -.0002776    .0101057
     banksize |   -.013426   .0275296    -0.12   0.031    -.0311602   -.0080122
         unem |   .4511025    .153891     0.53   0.018     .3144211    1.242006
        _cons |   19.55794   13.72389     1.43   0.000      15.6542    26.76989
--------------+----------------------------------------------------------------
      sigma_u |  4.0424216
      sigma_e |  3.3278667
          rho |  .59604794   (fraction of variance due to u_i)
```

2.8.8 Model 3

```
Fixed-effects (within) regression               Number of obs     =      1,212
Group variable: country                         Number of groups  =        105

R-squared:                                      Obs per group:
     Within  = 0.0779                                         min =          3
     Between = 0.0190                                         avg =         11
     Overall = 0.0325                                         max =         12

                                                F(12, 104)        =       2.13
corr(u_i, Xb) = -0.4808                         Prob > F          =     0.0207

                              (Std. err. adjusted for 105 clusters in country)
------------------------------------------------------------------------------
             |               Robust
        NPLs | Coefficient  std. err.      t    P>|t|     [95% conf. interval]
-------------+----------------------------------------------------------------
         cr5 |    -.084246   .0275767    -3.05   0.003    -.1456722    1.389264
             |
 c.cr5#c.cr5 |    .016191   .0019901     3.11   0.002     .0101375    .0322455
             |
         hdi |   -.12366     .036547    -1.70   0.002    -.2212659   -.0793281
             |
 c.cr5#c.hdi |   -.2519532   .034709    -2.51   0.013    -.3205038    -.171856
             |
 c.cr5#c.cr5#|
      c.hdi  |   .0105982   .0040771     2.60   0.011     .0086823    .0225142
             |
      loggdp |
         --. |  -.8988471   .1399352    -1.66   0.000    -1.969439    .1717447
         L1. |   .4858153   .0380811     1.28   0.005    -.2692634    1.240894
reignbanksamongtotalbank |  -.0205892    .012702    -1.62   0.018    -.0457748    .0045964
         roa |  -.2740514   .1111596    -2.47   0.015    -.4944602   -.0536425
loandepositratio |   .0048798   .0027344     1.78   0.027     -.000542    .0103017
    banksize |   -.007081    .024337    -0.29   0.032    -.0553368    .0411747
        unem |  -.2671825   .1708579    -0.31   0.020    -1.993933    1.459568
       _cons |   19.32725    4.05767     0.80   0.000     15.37467    27.02917
-------------+----------------------------------------------------------------
     sigma_u |  4.2387467
     sigma_e |  3.2951475
         rho |  .62331282   (fraction of variance due to u_i)
```

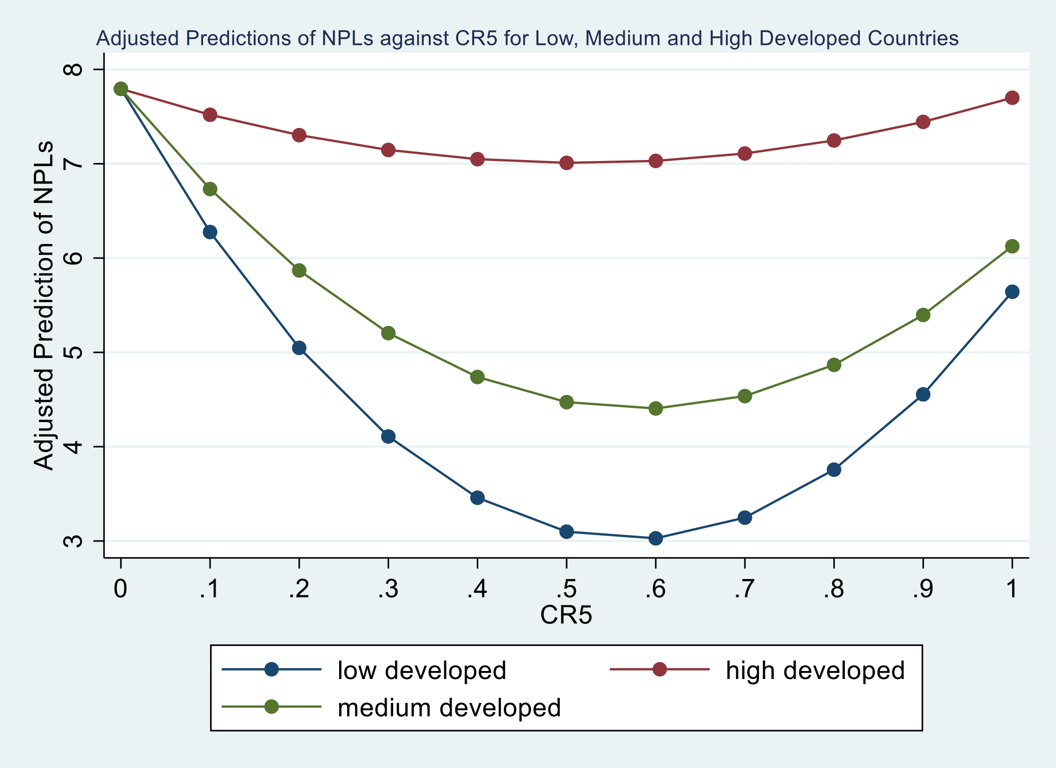
2.8.9 Model 4

```
IV (2SLS) estimation
--------------------

Estimates efficient for homoskedasticity only
Statistics robust to heteroskedasticity and clustering on country
                                                      Number of obs =     1165
                                                      F(  9,   104) =     1.52
                                                      Prob > F      =   0.0058
Total (centered) SS     =  24619.30115                Centered R2   =   0.0302
Total (uncentered) SS   =  66030.67517                Uncentered R2 =   0.6384
Residual SS             =  23875.71018                Root MSE      =    4.775

------------------------------------------------------------------------------
             |               Robust
        NPLs | Coefficient  std. err.      t    P>|t|     [95% conf. interval]
-------------+----------------------------------------------------------------
         cr5 |  -.136184   .0123444     0.25   0.002    -.2407737   -.0820105
             |
 c.cr5#c.cr5 |  .0216917   .0052068    -0.32   0.005     .0118969    .0385134
             |
      loggdp |
        --.  |  -.8079801   .1515254    -1.65   0.000     -1.28895    -.729898
         L1. |   .5637739   .0349829     1.57   0.016     .4138983    1.41446
             |
eignbanksamongtotalbank |  -.0254062   .0218276    -1.16   0.024    -.0681875    .0173752
         roa |  -.2815176   .2135154    -1.32   0.007    -.7000001     .136965
loandepositratio |   .0051948   .0029637     1.75   0.020    -.0006141    .0110036
    banksize |   -.013922   .0268682    -0.52   0.024    -.0665826    .0387387
        unem |   .1824052   .0140024     0.35   0.013     .1250209    1.189831
       _cons |   16.15746    2.58407     0.19   0.000     11.370613   17.20210
------------------------------------------------------------------------------
Underidentification test (Kleibergen-Paap rk LM statistic):             4.833
                                                   Chi-sq(3) P-val =    0.0044
------------------------------------------------------------------------------
Weak identification test (Cragg-Donald Wald F statistic):              15.020
                         (Kleibergen-Paap rk Wald F statistic):        12.156
Stock-Yogo weak ID test critical values:  5% maximal IV relative bias    11.04
                                         10% maximal IV relative bias     7.56
                                         20% maximal IV relative bias     5.57
                                         30% maximal IV relative bias     4.73
                                         10% maximal IV size             16.87
                                         15% maximal IV size              9.93
                                         20% maximal IV size              7.54
                                         25% maximal IV size              6.28
Source: Stock-Yogo (2005).  Reproduced by permission.
NB: Critical values are for Cragg-Donald F statistic and i.i.d. errors.
------------------------------------------------------------------------------
Hansen J statistic (overidentification test of all instruments):        2.242
                                                   Chi-sq(2) P-val =    0.3259
------------------------------------------------------------------------------
Instrumented:         cr5 c.cr5#c.cr5
Included instruments: gdp L.loggdp Foreignbanksamongtotalbank roa
                      loandepositratio banksize unem
Excluded instruments: regulatorytradebarriers
                      c.regulatorytradebarriers#c.regulatorytradebarriers
                      freedomtoentermarketsandcompete
                      c.freedomtoentermarketsandcompete#c.freedomtoentermarketsandcompete
```

2.8.10 **Model 5**

```
IV (2SLS) estimation
IV (2SLS) estimation
--------------------

Estimates efficient for homoskedasticity only

Statistics robust to heteroskedasticity and clustering on country

                                                     Number of obs =     1165
                                                     F( 12,  104)  =     5.82
                                                     Prob > F        =  0.0000
Total (centered) SS      =        12825.56101        Centered R2     =  0.1505
Total (uncentered) SS    =        34732.43065        Uncentered R2 =   0.6121
Residual SS              =        13472.96089        Root MSE        =   4.828

---------------------------------------------------------------------------------------------
                                 |                Robust
                            NPLs |      Coef.   Std. Err.       t  P>|t|     [95% Conf. Interval]
 -------------------------------
                             cr5 |   -.118638     .018053   -1.10  0.002      -.8767089   .1139846
                                 |
                     c.cr5#c.cr5 |   .0108572    .0108362    1.00  0.016       .0080958   .0113814
                          hdi |  -.1140938   .0513504    -2.42  0.016      -.1502349   .0824738
                                 |
                     c.cr5#c.hdi |  -.2857234    .0118184   -0.40  0.038      -.6808626   1.109415
                                 |
               c.cr5#c.cr5#c.hdi |   .0068747    .0108922    0.63  0.028       .0044736    .028223
                                 |
                         loggdp  |
                             --. |  -.779061     .1892116   -2.25  0.024      -3.325887  1.2322346
                            L1.  |   .543133     .0646898    2.39  0.017       .2752352   2.811031
                                 |
      foreignbanksamongtotalbanks |  -.0093595    .0293542   -0.32  0.050      -.0668926   .0481737
                             roa |  -.4827697    .3346306   -1.44  0.029      -1.138634   .1730942
                loandepositratio |   .0103691    .0134999    0.27  0.055       .0071502   .0207683
                        banksize |  -.0881379    .0841415   -1.05  0.025      -.2530522   .0767763
                            unem |   .0530946    .0663423    0.80  0.014       .0412338   .0693395
                           _cons |   25.54928    31.35757    0.81  0.015       20.91042   42.00899
---------------------------------------------------------------------------------------------
---

Underidentification test (Anderson canon. corr. LM statistic):           3.893
                                                  Chi-sq(3) P-val =    0.0032
 ------------------------------------------------------------------------------
Weak identification test (Cragg-Donald Wald F statistic):                0.636
Stock-Yogo weak ID test critical values:                       <not available>
 ------------------------------------------------------------------------------
Sargan statistic (overidentification test of all instruments):           2.425
                                                  Chi-sq(2) P-val =    0.2974
 ------------------------------------------------------------------------------
Instrumented:         cr5 c.cr5#c.cr5 c.cr5#c.hdi c.cr5#c.cr5#c.hdi
Included instruments: loggdp L.loggdp
foreignbanksamongtotalbanks
                      roa loanratio banksize unem

Excluded instruments: regulatorytradebarriers
                      c.regulatorytradebarriers#c.regulatorytradebarriers

                      freedomtoentermarketsandcompete
                      c.freedomtoentermarketsandcompete#c.freedomtoentermarketsandcompete

                      c.regulatorytradebarriers#c.cr5
                      c.freedomtoentermarketsandcompete#c.cr5

------------------------------------------------------------------------------
```

2.8.11: Adjusted Prediction of NPL for Low, Medium and High Developed Countries



2.8.12 Z-Score as a Measure of Financial Stability

```
IV (2SLS) estimation
--------------------

Estimates efficient for homoskedasticity only
Statistics robust to heteroskedasticity and clustering on country

                                                    Number of obs =     1165
                                                    F( 12,  1152) =     1.12
                                                    Prob > F      =  0.3388
Total (centered) SS      =         62560.54863       Centered R2   =  0.3236
Total (uncentered) SS    =         197539.0291       Uncentered R2 =   0.5808
Residual SS              =          82802.1592       Root MSE      =   11.41

-----------------------------------------------------------------------------------------------
                                |                Robust
                         zscore |     Coef.     Std. Err.   t    P>|t|   [95% Conf. Interval]
 --------------------------------
                   Lernerindex|     .0612987  .0291815    2.10   0.036     .0184934  .1041041
                           hdi |  .0434576  .0470516    0.92   0.026     .0407619  .1356771
     c. Lernerindex#c.Lernerindex | -.1219828  .0510387   -2.39   0.017     -.219488  .0920168
                                |
          c.Lernerindex#c.hdi |    .002371  .0008941    2.65   0.008     .0006187  .0041234
                                |
                c.Lernerindex#|
           c.Lernerindex#c.hdi| -.0011944  .0005143   -2.32   0.020    -.0022024 1.0001864
                                |
                         loggdp|
                            --. |  .8828631   .140554    6.28   0.000     .7158344 .96073823
                            L1. |  .5301452   .129374    4.10   0.000     .2765756  .7837147
                                |
     Foreignbanksamongtotalbanks|    .0019576  .0102345    0.19   0.048    -.0181017  .0220168
                            roa | .4009411  .0706276     5.68   0.000     .2625284  .5393538
              loandepositratio |  -.003938   .002669   -1.23   0.047   -.004937    1.002253
                      banksize |  .0407643  .0156301    2.61   0.009       .01013  .0713987
                          unem| -.2782638    .3382119   -0.82   0.031    -.3846193 1.2411469
                          _cons |  22.60703   22.7735    3.63   0.000     17.97167   27.2424

-----------------------------------------------------------------------------------------------
---

Underidentification test (Anderson canon. corr. LM statistic):          19.510
                                                Chi-sq(3) P-val =    0.0002

-----------------------------------------------------------------------------

Weak identification test (Cragg-Donald Wald F statistic):               3.276
Stock-Yogo weak ID test critical values:                       <not available>

-----------------------------------------------------------------------------
Sargan statistic (overidentification test of all instruments):           0.055
                                                Chi-sq(2) P-val =    0.9729

-----------------------------------------------------------------------------

                           Instrumented:      lernerindex c.lernerindex#c.lernerindex
                             c.lernerindex#c.hdi c.lernerindex #c.lernerindex #c.hdi

Included instruments: gdp L.gdp foreignbanksamongtotalbanks roa loandepositratio banksize unem
Excluded instruments: regulatorytradebarriers
                      c.regulatorytradebarriers#c.regulatorytradebarriers
                      freedomtoentermarketsandcompete
                      c.freedomtoentermarketsandcompete#c.freedomtoentermarketsandcompete

                      c.regulatorytradebarriers#c.lernerindex

                      c.freedomtoentermarketsandcompete#c.lernerindex
```

2.8.14 Estimations before the Global Financial Crisis

```
IV (2SLS) estimation
--------------------

Estimates efficient for homoskedasticity only

Statistics robust to heteroskedasticity and clustering on country

                                                    Number of obs =      323
                                                    F( 12,    310)  =    3.00
                                                    Prob > F        =  0.0007
Total (centered) SS      =         6078.368611      Centered R2     =  0.0137
Total (uncentered) SS    =         15582.50204      Uncentered R2   =  0.6153
Residual SS              =         5995.120148      Root MSE        =   5.185

------------------------------------------------------------------------------------------------
                                |                Robust
                           NPLs |     Coef.   Std. Err.       t    P>|t|  [95% Conf. Interval]
 --------------------------------
                    lernerindex |  .7037516   .068675      0.06    0.043     .6221788  .9170291
                                |
    c.lernerindex #c.lernerindex |   .071746  .019627      0.13    0.098      .367236  1.181585

           c.lernerindex #c.hdi | -.5033852    0.072907   -0.21    0.074  -.722797      1.16026
                                |
                 c.lernerindex#|
            c.lernerindex#c.hdi |   -.16016     .044223   -0.03    0.078     -.259613   1.37581
                         loggdp |
                           --. |  -.212985    .0631167   -1.97    0.049  -.410014    -.0159574
                           L1. |   .653949    .0464325    1.81    0.040    -.2160744  5.523972
                                |
    Foreignbanksamongtotalbanks  | -.0641251    .0109063   -0.59    0.057     -.277897  .1496469
                            roa | -.8342774    .0835052   -1.00    0.018    -2.470949  .8023945
             loandepositratio |  .0541972       .00547    0.91    0.052  .0207564      .0623619
                     banksize  | -.3676351   .01972814   -1.86    0.052    -.7542996  .0190293
                         unem  |  .5771333   .06221129    0.93    0.054     .4596452  .6421857
                          _cons |   34.3818     5.35391    2.43    0.015     25.89009   42.8734
------------------------------------------------------------------------------------------------

---
Underidentification test (Anderson canon. corr. LM statistic):                          1.375
                                                Chi-sq(3) P-val =                       0.0114
                 ------------------------------------------------------------------------------
Weak identification test (Cragg-Donald Wald F statistic):                               0.215
Stock-Yogo weak ID test critical values:                                        <not available>
                 ------------------------------------------------------------------------------
Sargan statistic (overidentification test of all instruments):                          0.388
                                                Chi-sq(2) P-val =                       0.8237
                 ------------------------------------------------------------------------------
Instrumented:        lernerindex       c.lernerindex#c.lernerindex       c.lernerindex#c.hdi
                      c.lernerindex#c.lernerindex#c.hdi

Included instruments: gdp L.gdp foreignbanksamongtotalbanks roa loanratio banksize unem
Excluded instruments: regulatorytradebarriers
                      c.regulatorytradebarriers#c.regulatorytradebarriers

                      freedomtoentermarketsandcompete
                      c.freedomtoentermarketsandcompete#c.freedomtoentermarketsandcompete

                      c.regulatorytradebarriers#c.lernerindex
                      c.freedomtoentermarketsandcompete#c.lernerindex
```

2.8.16 Estimations after the Global Financial Crisis

```
IV (2SLS) estimation
--------------------

Estimates efficient for homoskedasticity only
Statistics robust to heteroskedasticity and clustering on country

                                                      Number of obs =      744
                                                      F( 12,    731)  =    4.94
                                                      Prob > F        =  0.0000
Total (centered) SS      =         11317.70141        Centered R2     =  0.1334
Total (uncentered) SS    =         29943.57302        Uncentered R2   =  0.6725
Residual SS              =         9807.910451        Root MSE        =     4.7

----------------------------------------------------------------------------------------------
                                |              Robust
                           NPLs |     Coef.  Std. Err.       tP>|t|      [95% Conf. Interval]

                    lernerindex | -.0921225  .056014     -0.70 0.014       -.345708  .3768659
                                |
    c.lernerindex#c.lernerindex |  .5717545 .0338606      0.64  0.024       .7303138  1.174548
                                |
            c.lernerindex#c.hdi |   .034173  .007732      0.41  0.033      .0238845  1.122663
                                |
                  c.lernerindex# |
            c.lernerindex#c.hdi |  -.053159  .005568     -0.34  0.030      -.747405    .37732
                                |
                          logdp |
                            --. | -.5012016 .085131      -1.25 0.011    -.8596672    .572641
                            L1. |  .8771946 .07545198     1.16 0.045     -.6016369  2.356026
                                |
     Foreignbanksamongtotalbanks  | -.0534194  .037894     -1.41 0.159     -.1276902  .0208514
                            roa | -.6133567 .02257833    -2.72 0.007     -1.055884 -.1708295
               loandepositratio |  .0124178  .0238019     0.52 0.042    .0090687    .0342332
                       banksize  | -.1613564  .0108844    -1.48 0.038     -.3746867  .0519738
                           unem|    .1793502  .03264537    0.55 0.053    .1591877    .2604874
                          _cons |  43.08083 35.37699      1.22 0.023      26.25679  52.41784

----------------------------------------------------------------------------------------------
---

Underidentification test (Anderson canon. corr. LM statistic):            7.976
                                                  Chi-sq(3) P-val =    0.0365

------------------------------------------------------------------------------
Weak identification test (Cragg-Donald Wald F statistic):                1.308

Stock-Yogo weak ID test critical values:                       <not available>
------------------------------------------------------------------------------

Sargan statistic (overidentification test of all instruments):            1.116
                                                  Chi-sq(2) P-val =    0.5723

------------------------------------------------------------------------------

Instrumented:         lernerindex c.lernerindex#c.lernerindex c.lernerindex#c.hdi
                      c. lernerindex#c.lernerindex#c.hdi

Included instruments: gdp L.gdp foreignbanksamongtotalbanks
                      roa loandepositratio banksize unem

Excluded instruments: regulatorytradebarriers
                      c.regulatorytradebarriers#c.regulatorytradebarriers

                      freedomtoentermarketsandcompete
                      c.freedomtoentermarketsandcompete#c.freedomtoentermarketsandcompete
                      c.regulatorytradebarriers#c.lernerindex
                      c.freedomtoentermarketsandcompete#c.lernerindex

-----------------------------------------------------------------------------
```

Chapter 3

Multilevel Modeling with Crossed Random Effects: The Impact of Competition on Bank Loan Performance

3.1 Introduction

Over the past decade a significant increase in banks' non-performing loans (NPLs) has been recorded. This increase has been attributed to the deregulation process of financial markets and the development of information technologies in the banking industry, which in turn led to the enhancement of competition in the industry (Orhangazi, 2015). Prior to the 2008 global financial crisis, competition in the banking industry was not encouraged as some banks which were perceived as "too big to fail", were encouraged via policies, regulations, and bailouts to consistently remain major players in the industry. Fast forward to the 2008 global financial crisis, these major players and many economies were hit so hard by the crisis that the rate of bank's NPLs skyrocketed and unfortunately, resulted to the shutting down of many banks which significantly threatened the financial stability of many countries. This occurrence made the regulatory authorities of several countries to re-evaluate their existing policies and regulations regarding competition in the banking industry, thereby leading to the encouragement of more conducive atmosphere for banking competition (Claessens, Kose & Terrones, 2010). Despite encouraging banking competition, the rate of banks' NPLs has still been seen to be quite high and on the increase (Beck, De Jonghe, & Schepens, 2013). In Italy, for example, despite efforts to encourage banking competition, the rate of non-performing loans remained high in the years following the 2008 financial crisis. According to a report by the Bank of Italy, the NPL ratio for Italian banks reached 18% in 2015, one of the highest in the Eurozone, highlighting the ongoing challenges in reducing bad loans even in a competitive banking environment.

This has raised a lot of concern among regulatory authorities and in the academia as many worry that if not properly managed might lead to yet another significant threat to the financial stability of many countries (Aiyar et al., 2015). Researchers and regulatory authorities are all asking these questions: Is competition in the banking industry truly healthy for banks' loan performance and their financial stability? Should banking competition be encouraged?

The banking industry (which happens to be a major component of the financial markets) as well as competition in this industry, have been an area of interest among researchers. This interest can be attributed to how relevant competition in the banking industry is to regulatory authorities, who are concerned with competition policy, overall banks' management, stable financial markets, and overall financial stability. Financial regulatory authorities understand that a loss of confidence in the banking system can have devastating effects on the entire financial system. For this reason, these authorities always consider banking stability as a top regulatory and supervisory policy objective (World Bank, 2016).

As earlier stated, before the 2008 global financial crisis, some banks were seen as "too big to fail" due to the existing limited competition in the banking industry. These individual banks were so interconnected with the economy to the extent that measures had to be taken if they were ever in trouble, to ensure they could continue to provide services. However, this already laid down approach didn't benefit the economy quite well during the 2008 global financial crisis. This is because these banks that were seen as too big to fail, realized that they will be bailed out and hence took advantage of the system, therefore making them take up more risks. The high-risk taking behavior of these banks led to the collapse of some of them through their high rates of non-performing loans which seriously increased the impact of the 2008 global financial crisis. An example of this is the collapse of the investment bank Lehman Brothers in 2008. Extreme risk-taking led to bankruptcy. This increased the impact on the economy and so huge bailouts were made to prevent more harm being done.

Since the 2008 global financial crisis, there has been a rise in interest in the effect of competition in the banking industry. Understanding this effect is important because any form of market failure on the part of banks could threaten production efficiency, consumer welfare and economic growth. Some research has shown that the stability of the banking industry is highly dependent on banks' loan performance (Boyd and Nicole, 2005; Balgova et. al., 2016; Ozili, 2018). This is because poor loan performance does not only affect banks' profitability. Through the slowdown of new credit creation and worsening market expectations, it can also pose a credible threat to banks' stability and by extension the overall financial stability. Hence, this paper investigates how competition in banking affects the overall stability of banks through non-performing loans (NPLs) at the bank level. Competition in the banking industry has been seen to improve the growth and competitiveness of the manufacturing and service sectors, access to finance and capital funds allocation (Petersen and Rajan, 1995; Cetorelli, 2004; Di Patta and Dell'Aricca, 2004; Beck et al., 2004) yet there has been no consensus as to whether high competition leads to financial stability in the banking system.

Generally, it is true that competition in other industries encourages innovation, better quality products, lower prices, and efficient allocation of services within these industries. However, in the banking industry, using different measures of competition, contradictory views exist on the effect of competition as discussed in detail in my previous chapter. The most popular/traditional notion on competition in the banking industry is that increased competition leads to a more fragile banking system through a decrease in banks' franchise value which in turn leads to a reduction in the penalty for failure and thus reduces the incentive for caution (Marcus, 1984; Keeley, 1990). This notion can be referred to as the competition-fragility view. It assumes that more competition increases the incentives to take on more risks on the side of the bank and therefore leads to a rise in failure probabilities. This view shows a trade-off between competition and solvency. It supports the notion that the incentive to engage in riskier policies significantly increases as competition increases. This view also argues that increased competition in the banking industry can been linked to a decrease in the banks' incentive to properly screen borrowers in order to avoid losing them to competitors thus, increasing the risks associated to the banks' credit portfolios (Allen and Gale, 2004).

Notwithstanding, despite the view that competition is negatively related to banking performance, some potential positive aspects of competition have begun to be highlighted by researchers (competition-stability view), thus raising doubts about the overall beneficial impact of competition in the banking industry. Boyd and De Nicoló (BDN, 2005) argue that restricting competitive forces lead to welfare losses through an increase in monopoly power, as banks with monopoly power tend to charge higher loan interest rates to businesses and individual customers. Their model proposes that these higher loan rates lead to an increase in the probability of entrepreneurs and individual customers to venture into risky projects, thereby leading to an increase in default risk and a potential increase in non-performing loans, thus weakening the stability of the credit market and increasing the chances of systematic failure. The competition-stability view argues that the trade-off between competition and financial stability that was implied by the competition-fragility view (which focused mainly on the deposit market), could be eliminated through the introduction of the loan-market channel. This view refers to this effect as the "risk-shifting" effect. It argues that increased competition across both the loan and deposit markets could lower loan rates, decrease borrower credit risk, and enhance financial stability. They are of the view that competition in the banking industry is one way to help avoid another episode of the 2008 global financial crisis through a decrease in borrowers' credit risks. The studies by Berger et al., (2009) and De Nicoló and Loukoianova (2007), provide empirical evidence to support the competition-stability view, by finding a significant negative relationship between competition and bank risk.

In addition, this study further investigates whether the optimal level of banking competition, observed at the bank level, varies according to the country's level of development. Specifically, this study examines if the relationship between banking competition and non-performing loans

(NPLs) is quadratic, determining whether it follows a U-shaped or inverted U-shaped pattern. The study then examines the extent to which this quadratic relationship is influenced by the level of competition in the banking industry. It is argued that the strength and structure of the banking system has a significant role to play in the way banks' NPLs react to competition (Martinez-Miera and Repullo, 2010). Delis (2012) confirmed the importance of institutional quality and institutional development in relation to bank competition. He argued that the level of institutional development is vital for the enhancement of banking competition and the overall banking industry. Naude (2009), also argued that the level of financial development in a country is important because it can influence the severity of financial or economic crises, and it can affect the domestic mobilization of resources needed to tackle an existing crisis. He also stated that the quicker rate of recovery by more financially developed countries from the 2008 global financial crisis could be attributed to their level of financial development. However, let's not forget that the strength, structure, financial and institutional development of the banking system is highly dependent on certain indices that portray a country's level of development such as the state of her economic situation, dependence on external funding, level of public debt and level of risk in her financial institutions (Abascal, et. al., 2010). Hence, will it be safe for researchers to imply that the relationship that might exist between banking competition and NPLs might depend on a country's overall level of development? If yes, could this be attributed to why more developed countries recovered faster from the 2008 global financial crisis despite the high rate of NPLs across the industry and even though increased competition was introduced across different groups of countries? There is a knowledge gap in this area of research as this area is yet to be explored. Figure 3.1 shows the mean of NPL and banking competition across different levels of development (high, medium, and low developed). From this figure, we can observe that these different groups, on an average, experience different levels of competition and non-performing loans. Therefore, pointing to the fact that it is important to consider a country's level of development when trying to identify the relationship that exists between NPL and competition in that country.

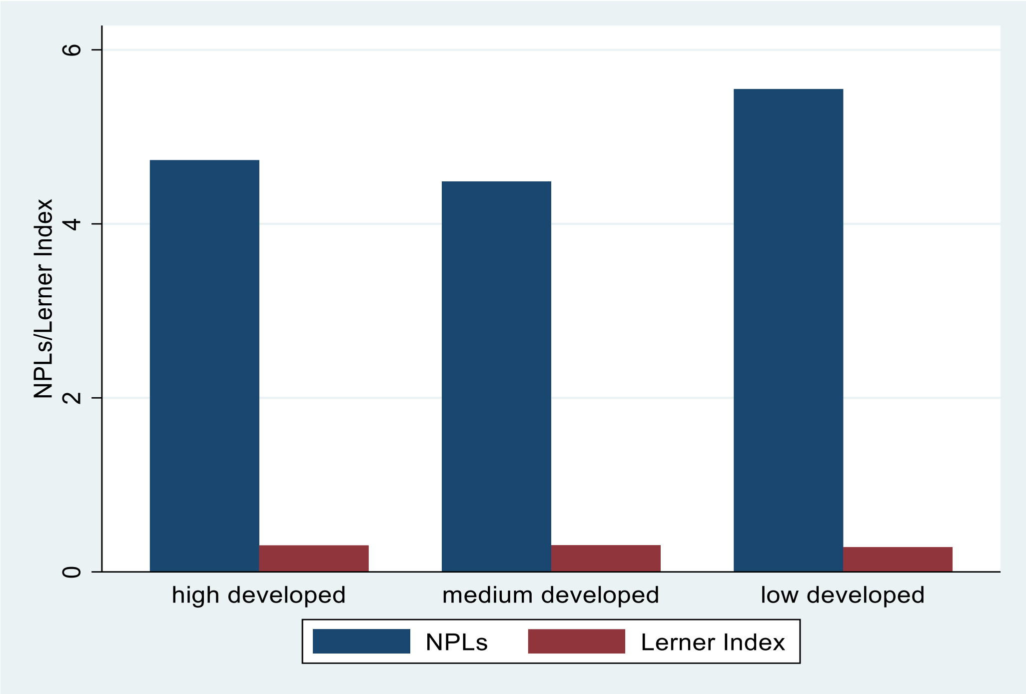


Figure 3.1: Graph Showing the Mean of NPLs and the Lerner Index in High Developed, Medium Developed and Low Developed Countries

Many scientific financial studies have focused on examining the relationship that exists between credit risk in the banking sector and the pace of economic growth in which commercial banks operate. These studies use GDP (Gross Domestic Product) as a measure of economic growth. None of them control for the effect of development on bank credit risk or the effect on bank credit risk when development interacts with banking competition. Taking into consideration the level of development, especially its interaction with banking competition, gives a clearer picture of the role the level of development plays in the overall banking industry as well as its role in the relationship that might exist between banking competition and NPLs. Unlike economic growth (GDP), development gives a wholesome view of the economy. It considers both economic and social factors. That is, it considers both qualitative and quantitative changes in all sectors of the economy including the financial sector. It encompasses the entire social system in terms of income, savings, investment, standard of living, inequality, institutional, financial, and technological changes in the economy.

This paper contributes to the existing literature by providing empirical evidence using the multi-level model approach to examine at the bank-level, the relationship between banking competition and NPLs and also examines how this relationship varies across individual banks when the country's level of development in which each bank operates is taken into consideration. One of the most important contributions of this study to existing literature is the application of the multi-level modelling approach while also controlling for the potential issue of endogeneity of banking competition by incorporating the instrumental variable 2SLS technique. To the best of my knowledge no study has applied this approach in the existing literature. Most existing studies on competition and bank loan performance use traditional econometric methods that may not adequately capture the issue of endogeneity together with the complexity of hierarchical and crossed structures in banking data. By employing multilevel modeling with crossed random effects, this study accounts for the nested nature of the data (e.g., loans nested within branches, and branches nested within banks) and the potential for cross-level interactions (e.g., competition at the regional level affecting branch-level loan performance). This approach provides more accurate and reliable estimates of the impact of competition on loan performance (Goldstein, 2011; Raudenbush & Bryk, 2002). Multilevel models with crossed random effects are particularly good at addressing unobserved heterogeneity across different levels. This is crucial in banking research, where unobserved factors at the bank, branch, and loan levels can significantly influence loan performance. Multilevel models with crossed random effects are used because they are highly flexible and can be extended to include random slopes, allowing the relationship between predictors and outcomes to vary across levels. This flexibility makes the model more generalized to different contexts and can uncover interactions between predictors at different levels. By modeling these effects, the study provides more robust insights into how competition impacts loan performance across different contexts (Gelman & Hill, 2006).

While prior research has explored competition and stability dynamics, it often employs aggregate data at the industry or country level (Skarica, 2014; Noman et al., 2017; Saif-Alyousfi et al., 2020). These studies, though informative, fail to capture the heterogeneity in banks' responses to competition. For instance, large, diversified banks may behave differently under competitive pressures compared to small, community-oriented institutions. By utilizing both bank level and country level data and employing the multi-level modelling technique, this study puts itself within a growing body of literature that recognizes the importance of micro-level analysis while incorporating macro-level influences. This combination expands on earlier frameworks, such as those using generalized linear models or simpler fixed-effects designs, which cannot fully disentangle effects across multiple levels. Employing the multi-level model in this study accounts for these hierarchical dependencies, acknowledging that banks operate within broader, nested frameworks that influence their risk profiles. The Multi-level modelling technique helps to effectively capture the interaction between bank-specific variables and macroeconomic conditions, which single-level models risk omitting, leading to biased or oversimplified conclusions.

Existing literature on the relationship between banking competition and non-performing loans (NPLs) has often relied on simpler econometric models, focusing on direct relationships without delving deeply into causal complexities. While the studies in existing literature provide valuable baseline insights, their limited ability to address endogeneity restricts their explanatory power. Endogeneity is a well-documented challenge in analyzing the competition-NPL relationship, as competition and NPLs can influence one another. While some studies attempt to mitigate this issue using lagged variables, fixed effects or GMM (Skarica, 2014; Kasman and Kasman, 2015; Bashir et al., 2017), these methods are either limited in isolating true exogenous variation or lacks flexibility in modelling hierarchical dependencies. The inclusion of the instrumental variable 2SLS technique in this study represents a methodological advancement, offering a more rigorous solution to endogeneity. For example, the instrumental variables used in this study such as freedom to enter the banking market and regulatory barriers can isolate the exogenous component of competition, ensuring that observed effects are not driven by reverse causality or omitted variables. Compared to studies that overlook endogeneity, this approach significantly enhances the credibility of the causal claims. Hence, incorporating the instrumental variable 2SLS technique into the multilevel model, allows for deeper exploration of these relationships, revealing patterns often masked in simpler frameworks.

Finally, by combining the multi-level modelling approach with the instrumental variable 2SLS technique, this study sets a precedent for future research. It demonstrates how these methodologies can be integrated to address complex relationships, offering a robust template for exploring other multidimensional phenomena in banking.

The remainder of this paper is organized as follows; section 3.2 presents an empirical literature review on the relationship between banking competition and bank risk. Section 3.3 describes the data, methodology and model specification. Section 3.4 provides empirical results and discussions. Finally, section 3.5 concludes the results.

3.1 Empirical Literature

For this paper, we will focus only on empirical literature that looks at the relationship between competition and bank risk as well as financial development and bank risk. Narrowing the focus to these relationships allows for a more in-depth examination of the underlying factors. By concentrating on competition and financial development in relation to bank risk, the study can provide detailed insights and a comprehensive understanding of these critical factors affecting bank stability. These existing empirical works offer conflicting findings on the competition-risk relationship and some of them applied a different measure of bank competition and bank risk.

In a more recent theoretical study, Martinez-Miera and Repullo (2010), argue that a U-shaped relationship exists between competition in banking and the risk of bank failure through non-performing loans. Their study considers the fact that lower interest rates also reduce the banks' revenues from performing loans. They do this by expanding the BDN model (competition-stability) through introducing imperfect correlation in loan defaults. Two potentially counterbalancing effects are observed under this assumption. Just as in the BDN model, the "risk-shifting" effect still plays out. This effect captures the result that an increase in competition leads to lower lending rates, lower risk of default, lower non-performing loans, and lower risk of systematic failure. However, in as much as the "risk-shifting" effect is observed, another effect is being observed alongside. The authors call this effect the "margin" effect. This effect captures the result that an increase in competition leads to lower lending rate, a decrease in overall bank's revenue, a decrease in franchise value, a reduction in the penalty for failure, a decrease in the incentive for caution especially towards the screening of potential borrowers, and finally a higher probability of loan default and systematic failure. The quadratic relationship found by this model represents the net effect of "risk-shifting" and "margin" effects. The model further explains that the "risk-shifting" effect tends to dominate in very concentrated markets such that, an increase in competition leads to a more stable banking system through an improvement in the bank risk measures. In already competitive markets, the model explains that the "margin" effect dominates such that any further increase in competition worsen bank credit risks and a more fragile banking system. The authors conclude that the lowest degrees of bank risk, especially in the loan market, are obtained at moderate levels of competition.

The study by Martinez-Miera and Repullo (2010), has raised a special interest in competition in the banking industry as it does not only provide a sound theoretical evidence that suggests that a quadratic relationship exist between banking competition and bank credit risk, but it also suggests that there is an optimal level of competition in the banking industry. It is based on this that the study, using bank-level data, tends to empirically examine whether there is an optimal level banking competition at which non- performing loans (NPLs) are at their minimum. This study argues that while aggregate-level data provides useful overviews and summaries, bank-level data provides a more detailed view of each of the banks under study which allows for a more accurate understanding of the impact of banking competition on NPLs. Bank-level data offers the precision, detail, and flexibility needed for deep, accurate, and actionable insights. By leveraging bank-level data, researchers, policymakers, and banks can make more informed decisions, design more effective banking policies, and ultimately achieve better outcomes.

Boyd et. al., (2006) using two different samples and fixed effect estimations, examined this relationship by testing the BDN model discussed earlier which supports the competition-stability view. The first sample consisted of data from 2500 rural banks in the US in 2003, and the second sample consisted of data from 2700 banks in 134 non-industrialized countries between 1993 and 2004. Results from their study using both samples provide empirical evidence that is consistent with the prediction of BDN model. They find a negative significant relationship between competition and bank risk. That is, more concentrated banking markets are associated with greater risk of bank failure. De Nicoló and Loukoianova (2007) using data from 133 non-industrialized countries from a period of 1993 to 2004, find evidence to support this result. They find that this relationship is stronger when bank ownership is taken into consideration and is strongest when state owned banks have sizeable market shares.

Saurina et. al., (2007), using GMM estimation and data from the Spanish banking system also examined the competition-bank risk relationship. Covering the period of 1988 to 2003, non-performing loans ratio was used as a measure of bank risk while the Lerner index was used as a measure of competition. In contrast, the results from their study show that a negative significant relationship exists between the Lerner index and non-performing loans. That is, the results provide evidence to support the competition-fragility view (franchise value paradigm).

Using the H-statistics which measures the intensity of competition, Schaeck et. al., (2009) find that the national banking systems that are more competitive are less prone to systematic crisis. They carried out logit model estimations using 45 countries over the period from 1980 to 2005. The result from their study provides evidence to support the competition-stability view. Jimenez et. at., (2013) also find evidence to support this view. They use data from the Spanish banking system over the period 1988 to 2003 and non-performing loan as a measure of bank risk. Results from their study show that encouraging competition in banking markets promotes banking stability.

Beck et. al., (2013), focusing on bank level indicators of stability, use the bank Z-score as a measure of bank stability and the Lerner index as a measure of competition, to investigate the competition- bank risk nexus. Considering regulatory/institutional features of the countries and applying fixed effect estimation model, the results from their study which covers 79 countries and the period of 1994 to 2009 show that, an increase in competition will have a larger impact on banks' fragility in countries with stricter activity restrictions. They suggest that a different result might be obtained if banks sample from countries with less strict activities restrictions are used. The results from the study carried out by Fungáčová and Weill (2013), also support this notion. Using a large sample of Russian banks from the period 2001-2007, they analyze the effect of bank competition on bank failures. Their findings support the notion that more bank competition could undermine financial stability through an increase in bank failures. These results support the findings of Saurina et. al., (2007), Soedarmono et. al., (2013), Repullo (2004), Caminal and Matutes (2002).

Kick and Prieto (2015) tested the competition-fragility view using a dataset provided by the Deutsche Bundesbank over the period of 1994 to 2010. However, they find strong evidence to support the competition stability view. Using the Boone Indicator as a proxy for bank competition, their results support the view that competition in banking tends to reduce the default probability and the riskiness of banks thereby reducing the probability of financial instability.

In regard to the relationship between economic development and bank risk, this area of research is yet to be explored. However, a few studies that focus only on financial development show that the level of financial development in a country is important.

Tanasković and Jandrić (2015) using some countries in Central, Eastern, and Southeastern Europe regions (CESEE) during the 2006 to 2013 period control for financial sector development in their study. They use private credit to GDP ratio as a measure of financial sector development. They find that NPL is negatively correlated to financial sector development. In contrast, Ozili (2019), uses foreign bank presence and financial intermediation as measures of financial development. He employs cross country data analysis consisting of 134 countries over a period of 12 years (2003-2014). His study finds that NPLs increase with greater financial development. He attributed this relationship to weak supervision of the lending standards of all banks and non-bank financial institutions actively involved in the financial intermediation process. He also controls for competition using the Lerner Index. Results from his study show that the Lerner Index coefficient is negatively significant, indicating that countries with competitive banking systems experience fewer NPLs.

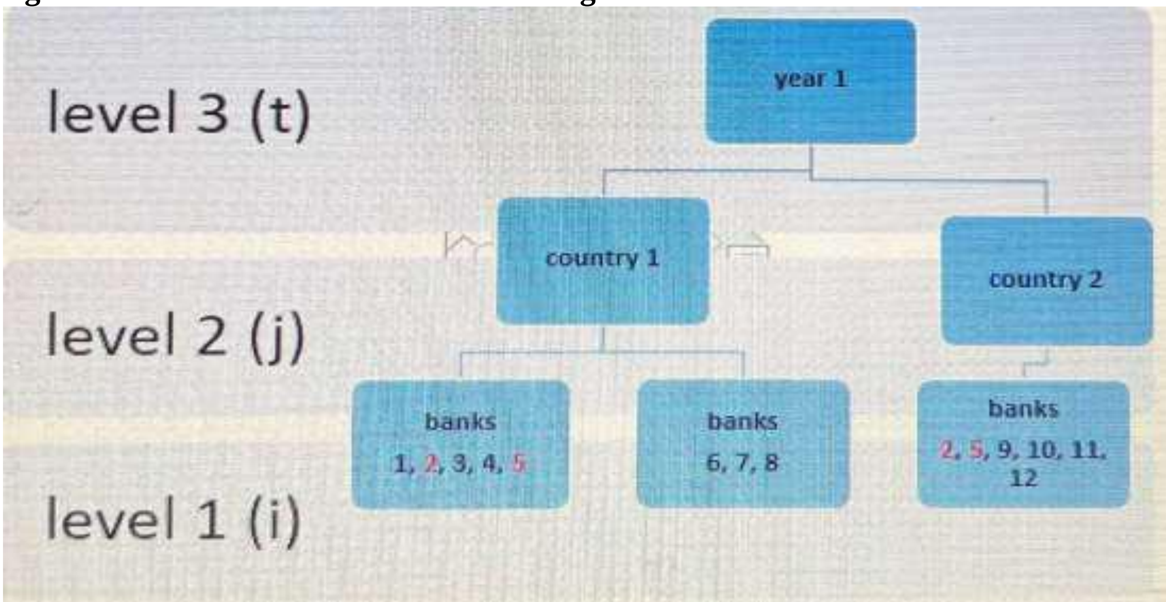
3.2 Data and Model Specification

In this paper, precise measures of bank competition and bank credit risk are used to test the MMR model. Our dependent variable measure of bank credit risk is bank's non-performing loan (NPL) ratios, which is an ex-post measure of credit risk, and our measure of competition is the Lerner index (which is our variable of interest). In the banking literature, the Lerner index, which belongs to the group of non-structural approaches, is a commonly used measure of competition. Structural measures of bank competition focus on the characteristics and structure of the banking market. These measures typically involve assessing the concentration and distribution of market shares among banks. On the other hand, nonstructural measures assess bank competition based on the behavior and performance of banks, rather than the market structure. These measures typically use empirical models to infer the level of competition from observed outcomes.

Studies have shown that unlike the non-structural approaches that truly measure competition, the structural approaches (such as the share of assets held by the top 3 to 5 banks or the Herfindahl- Hirschman index) measure market concentration and as such, should not be ideal to use as measures of competition (Demirguc-Kunt and Martínez, 2010). They argue that concentration is not the same as competition and that even very concentrated banking markets can still be competitive if barriers to the entry and exit of banks are low. Also, it considers the differences between banks, such as size, product, and geographic differentiation. The Lerner index ranges from 0 to 1 and the higher the value, the lower the banking competition. A high Lerner Index indicates a banking market with very little competition while a low Lerner Index indicates a banking market that is very competitive.

The data set for this study covers 706 banks operating in over 85 countries, which was observed during the period from 2004 to 2016. In addition, the structure of data for this study is multilevel, one of the major reasons for employing multilevel model analysis. The crossed random effects occur when multiple grouping factors intersect, with each observation being influenced by these factors independently. In the case of our data set, the structure shows that banks are not exactly nested within countries. Instead, we observe an intersection between banks and countries. That is, we observe that some banks operate in more than one country. Unlike nested models where banks operate within a country, the crossed random effects model allows for the unique structure of our data set where some banks operate in multiple countries as seen in figure 3.2. The crossed random effects model allows us to identify the variability between banks and the variability between countries and further identifies how each of these variations independently affect NPLs. By accounting for each of these independent variations, crossed random effects provide more precise estimates and improve the reliability of inferences drawn from our data set. This precision comes from the model's ability to separately attribute variability to different sources, thereby reducing bias and enhancing the accuracy of parameter estimates related to the effects of interest.

Figure 3.2: Structure of the dataset showing Crossed Random Effects



The data was compiled by combining data from Bank Scope database as well as that of the World Bank. The data used for this study is limited to its availability on Bank Scope database as at the time of this study. One of the main objectives was to collect data from banks in different countries across different levels of development over the stated time period. The composition of the observation is presented in Table 3.1.

Table 3.1: Number of Banks per Country Grouped according to the Country's Level of Development

Level of Development	Country	Number of Banks	Country	Number of Banks
Low Developed	Burundi	1	Madagascar	2
	SierraLeone	1	Lesotho	3
	Gambia	1	Rwanda	6
	Afghanistan	1	Swaziland	6
	Senegal	7	Nigeria	7
	Uganda	14	Tanzania	19
Medium Developed	Cameroon	1	India	26
	Pakistan	10	Namibia	6
	Angola	5	Tajikistan	3
	Cambodia	7	El Salvador	5
	Zambia	14	Bolivia	2
	Kenya	22	Indonesia	35
	Ghana	8	Viet Nam	14
	Bangladesh	9	Egypt	11
	Honduras	7	Philippines	14
			South Africa	3
High Developed	Gabon	3	Armenia	4
	Paraguay	4	Thailand	4
	Uzbekistan	1	Azerbaijan	1
	Botswana	7	Lebanon	11
	Tonga	1	Brazil	3
	Tunisia	2	Venezuela	7
	Dominican Republic	2	Sri Lanka	2
	Colombia	9	Mexico	39
	Peru	19	Georgia	63
	Ukraine	10	Albania	3
	China	38	Serbia	4
	Ecuador	1	Panama	14
	Algeria	2	Mauritius	10
	Turkey	4	Costa Rica	11
	Kazakhstan	12	Greece	1
	Malaysia	24	Italy	3
	Kuwait	19	France	25
	Romania	12	Korea	9
	Bulgaria	2	Japan	13
	Russian Federation	5	Belgium	5
	Argentina	7	New Zealand	8
	Croatia	1	United Kingdom	27
	Hungary	1	United States	28
	Portugal	3	Canada	20
	United Arab Emirates	1	Denmark	1
	Cyprus	9	Netherlands	1
	Australia	8	Singapore	5
	Switzerland	10	Ireland	9
	Norway	3		

Also, the data set consists of both country-level variables and bank-level variables. Other variables that have been found to affect the vulnerability of banks non-performing loans in past literature were included in this study. These variables are; Unemployment (UNEM), Gross Domestic Product Per Capita (GDP), Bank Size (SIZE), Return on Assets (ROA), Foreign Banks among Total Banks (FBA) and Loan Deposit Ratio (LDR).

Bank loan performance has been observed to have a relationship with the macroeconomic environment. This relationship has been studied in literature that relates banking stability with phases of the business cycle. It is expected that when the economy is doing well, the number of banks with bad loans will reduce. This is because customers have sufficient income to cover their debts within the pre-agreed timeframe. However, in the recession phase, increases in bad debts are observed which has severe consequences for banking stability. The academic literature provides evidence to suggest a strong relationship between the NPL and certain macroeconomic variables such unemployment and the state of the economy. It is based on this that this study tends to introduce the country's level of overall development as a variable and also interacts it with our key variable of interest "competition". For the purpose of this study, the Human Development Index (HDI), which is a generally accepted measure of development in academia and the best measure of development, is used as a measure of development.

Likewise, certain bank specific variables have been seen to exhibit a relationship with bank loan performance such as bank size, ROA and loan deposit ratio. The bank size is also a key variable that affects NPLs. The bank's total assets are used as a measure of the bank's size. Studies show that banks with larger assets tend to be more rigorous in their loan process and hence their loans tend to perform better than banks with smaller assets. Thereby making the probability of banks with larger assets producing non-performing loans considerably reduced. The study by Miller and Noulas (1996) provides evidence to support that large-scale and profitable banks have better loan performance.

The sources and definition of the variables used for this study are displayed in Table 3.2 while their descriptive statistics are presented in table 3.3.

Table 3.2: Variables Used in the Study, Definition, Sources and Expected Sign

Variable	Definition	Source	Expected Sign
Foreign Banks among Total Banks (%)	Percentage of the number of foreign owned banks to the number of the total banks in an Economy.	World Bank National Accounts Data Base, and OECD National Accounts Data Files.	**(+)/(-)** An increase in foreign ownership could be associated with a decrease in non-performing loans Lin and Zhang (2009). This is linked to the high level of efficiency that exists among foreign owed banks. It could also be associated with a higher NPL due to lack of adequate information and understanding of the environment they operate it thereby leading to decision taking that might increase the riskiness of the loan portfolio Rokhim and Susanto (2011).
Return on Assets (ROA)	It is a measure of the profitability of a commercial bank in relation to its total assets.	Bankscope, Bureau van Dijk (BvD)	**(-)** This is because high profitability and good financial leverage should lead to lower NPL Garciya-Marco and Robles-Fernandez (2008).
Bank Size (Total Assets)	This is the sum of the total earning assets, foreclosed real estate, fixed assets, goodwill, current assets and other assets.	Bankscope, Bureau van Dijk (BvD)	**(-)** An increase in bank size could be associated with a decrease in non-performing loans Yulianti et. al., (2018). This is linked to the low interest rates that are facilitated by big banks.
Loan Deposit Ratio (LDR)	This is the measure of the liquidity of a bank in paying back withdrawals made by depositors.	Bankscope, Bureau van Dijk (BvD)	**(+)** This is because the higher the amount of credit extended, the less NPL at commercial banks will be reduced (Riyadi et. Al., 2014; Mentari, 2017; Harutiyansari, 2018)
Unemployment	Unemployment refers to the share of the labor force that is without work but available for and seeking employment.	World Bank National Accounts Data Base, and OECD National Accounts Data Files.	**(+)** An increase in unemployment will make it difficult for borrowers to meet their debt obligations hence leading to an increase in NPL (Salas and Saurina, 2002; Fofack, 2005; Skarica, 2014).
Gross Domestic Product per Capital (GDP)	GDP is the sum of gross value added by all resident producers in the economy plus any product taxes and minus any subsidies not included in the value of the products.	World Bank National Accounts Data Base, and OECD National Accounts Data Files.	**(-)** A downturn in the economy, that is a negative growth in GDP, will affect the ability of borrowers to repay their loans which will therefore lead to an increase in the level of bad debts experienced (Ghosh, 2015).
Lerner Index	A measure of market power in the banking market. An increase in the Lerner index indicates a deterioration of the competitive conduct of financial intermediaries.	Bankscope, Bureau van Dijk (BvD)	**(+)** supports competition stability view. **(-)** supports competition fragility view. Jimenez et al. (2013).
Boone Indicator	It measures the effect of efficiency on performance in terms of profits. It is calculated as the elasticity of profits to marginal costs.	Bankscope, Bureau van Dijk (BvD)	**(+)** supports competition stability view. **(-)** supports competition fragility view.
CR5	CR5 is the share of assets held by the 5 largest banks in a given economy.	Bankscope, Bureau van Dijk (BvD)	**(+)** supports competition stability view. **(-)** supports competition fragility view.
Non-performing Loans (NPL)%	The percentage of defaulting loans (payments of interest and principal past due by 90 days or more) to total gross loans (total value of loan portfolio).	World Bank National Accounts Data Base, and OECD National Accounts Data Files.	
Z-Score	It is a measure of the probability of default of a country's banking system.	Bankscope, Bureau van Dijk (BvD)	
Human Development Index (HDI)	The HDI is a measure of the level of development within a country taking into consideration both economic and social indicators.	World Bank National Accounts Data Base, and OECD National Accounts Data Files.	For developed countries, we expect a less significant effect because they are known to experience more competition and better access to credit facilities due to good governance, better structure, better economic policies, and less corruption. Hence a shock in competition might have a less significant effect in the countries while we expect a more significant result for developing countries due to their relatively less developed banking industry.

Table 3.3: Descriptive Statistics of the Variables

Variable	Observations	Mean	Standard Deviation	Minimum Value	Maximum Value
Non-Performing Loans (NPLs)	**5,127**	4.3172	7.2688	0	96.93
Lerner Index	**5,127**	0.3010	0.12389	0.0030	0.9386
Log_GDP	**5,003**	8.9521	1.3148	5.3858	11.2439
Unemployment (UNEM)	**5,114**	7.0256	4.3889	0.16	24.757
Return on Assets (ROA)	**5,127**	0.9197	2.6680	-41.02	21.66
Log_Bank Size	**5,127**	2.6696	0.1759	1.9464	3.9340
Foreign Bank among Total banks	**5,120**	26.9778	25.4044	0	55
Loan Deposit Ratio (LDR)	**5,127**	29.1202	47.701	10	91.342
Human Development Index (HDI)	**5,006**	0.7561	0.1155	0.29	0.914

From Table 3.3, the average NPL (non-performing loan) is 4.3% with a minimum of 0% and a maximum of 96.93%. This shows that there were some banks, who within the time frame lost almost all their loans to bad debts and, there were some banks whose loans were all performing. The Lerner Index, which is measured in percentage for this study, has a minimum of 0.30% and a maximum of 93.87%, this indicates that the banking market in which banks operated in some countries were highly competitive while some operated in markets that are less competitive. Unemployment shows a minimum of 0.16% and a maximum of 24.76%, indicating that in some countries, the share of the labor force that was without work but available for and seeking employment was as high as 24.76%, while some countries' economies seemed to have performed better with an unemployment rate as low as 0.16%. Log Size, which represents the bank size/total assets of the bank, has a minimum of 9.1 and a maximum of 21.93. This shows that some banks have a stronger net-worth than others hence placing them in a higher tier/ranking than their counterparts. ROA (Return on assets) shows a minimum of -41.02%, indicating that some banks experienced losses and bad managerial efficiency. On the other hand, its maximum figure is 21.66% which shows that some banks can be seen to have experienced more banking profitability, better managerial efficiency and more financial leverage between the year 2004 and 2016. Loan Deposit ratio recorded a minimum of 10% and a maximum of 91.3%, indicating that some commercial banks in some countries observe more liquidity and have a higher chance of being able to pay back withdrawals made by depositors.

Log_Bank Size has a minimum of 1.9 and a maximum of 3.93, indicating that commercial banks in some countries have more assets and are bigger in size than some commercial banks in other countries. Foreign Banks among total banks shows a minimum of 0% and a maximum of 55%, indicating that the Percentage of the number of foreign owned banks to the number of the total banks in some countries was zero. That is, in some countries foreigners did not own any shares in commercial banks. Finally, the Human Development Index shows a minimum of 0.29 and a maximum of 0.91, indicating that over the period of 2004 to 2016, some commercial banks operated in countries with a higher level of development than others.

3.3 Empirical Methodology: Multilevel Modelling

In this section, we empirically test the model introduced by Martinez-Miera and Repullo (MMR) (2010). As stated earlier, an unbalanced panel data set consisting of bank level and country level variables is used. We include a quadratic term through which non-performing loans can exhibit a non-linear relationship with banking competition as suggested by Martinez-Miera and Repullo (2010). We also include year dummy variables which helps to capture the influence of the aggregate trends on NPLs and further proceed to examine the relationship between NPLs and competition when the country's level of development is taken into consideration.

The model developed by Martinez-Miera and Repullo in 2010 provides an important theoretical rationale for the relation between banking competition and financial stability, urging its empirical testing. Their model develops a non-monotonic relation of competition with non-performing loans, whereby low or moderate levels of bank competition decrease risk, while the opposite happens with high levels of competition that result in decreased profitability. Most of the studies carry this hypothesis of competition and stability further on (Beck et al., 2013). By adding a quadratic term to our model, we will be able to see if NPLs exhibit a similar nonlinear pattern in our data.

For this study, we exploit the hierarchical structure of our data set by employing multilevel modeling. We also address the likely issue of endogeneity of our competition variable by including instrumental variable 2SLS technique in our multilevel model. Our dataset consists of observations at various levels (bank level and country level). The multilevel model allows for the inclusion of predictors at these various levels, which provides a more comprehensive analysis of how the hierarchical factors of our data set impact NPLs. Panel data fits perfectly with banking studies, as it controls both for cross-sectional variation across entities and for time variation, hence allowing one to precisely analyze how competition affects banking under different macroeconomic conditions. Following Claessens and Laeven (2004), we add bank and country-specific variations to account for differences in the regulatory framework, economic development, and banking structure. Year dummies will also be included to capture trends in the global financial environment. We implement the methodology of Arellano and Bover (1995).

Since we have ordered data with observations nested at both the bank and country levels, we estimate the model using the multilevel technique. This method is particularly appropriate when data is arranged in such a manner because GSEM allows dependencies within groups to be taken into consideration while at the same time making comparisons between them (Raudenbush and Bryk, 2002; Hox, 2010). Since there is a possibility of reverse causality when using the competition variable as an independent variable in the model, we use the instrumental variable method through the 2SLS technique, which authors often employ to reduce endogeneity bias (Blundell & Bond, 1998; Angrist & Pischke, 2009). Also, acknowledging the cross-country differences in the NPL-competition and comparing it at various degrees of national development makes a further sense of reflecting on the institutional and economic disparity and dexterity between the countries which brings more to the paradigm of banking competition and financial stability (Demirgüç-Kunt et al., 2004).

Multilevel modeling is a methodological framework which is popularly used in the social sciences to analyze data that is hierarchical in structure. It is used to analyze data that are grouped into different levels where lower units of aggregation are 'nested' in higher units. Multilevel modeling has a unique advantage of allowing for the examination of cross-level interactions, which are interactions between variables at different levels of analysis. It allows for the simultaneous combination of individual-level and group-level predictors in single regression framework, while also avoiding the drawbacks that might be associated with aggregating individual-level variables to the group level and disaggregating group-level variables to the individual level (Oshchepkov and Shirokanova, 2020). Applying multilevel analysis to empirical work on bank data begins from the simple observation that banks operating within the same regulatory environment or market tend to exhibit more similar performance and behavior than banks operating in different regulatory environments or markets. Therefore, it is important that while we assess the extent of variability in individual bank performance, we also assess the extent to which this variability is attributed to between-bank variance or between-market/regulatory environment variance.

Multilevel analysis is a statistical method that helps to examine how characteristics or behaviors at a higher, aggregate level (such as a country or market) relate to characteristics or behaviors at a lower, individual level (such as individual banks or loans). Specifically, it helps to determine whether and how higher-level factors (like market regulations or economic conditions) are linked to lower-level outcomes (such as bank performance or loan default rates). Thus, for the purpose of this study, it helps to assess the extent to which variance in banks' loan performance can be attributed to between country-variance and between bank-variance and further identifies factors that explain it, thus, helping to draw more precise conclusions.

This approach of analysis also provides a unique additional advantage. While other regression models are designed to model the mean, multilevel analysis focuses on modeling variances explicitly (Van et. al., 2020). That is, it allows us to incorporate unobserved heterogeneity into the model by including random intercepts and slopes and allowing relationships to vary across contexts thus, improving the accuracy and reliability of our estimates.

The application of the multilevel model approach for this study also helps to avoid the problems posed by compositional and ecological misconceptions (Pettigrew, 1996). That is, the problems that arise because of drawing conclusions at the aggregate-level of analysis from using only individual data as well as drawing conclusions about individuals from using only aggregate-level data. These are misconceptions because aggregate data alone are too broad to determine individual data, and individuals also have unique properties that cannot be inferred from aggregate data. The application of multilevel analysis protects against these misconceptions in social sciences by working at both levels simultaneously, thereby ensuring more accurate and reliable results (Pettigrew, 2006).

For the purpose of this study, it is quite logical to assume that banks operating within the same country in a particular year experience the same external environment and hence are likely to be more similar to each other than banks operating in different countries. This similarity violates the assumption of independence of errors. Additionally, the same banks operating in different countries may also exhibit similar unobservable due to shared internal practices, strategies, or management styles. This issue is addressed by the multilevel approach, which ensures efficient estimates since it controls for spatial dependence and corrects the measurement of standard errors, thereby avoiding misleading inference (Aiello and Ricotta, 2014). Therefore, a mixed approach is used here to account for both within-country similarities and cross-country unobservable, providing a more comprehensive and accurate analysis. In fact, whereas standard regressions are designed to only model an overall mean coefficient, the multilevel analyses allow the coefficients to vary at the country level by allowing a distribution around the coefficients. MLM also helps to allow for cross random effects which we allow for in this study. That is, we allow for the fact that a bank can appear in more than one country. We do this by creating banks and country identifiers. For instance, if Barclays Bank operates in more than one country, we treat Barclays Bank as one bank across all the countries it operates in.

The MLM allows us to appropriately account for the intra-group correlation, ensuring that standard errors are not underestimated, which can lead to incorrect inferences. It also allows for the inclusion of predictors at multiple levels, thereby providing a more comprehensive analysis of how the hierarchical factors impact NPLs. MLM helps us to understand the variability across both the bank level and the country level which will provide valuable insight as to how economic policies on banking competition will impact NPLs of individual banks differently.

In summary, employing a multilevel modeling approach offers advantages that enhance the understanding of the complex economic relationship between banking competition and non-performing loans. By modeling data at both the country and bank levels, MLM facilitates the exploration of hierarchical structures, cross-level interactions, heterogeneity, and dynamics over time. By capturing both within-country and between-country variations, these models offer insights into how macroeconomic conditions, regulatory environments, and institutional factors influence bank-specific outcomes. This approach not only enhances the precision of estimates but also supports more informed policy decisions aimed at promoting financial stability and sustainable economic growth across diverse contexts.

Below is an econometric specification of a multilevel model:

$$NPL_{ijt} = \beta_{0ij} + \beta_1 X_{ijt} + \beta_{2ij} L_{ijt} + e_{ijt} \qquad (1)$$

Equation 1 refers to the lowest level of data, that is, bank level. Where NPL_{ijt} is the non-performing loans of bank i in country j in year t, j is for countries (j = 1, …r), i for banks (i = 1, …N)e, j and t for year (t = 1, …13). X comprises of the other explanatory variables, L denotes our variable of interest (banking competition), β_{0ij}, β_1 and β_{2ij}, are the intercept and slope coefficients which are allowed to vary across banks and countries. However, in our analysis, we allow for the intercepts and only the slope of our variable of interest (competition) β_{2ij} to vary across banks and countries, e_{ijt} is the random error term

with zero mean and variance σ^2.

Since the intercept and slope coefficient (competition) are random variables that vary across both bank and country, they are often called random coefficient. The specification used here is a random intercept model, which is:

$$\beta_{0ij} = \gamma_{00} + \gamma_{01} * \mathrm{X}_{ij} + \mathrm{u}_{0ij} \tag{2}$$

$$\beta_{2ij} = \gamma_{20} + \gamma_{21} * \mathrm{L}_{ij} + \mathrm{u}_{2ij} \tag{3}$$

From equation (2), we can see that β_{0ij} differs across banks and countries if these intercepts depend on both bank-level and country-level explanatory variable X_{ij} with the coefficient γ_{01}. The constant term γ_{00} is the expected value of β_0 when X_{ij}=0, while u_{0ij} is the error term that represents the remaining variability in the intercepts after controlling for X_{ij}. In a similar way, Equation 3 model variations in slopes β_{2ij} which is assumed to depend on L_{ij} with the coefficient γ_{21}, where γ_{20} is the constant terms and u_{2ij} and u_{2ij} are the error terms.

All error terms in equation (1), (2), and (3) are assumed to be identically (normally) and independently distributed and averaged at zero, given the values of X and L: e_{ij}~N(0, σ_2), u_{0ij}~N(0, τ_{00}), and u_{2ij} ~N(0, τ_{00}) . u_{0ij} and $_{2ij}$ are called 'random effects', thereby assuming that intercepts β_{0ij} and slopes β_{2ij} contain random bank- level and country-level components.

Going further, we obtain the general form of our multilevel model equation by substituting equation (2) and (3) into equation (1) yielding:

$$NPL_{ijt} = \gamma_{00} + \gamma_{01}X_{ij} + \beta_1 X_{ijt} + \gamma_{20} + \gamma_{21}L_{ij} + u_{2ij} + u_{0ij} + e_{ijt} \qquad (4)$$

The deterministic part of the model, $\gamma_{00} + \gamma_{01}X_{ij} + \beta_1 X_{ijt} + \gamma_{21}L_{ijt}$ consists of all the coefficients including the coefficients while $u_{0ij} + u_{2ij} + e_{ijt}$ is the stochastic component.

The error terms capture the bank-to-bank and country-to-country variability of the random intercepts and the residual variance, in the same way OLS regression does. However, in equation (4), the composite error term is not independently distributed across banks within the same country. This is attributed to the fact that we control for time dimension, hence banks belonging to the same country tend to have correlated residuals, therefore violating the assumption of independence.

We further expand equation (4) by introducing two interaction terms ($L *$ HDI) and ($L^2 *$HDI), that capture the interactions between banking competition and development and the square of the interaction between banking competition and development respectively. This helps us to investigate if the MMR hypothesis still holds when the country's level of development in which the banks operate is taken into consideration. ($L *$ HDI) is the product of banking competition and development.

$$NPL_{ijt} = \gamma_{00} + \gamma_{01}X_{ij} + \beta_1 X_{ijt} + \gamma_{20} + \gamma_{21}L_{ijt} + \theta_{1j}(L * \text{HDI}) + \theta_{2j}(L^2 * \text{HDI}) + u_{0ij} + u_{2ij} + e_{ijt} \qquad (5)$$

Where;

θ_{1j} Measures the difference in the effect of banking competition across different levels of development while θ_{2j} measures the difference in the effect of the square of banking competition between different level of development.

Finally, to address the potential issue of endogeneity, we incorporate the instrumental variable 2SLS technique into our multilevel model. We employ freedom to enter the banking market and regulatory barriers as instruments to explain banking competition as used in the previous chapter. Regulatory barriers are a key determinant for the scope of operations of banks and are likely to affect the level of competitiveness. This index provides information on whether banks can engage in securities, insurance, and real estate activities, and whether they can hold stakes in non-financial institutions. Freedom to enter the banking market represents a broad indicator for the openness of a banking system, capturing whether foreign banks are allowed to operate freely, whether difficulties are faced when setting up domestic banks, and whether the government influences the allocation of credit.

To incorporate the instrumental variable 2SLS technique into our multilevel model, we first estimate the first stage regression where we use our instruments to predict the endogenous variable (banking competition) as seen appendix 3.7.1. We also test the validity and joint significance of the endogenous variable as seen in appendix 3.7.1. The results from the first stage regression show that our instruments are not weak and are both jointly significant in explaining the endogenous variable. After estimating the first stage regression, we then estimate the multilevel model where we use the predicted values of the endogenous variable (banking competition) gotten from the first stage regression.

When we incorporate the instrumental variable 2SLS technique into equation (5) and (6) to account for the potential issue of endogeneity, equation (5) and (6) become;

$$NPL_{ijt} = \gamma_{00} + \gamma_{01}X_{ij} + \beta_1 X_{ijt} + \gamma_{20} + \gamma_{21}\hat{L}_{ijt} + u_{0ij} + u_{2i} + e_{ijt} \qquad (6)$$

$$NPL_{ijt} = \gamma_{00} + \gamma_{01}X_{ij} + \beta_1 X_{ijt} + \gamma_{20} + \gamma_{21}\hat{L}_{ijt} + \theta_1(\hat{L} * \mathrm{HDI})_j + \theta_{2j}(\hat{L}^2 * \mathrm{HDI}) + u_{0ij} + u_{2i} + e_{ijt} \qquad (7)$$

Where $\hat{L}$ and $\hat{L}^2$ are the predicted values of banking competition and the squared of banking competition respectively.

3.4 Results

Table 3.4 reports the regression results from our main models (6 and 7). These models control for the possible issue of endogeneity by employing the predicted values of the endogenous variable from the stage regression in our multilevel model. Table 3.4 also reports the regression results when we allow for crossed random effects.

Table 3.4: Multilevel Regression Results

Variables	Equation 6	Equation 7	Crossed Random Effect
Regression Coefficients (Fixed Effect)			
Intercept	49.01	46.62	47.52
Lerner Index	**-0.1384** (0.116)**	**-0.1725 ** (0.1311)**	**-0.1137*** (0.154)**
Lerner $Index_2$	**0.0760** (0.035)**	**0.0658*** (0.024)**	**0.0113** (0.024)**
Log_GDP	**-0.7280** (0.010)**	**-0.8412** (0.112)**	**-0.6902** (0.040)**
Log_GDP_{it-1}	**0.2333** (0.013)**	**0.4225*** (0.107)**	**0.3128*** 0.053**
Unemployment	**0.8646** (0.029)**	**0.4486 *** (0.012)**	**0.3132*** (0.048)**
Bank Size	**-0.0458 ** (0.094)**	**-0.2421** (0.222)**	**0.6383** (0.279)**
Return on Assets (ROA)	**-0.0661*** (0.049)**	**-0.1040** (0.059)**	**-0.1162** (0.063)**
Foreign Banks Among Total Banks	**-0.3151** (0.138)**	**-0.1614** (0.066)**	**-0.3320*** (0.087)**
Loan Deposit Ratio (LDR)	**0.0039** (0.002)**	**0.0020** (0.000)**	**0.0044*** (0.001)**
HDI		**-0.8055**** (0.595)	**-0.8509 ** (0.039)**
Lerner Index*HDI		**-0.5029** (0.054)**	**-0.3436** (0.093)**
(Lerner $Index_2$*HDI)		**0.2083** (0.051)**	**0.2229** (0.031s)**
Variance Components (Random Effects)			
Country (slope) (Intercept)	0.4284 2.8461	0.6619 1.5275	3.6608
Bank (slope) (Intercept)	0.9523 2.0385	0.9280 2.0498	5.3847
Residual	3.8621	3.8663	4.1152
Chi-square	**213.15*** **	**251.88*** **	**234.78*** **
ICC (Country) (Bank)	0.0813 0.9465	0.0337 0.9589	

Note: Table shows the coefficients estimates (coefficients in boldface are significant). * Significance at the 10% level, ** significance at the 5% level, * significance at the 1% level.**

3.4.1 Discussion

Results from table 3.4 show that three regressions were estimated. In each regression, we consider countries and banks as sources of randomness in both intercept and slope. They show the impact of banking competition proxy by the Lerner index on loan performance.

Regarding our variable of interest, which is the Lerner Index, results from equation 6 show that, when a country's level of development is not put into consideration, a U-shaped relationship exists between the Lerner Index and banks' NPL as seen in appendix 3.7.2. This implies that when the country's level of development is not taken into account, a U-shaped relationship exists between banking competition and loan performance, thereby validating the model proposed by Martinez- Miera and Repullo (2010). This suggests that, although at low levels of the Lerner index (i.e, very high competition), an increase in the Lerner index corresponds to decreasing NPLs. However, the rate at which NPLs decreases with the Lerner index decreases as competition becomes lower. At some point, NPLs reach a minimum and then increase with the Lerner index. This indicates that high competition and high market power are both associated with riskier loan portfolios in the banking industry. This can be seen in Figure 3.2.

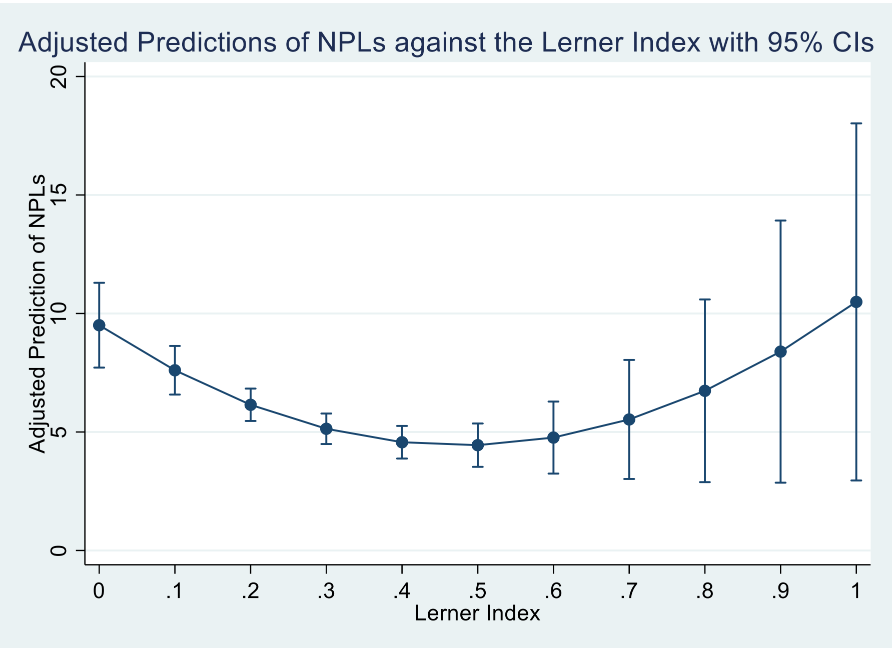


Figure 3.2b: Adjusted Prediction of NPL against Lerner Index

Martinez-Miera and Repullo (2010), describe this relationship we observe as the combination of both the risk-shifting effect and the margin effect. The risk shifting effect could be linked to the fact that as banking competition increases and the banking market becomes more competitive, loan rates reduce, which in turn makes it easier for customers to repay their loans hence, leading to lower probabilities of loan defaults and safer banks. On the other hand, the margin effect could be linked to the fact that as more competition leads to lower loan rates, it also leads to lower revenues from performing loans which serves as a buffer against loan losses, thereby leading to an increase in the risk associated with loan default and riskier banks. In line with Martinez-Miera and Repullo (2010), results from our study show that the risk-shifting effect tends to dominate in monopoly markets, whereas the margin effect dominates in competitive markets, so a U-shaped relationship between competition and banks loan performance generally obtains when the country's level of development is not considered.

Results from equation 7 show that, when we consider the country's level of development in which the banks operate and allow for the interaction between the Lerner Index and the country's level of development, a stronger quadratic and positive relationship exists between the Lerner Index and banks' NPL which is significant at 1% as seen in appendix 3.7.3. The results show that the interaction term between the Lerner Index and the HDI has a significant effect on banks' loan performance thereby, providing empirical evidence showing that the country's level of development in which a bank operates has a significant impact in the relationship between banking competition and NPLs.

Looking at the results from the crossed random effects model, which also accounts for the country's level of development as seen in appendix 3.7.4, we observe the same relationship as in equation 7. However, the crossed random model provides a better fit. Evidence of this can be observed in the results derived from the Likelihood-ratio test as seen in appendix 3.7.5. The p-value from the likelihood test, which is less than 0.05, shows that accounting for crossed random effects in our multilevel model provides a significantly better fit to our data set. Results from the crossed random effects model show that the coefficients of the interaction terms between the Lerner Index and HDI are significant, which indicates that the impact of banking competition on NPLs is dependent on the country's level of development in which the banks operate. The results show that the relationship between banking competition and NPLs differs across different levels of development and a U-shaped relationship does not hold across all levels. We observe that a U-shaped relationship only holds for low and medium developed countries. The results reveal that for developed countries, a banking market that is not so competitive tends to improve banks' loan performance in these countries as seen in figure 3.3. This behavior observed by banks in highly developed countries supports the findings by Allen and Gale (2004). They argue that more competition increases the incentive for banks to take on more risks and engage in riskier loan portfolios to maintain their customer base. They also argue that, because of this, banks' incentive to properly screen borrowers reduces thereby increasing the risks associated with the banks' loan portfolios**.** We also observe that for every level of banking competition, low developed countries tend to experience a higher level of NPL than medium developed and highly developed countries. This goes to show that the level of development in a country in which the banking market operates is of key importance in improving banks' loan performance within the country.

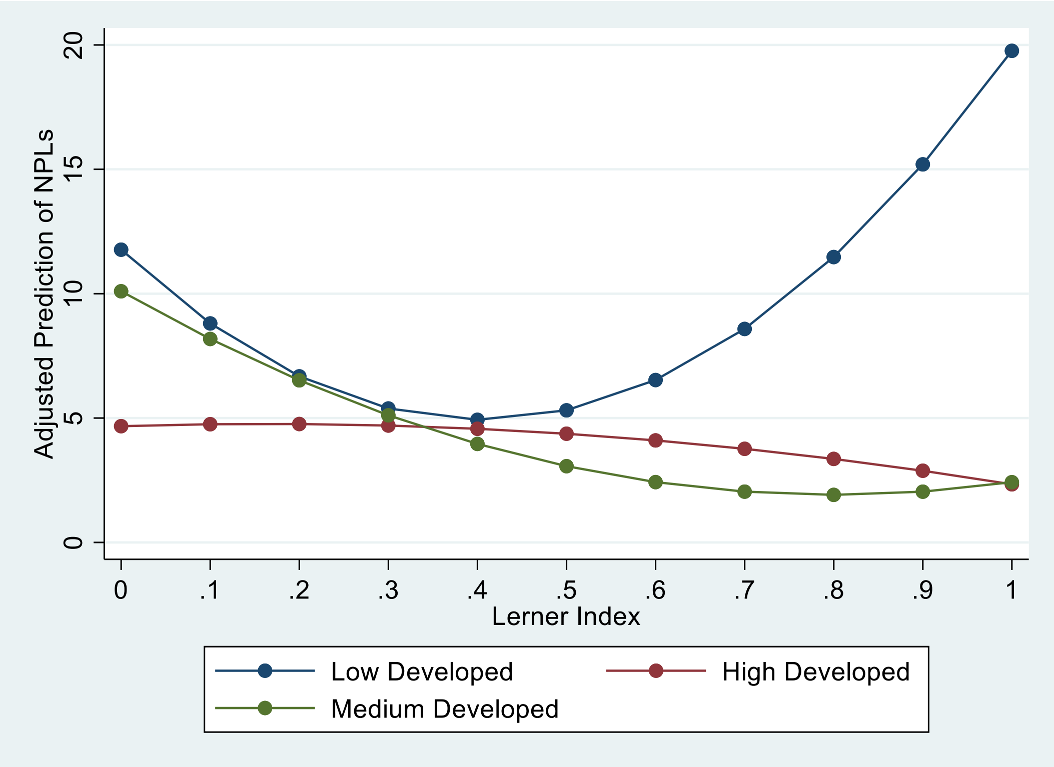


Figure 3.3: Adjusted Prediction of NPL against Lerner Index for Countries when Grouped according to their Level of Development

Taking advantage of the choice of our econometric model, the variance estimates from all the equations in table 3.4 show significant variation in NPL across banks and across countries. Results also showed the effect of competition on bank's NPL vary significantly across both banks and countries. However, the variation across banks is greater than the variation across countries. Going further, results from our estimations also show that bank specific factors capture a higher percentage of the total variance of banks' non-performing loans. This can be seen in the ICC segment in table 3.4. Looking at equations 7 and 8, we find that 94.7% and 95.9% of the variation in NPL respectively is explained at the bank level. From table 3.4, we observe the robustness of the bank effect, which is always higher irrespective of the model used, ranging from 94.7% to 95.9%. This indicates that a higher percentage of banks' NPL heterogeneity can be attributed to bank level specific factors. This also implies that the share of NPL variability due to observed bank specific factors always exceeds 94% and rises close to 96% when controlling for both country and bank random effects. These results imply that, in as much as country level factors affect loan performance, more attention should be given to bank level factors by bank managements and regulatory authorities.

In addition to this, results from our post estimations in regard to the random effects, which basically tell us the amount of variation for both the intercept and the estimated beta coefficient(s) show that the bank associated with the highest credit risk does not operate in the country that is associated with the highest credit risk as seen in figure 3.3b. This finding calls for further research into future studies as one would expect the bank with the highest credit risk to be found in the country with the highest credit risk.

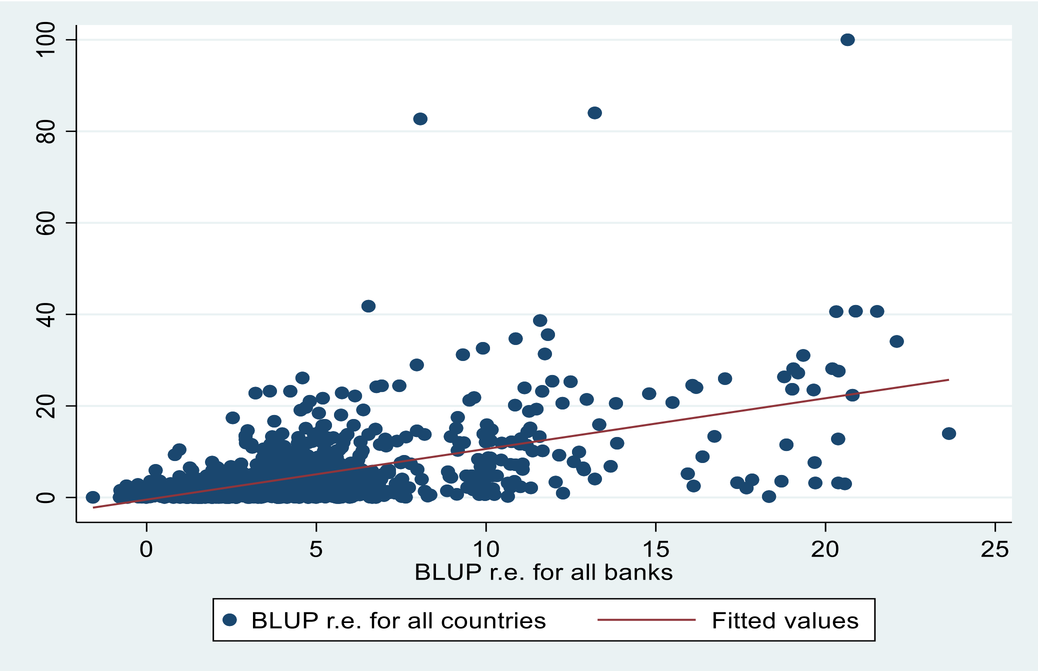


Figure 3.3b: Post Estimation Result showing BLUP for Bank Random Effects and Country Random Effects

BLUP, which stands for Best Linear Unbiased Predictor, is a statistical method used in multilevel modeling to estimate random effects. In the context of bank random effects, BLUP provides predictions for the random effects associated with each bank, given the data and the model. The prediction is optimal in the sense that it minimizes the mean squared error of the prediction. This means BLUP provides the most accurate estimates possible for the random effects. BLUP is used to predict the random effects, which in this case are the bank-specific deviations from the overall average effect. So, in practical terms, when applying BLUP to bank random effects in a multilevel model, the method predicts how much each bank deviates from the overall average, accounting for both the fixed effects (common to all banks) and the random effects (unique to each bank).

Accounting for the control variables, we observed from our results that a strong positive and significant relationship exists between a country's rate of unemployment and banks' NPLs. This suggests that banks that operate in countries with high rate of unemployment will tend to experience higher rates of NPLs. This finding can be attributed to the fact that unemployment weakens borrowers' ability to pay their loan installments, thereby leading to an increase in NPLs.

With regard to the other explanatory variables, we find that GDP is negative and statistically significant as expected, which suggests in a booming economy, the ratio of non- performing loans decreases. That is, when the economy performs, the rise in income enables borrowers to repay their loans that are due to the banks in stipulated time therefore, recognizing the loan as standard loan and not a bad loan. This finding was corroborated with Salas and Saurina (2002), Louzis, Vouldis, and Metaxas (2010), Nkusu (2011), and De Bock and Demyanets (2012). Additionally, the effect of lagged GDP growth is also significant but with a positive sign. This supports the notion that during boom periods, banks tend to loosen their credit standards, which subsequently leads to a deterioration in the quality of banks' assets.

Our results show that bank size has a significant negative effect on NPLs. This indicates that larger banks are more able to solve problems of information asymmetry in comparison to smaller banks. This is because they have better and more efficient means to employ more qualified skilled workers and carry out effective credit analysis as well as the proper monitoring of debtors. This is in line with results from Salas and Saurina (2002) as well as Curak et., al. (2013).

We observe that Percentage of the number of banks where 50% or more of its shares are owned by foreigners has a significant negative relationship with non-Performing loans. This evidence might be explained by the nature of foreign banks. That is, foreign banks can be described as having more capital, more experience, better efficiency, and better technological know-how which therefore leads to better loan screening and management skills and thereby leads to a decrease in non- performing loans.

Finally, we observe that ROA has a significant negative relationship between NPL. The results, as expected, indicates that a decrease in the profitability ratios will lead to an increase in non-performing loans, confirming the risk-taking behaviour of banks. This result is attributed to the fact that higher profitability makes bank managers less pressured in creating revenue from credit activities and thus, there is less exposure to credit risk and loan default. This negative relationship is also in line with the argument that bad management leads to riskier activities and riskier loan portfolios (Cotugno et. al. (2010), Louzis et. al. (2012).

3.5 Robustness Checks

To establish the robustness of our findings, we present results from estimating various alternative specifications. First, we introduce alternative measures to banking competition (the Boone indicator and the concentration index CR5) and re-run all our models. We present the results for these specifications in tables 3.5 and 3.6 respectively after using the first stage regression of our instrumental variables to estimate the predicted values of the Boone indicator and CR5 as seen in appendices 3.8.1 and 3.8.5 respectively.

Table 3.5: Boone Indicator as a Measure of Competition

Variables	**Equation 6**	**Equation 7**	**Crossed Random Effect**
Intercept	23.09	21.41	24.69
Boone Indicator	**-1.0540*** (0.017)**	**-1.5788*** (0.015)**	**-1.0103*** (0.037)**
Boone Indicator^2	**0.5088*** (0.038)**	**0.6297*** (0.020)**	**0.5393*** (0.033)**
Log_GDP	**-0.2390*** (0.040)**	**-0.5275** (0.011)**	**-0.5408** (0.049)**
Log_GDPit-1	**0.5629*** (0.039)**	**0.2176*** (0.029)**	**0.2873*** (0.014)**
Unemployment	**0.2038** (0.135)**	**0.7260*** (0.185)**	**0.2209*** (0.051)**
Bank Size	**-0.1139 ** (0.015)**	**-0.3910** (0.019)**	**-0.1534** (0.063)**
Return on Assets (ROA)	**-0.0333** (0.052)**	**-0.0056** (0.034)**	**-0.0003** (0.074)**
Foreign Banks Among Total Banks	**-0.0070** (0.052)**	**-0.0266*** (0.018)**	**-0.0830*** (0.055)**
Loan Deposit Ratio (LDR)	**0.0726** (0.024)**	**0.0923*** (0.044)**	**0.0736** (0.008)**
HDI		**-0.5260** (0.031)**	**-0.6659** (0.053)**
Boone Indicator*HDI		**-0.3830** (0.018)**	**-0.3033** (0.034)**
(Boone Indicator^2*HDI)		**0.8728** (0.034)**	**0.7825** (0.046)**
Variance Components (Random Effects)			
Country (slope) (Intercept)	0.6226 1.2782	0.5713 1.2387	 3.2653
Bank (slope) (Intercept)	0.9945 1.8541	1.0113 1.8516	 6.3513
Residual	4.0242	4.0428	4.2717
Chi-square	**175.94*** **	**223.84*** **	**214.42*** **
ICC (Country) (Bank)	0.0813 0.9465	0.0337 0.9589	

Note: Table shows the coefficients estimates (coefficients in boldface are significant). * Significance at the 10% level, ** significance at the 5% level, * significance at the 1% level.**

Table 3.6: CR5 as a Measure of Competition

Variables	Equation 6	Equation 7	Crossed Random Effect
Intercept	17.411	22.45	24.68
CR5	**-0.1556*** (0.012)**	**-0.3953*** (0.036)**	**-0.5023*** (0.037)**
$CR5^2$	**0.0012** (0.000)**	**0.0213** (0.010)**	**0.1228*** (0.017)**
Log_GDP	**-0.3339** (0.027)**	**-0.3138*** (0.055)**	**-0.5408** (0.049)**
Log_GDPit-1	**0.5076*** (0.064)**	**0.4762** (0.043)**	**0.7246** (0.046)**
Unemployment	**0.5657** (0.135)**	**0.5694*** (0.112)**	**0.5831*** (0.121)**
Bank Size	**-0.1450 ** (0.016)**	**-0.4217** (0.017)**	**0.5646*** (0.015)**
Return on Assets (ROA)	**-0.0630** (0.048)**	**-0.0475** (0.055)**	**-0.0714** (0.067)**
Foreign Banks Among Total Banks	**-0.0182** (0.019)**	**-0.0238** (0.017)**	**-0.0233** (0.020)**
Loan Deposit Ratio (LDR)	**0.0540*** (0.048)**	**0.0346*** (0.082)**	**0.0803** (0.075)**
HDI		**-0.7455** (0.015)**	**-0.6433*** (0.046)**
CR5*HDI		**-0.4491** (0.033)**	**-0.3803*** (0.020)**
($CR5^2$*HDI)		**0.5476** (0.029)**	**0.2399** (0.023)**
Variance Components (Random Effects)			
Country (slope) (Intercept)	0.4321 0.8348	0.3612 1.278	 4.7222
Bank (slope) (Intercept)	1.2871 1.4330	1.4842 1.9614	 6.0508
Residual	4.5545	4.6879	5.0614
Chi-square	**227.55*** **	**206.58*** **	**215.71*** **
ICC (Country) (Bank)	0.0723 0.6365	0.0337 0.8749	

Note: Table shows the coefficients estimates (coefficients in boldface are significant). * Significance at the 10% level, ** significance at the 5% level, * significance at the 1% level.**

The results from tables 3.5 and 3.6 generally show our findings to be robust to these alternative measures of competition with similar results to our main specification. These results provide evidence for both the competition-stability and competition-fragility hypotheses. They show the presence of a significant non-linear relationship between banking competition and non-performing loans with this relationship being more evident in low developed and medium developed countries as seen in appendix 3.8.A.

Furthermore, we introduce the Z-Score as an alternative measure of financial stability and re-run our main model (crossed random effects model). The Crossed random model allows us to account for the structure of our dataset where some banks operate in multiple countries. The findings presented in the second column in table 3.7 provide similar results in support of both the competition-stability and competition-fragility hypotheses. However, we observe an inverted U-shaped relationship for only low and medium developed countries as seen in figure 3.4. This difference in observation is attributed to how the Z-Score measures financial stability. That is, a higher Z-score indicates more stability in the banking industry while a higher NPL indicates less stability in the banking industry.

Table 3.7: Further Robustness Checks for Crossed Random Effects Model

Variables	**Z-Score as a Measure of Financial Stability**	**Before the Global Financial Crisis (NPL as the dependent Variable)**	**After the Global Financial Crisis (NPL as the dependent Variable)**
Intercept	3.49	5.52	37.06
Lerner Index	**0.7743*** (0.020)**	**0.5543** (0.025)**	**-0.0672*** (0.074)**
Lerner Index^2	**-0.0038*** (0.003)**	**0.0723* (0.004)**	**0.0771** (0.030)**
Log_GDP	**0.7671*** (0.038)**	**-0.2601** (0.082)**	**-0.5561** (0.015)**
Log_GDPit-1	**0.0950*** (0.035)**	**0.0049* (0.016)**	**0.0861*** (0.044)**
Unemployment	**-0.3615*** (0.082)**	**0.1755*** (0.019)**	**0.2238** (0.103)**
Bank Size	**0.0181 ** (0.041)**	**-0.1450** (0.014)**	**0.3089** (0.017)**
Return on Assets (ROA)	**0.033** (0.028)**	**-0.0208*** (0.055)**	**-0.0101*** (0.081)**
Foreign Banks Among Total Banks	**0.0433*** (0.011)**	**-0.0204*** (0.016)**	**-0.0274** (0.019)**
Loan Deposit Ratio (LDR)	**-0.0003** (0.000)**	**0.0006** (0.000)**	**0.0004** (0.000)**
HDI	**0.5323*** (0.029)**	**-0.6280** (0.037)**	**-0.2473** (0.093)**
Lerner Index*HDI	**1.1251*** (0.026)**	**-0.5920** (0.053)**	**-0.4395** (0.036)**
(Lerner Index^2*HDI)	**-0.0058** (0.003)**	**0.0928* (0.001)**	**0.0591** (0.058)**
Variance Components (Random Effects)			
Country (all)	4.8071	2.3986	1.9199
Bank (all)	7.7691	5.3072	5.8401
Residual	2.2912	1.3415	4.7940
Chi-square	**147.63*** **	**33.54*** **	**63.26*** **

Note: Table shows the coefficients estimates (coefficients in boldface are significant). * Significance at the 10% level, ** significance at the 5% level, * significance at the 1% level.**

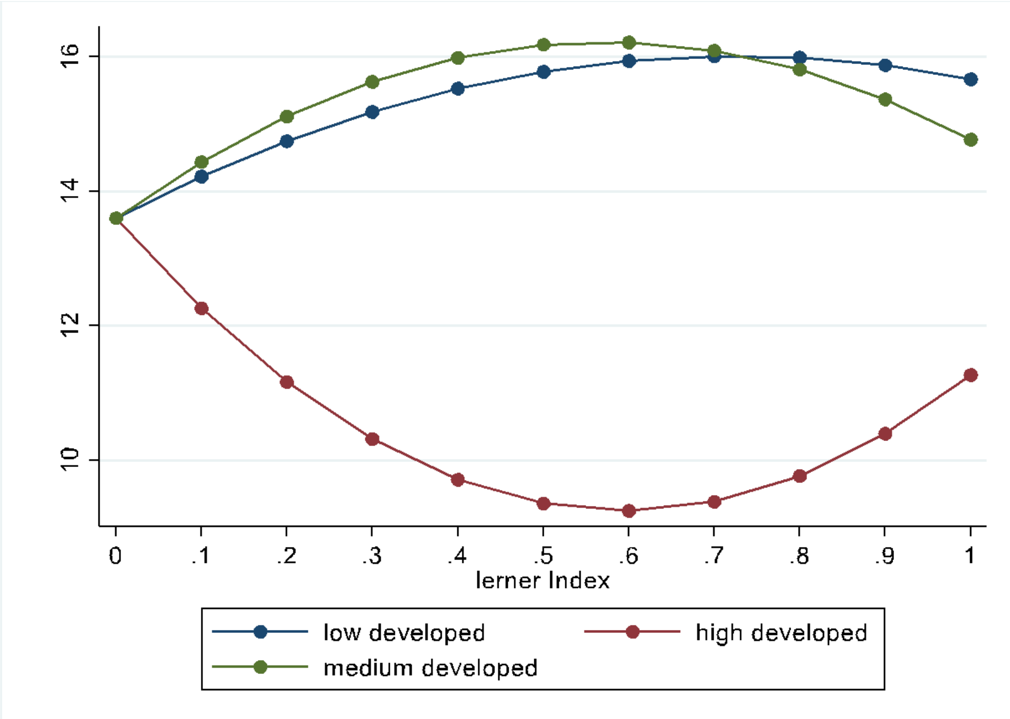


Figure 3.4: Adjusted Prediction of Bank Z-Score against the Predicted Values of the Lerner Index for Countries when Grouped according to their Level of Development

Finally, we investigate the periods before and after the global financial crisis. These results are also presented in the third and fourth columns of table 3.7. The result for the period before the global financial crisis provides evidence in support of only the competition-fragility hypothesis as seen in figure 3.5. That is, the result indicates that before the global financial crisis, banking competition was not very encouraged within the industry as it was believed to lead to more fragility in the banking industry.

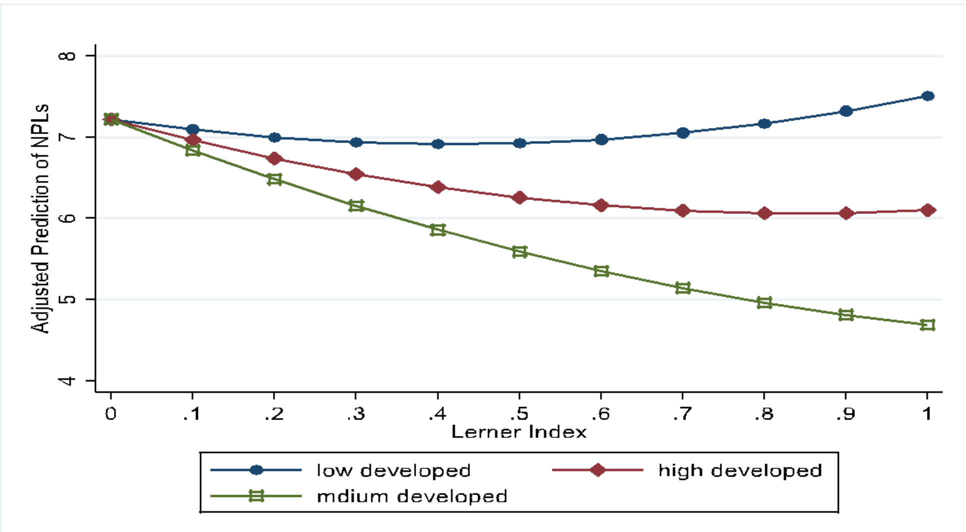


Figure 3.5: Adjusted Prediction of the NPLs for Low, Medium and High Developed Countries before the Global Financial Crisis

However, the results for the period after the global financial crisis provide evidence in support of both competition-fragility and competition-stability hypotheses as seen in figure 3.6. That is, for the period after the global financial crisis, the results show that a non-linear relationship exists between banking competition and financial stability, which is similar to our findings in our main specification. These results provide evidence suggesting that the banking industry was more receptive to competition in the banking industry after the global financial crisis.

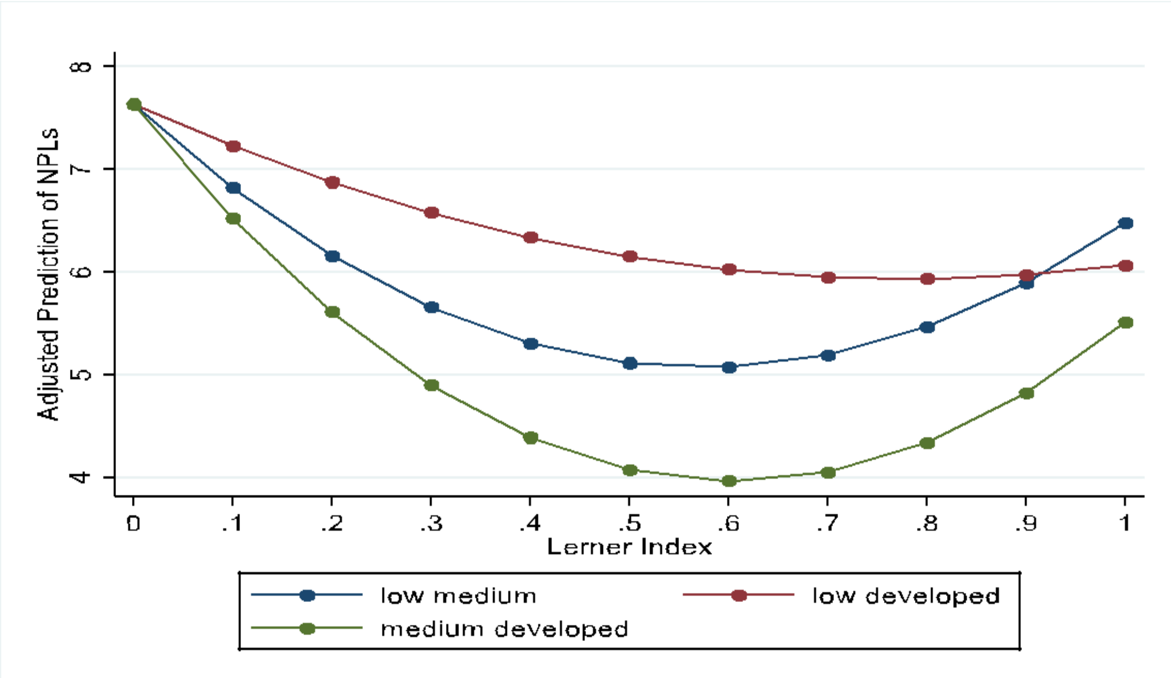


Figure 3.6: Adjusted Prediction of the NPLs for Low, Medium and High Developed Countries after the Global Financial Crisis

3.6 Conclusion and Recommendation

The purpose of this paper is to investigate the effect of competition on loan performance in the banking industry using bank-level data and as well test the hypothesis proposed by Martinez-Miera and Repullo (2010). By investigating this relationship across different levels of development, we are able to observe how this relationship differs across banks that operate in low developed, medium developed and high developed countries.

Our Multi level regression analysis, which incorporates the Instrumental Variable 2SLS technique, provides evidence for the effect of banking competition on NPLs. We show that within our preferred model specification which controls for crossed random effects and also incorporates countries' levels of development in which the banks operate, a U-shaped relationship seems to hold only for banks that operate in low and medium developed countries while we observe a weak non-linear relationship for banks that operate in high developed countries. This finding highlights the importance of controlling for the country's level of development when examining the relationship between banking competition and NPLs. When we compare it to the literature on banking competition and financial stability, our findings are not particularly uncommon, as few studies like Kasman and Kasman (2015), Noman et al. (2017), and Jiménez et al. (2013) have shown similar findings on banking competition. It is important to note, however, that some of these studies are not directly comparable due to differences in study indicators such banking competition variable measures, financial stability variable measures or group of country. Nevertheless, they are relevant in giving vital insights into the general impact of banking competition on financial stability.

In addition, the results for all our model specifications show the effect of competition on banks' NPL varies significantly across both banks and countries with more variation being observed across banks. This finding highlights the importance of our multilevel model which allows us to investigate the variation in the effect of competition across different levels and its impact on NPLs. The results reveal that, in as much as country level factors have an impact on banks non-performing loans, heterogeneity at bank level tends to be the main source of heterogeneity in banks' non-performing loans.

One of the major limitations of this study is our unbalanced sample size across low, medium and high developed countries. Having a relatively unbalanced sample size for each group of countries, as in the case of our study, comes at the cost of much more limited variation in our data, particularly in our results. Given this, future research that estimates the relationship between banking competition and financial stability may need to use a balanced sample size for each group of countries when controlling for the country's level of development in their study. Our findings call for further research, particularly within the context where equal data on all groups of countries is scarce. The implementation of higher quality datasets for low, medium and high developed countries will help to give further insight into the true nature of the relationship between banking competition and NPLs.

Overall, our results indicate that the country's level of development in which the bank operates has an impact on the relationship between banking competition and loan performance. They also reveal that the heterogeneity at the bank level tends to be the main source of heterogeneity in banks' non-performing loans. Therefore, we recommend to banking managements, regulatory authorities and policy makers that, as attention is given to the level of competition in which the banking markets operate, efforts should also be made in improving the county's level of development as well as improving bank level policies that help to improve bank level factors in the country as this will significantly help in improving banks loan performance and also enable a more stable financial system through better and more effective competition policies.

3.7 Appendix

3.7.1 First Stage Regression of the Instrumental Variables to Predict the Lerner Index

```
First-stage regression of lernerindex:

Statistics robust to heteroskedasticity and clustering on bankname
Number of obs =                   5127
Number of clusters (bankname) =    706
-------------------------------------------------------------------------------------------------
                                |               Robust
                    lernerindex |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
--------------------------------+----------------------------------------------------------------
        regulatorytradebarriers |   .0086679   .0040866     2.12   0.005     .0006343    .0167015
freedomtoentermarketsandcompete |   -.014282   .0053218     2.68   0.008     .0038209    .0247445
                       Log_gdp  |
                            --. |   .0554585   .0228517     2.43   0.216     .0105357    .1003813
                            L1. |  -.0009179   .0046648    -0.20   0.844    -.0100882    .0082524
                                |
                           unem |   .0001673    .003184     0.05   0.958     -.006092    .0064267
                            roa |   .0016242   .0010336     1.57   0.117    -.0004077    .0036561
                       log_size |  -.0178397   .0102225    -1.75   0.182    -.0379354    .0022561
                            fba |   -.000586   .0004451    -1.32   0.189     -.001461    .0002891
                            ldr |   .0000134   .0000543     1.50   0.134     .0000076     .000021
                          _cons |   .2062139   .1993015     0.31   0.035     .1539335    .3296556
--------------------------------+----------------------------------------------------------------
                        sigma_u |  .14196669
                        sigma_e |  .04996985
                            rho |  .88976521   (fraction of variance due to u_i)
```

```
F test of excluded instruments:
  F(  2,   705) =    24.61
  Prob > F      =   0.0000
Sanderson-Windmeijer multivariate F test of excluded instruments:
  F(  2,   705) =    24.61
  Prob > F      =   0.0000


Summary results for first-stage regressions
-------------------------------------------

                                           (Underid)            (Weak id)
Variable     | F(  2,   705)  P-val | SW Chi-sq(  2) P-val | SW F(  2,   705)
lernerindex  |      24.61    0.0000 |       49.65   0.0000 |       24.61
```

3.7.2 Multilevel Model using the Predicted values of the Lerner Index and allowing for Random Intercepts and Coefficients of the Lerner Index by Country and Bank

Mixed-effects regression   Number of obs = 4,820

Group Variable	No. of Groups	Observations per Group Minimum	Average	Maximum
Country	86	1	34.7	503
Bank	706	1	8	13

Wald chi2(20) = 213.15
Log pseudolikelihood = -3755.2922   Prob > chi2 = 0.0000

(Std. Err. adjusted for 86 clusters in country)

npl	Coef.	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
lernerindex_hat	-.1384226	.116298	-2.21	0.017	-.32242	-.044253
c.lernerindex_hat# c.lernerindex_hat	.0759874	.0346477	2.19	0.018	.0638955	.0980792
Log_gdp						
--.	-.7280015	.0997374	-1.18	0.028	-1.139464	-.6793411
L1.	.2332977	.0129433	2.50	0.012	.1434324	.3183637
roa	-.0661287	.0486549	-1.36	0.034	-.1614905	.0292332
fba	-.3151156	.1382854	-2.28	0.023	-.440912	-.181389
unem	.8646374	.0288971	2.47	0.014	.6160074	.9813267
ldr	.0039102	.0018396	2.13	0.034	.0025158	.0093046
log_size	-.045786	.0940133	-1.89	0.028	-.0664657	-.028038
year						
2006	.3255252	.3289032	0.99	0.322	-.3191132	.9701636
2007	1.320331	.4000645	3.30	0.001	.5362192	2.104443
2008	.9467537	.3826712	2.47	0.013	.1967318	1.696776
2009	1.929238	.7101947	2.72	0.007	.5372823	3.321194
2010	2.143301	.5855579	3.66	0.000	.995629	3.290974
2011	1.599969	.4970669	3.22	0.001	.625736	2.574202
2012	.8733728	.549448	1.59	0.112	-.2035255	1.950271
2013	1.778459	.6198983	2.87	0.004	.5634802	2.993437
2014	1.675223	.6610681	2.53	0.011	.3795532	2.970892
2015	1.833295	.4965349	3.69	0.000	.8601042	2.806485
2016	.1734637	.6560942	0.26	0.021	-1.112457	1.459385
_cons	49.0059	30.4066	2.47	0.014	39.61116	52.40807

Random-effects Parameters	Estimate	Robust Std. Err.	[95% Conf.	Interval]
country: Independent				
sd(lerner~t)	.4283596	.4932442	.0448408	4.092074
sd(_cons)	2.846128	.8959753	1.535649	5.274933
bank: Unstructured				
sd(lerner~t)	.9524635	1.014005	.1182084	7.674469
sd(_cons)	2.038467	1.659275	.4134675	10.05
corr(lerner~t,_cons)	.9353116	2.774916	-1	1
sd(Residual)	3.862067	1.076941	2.235947	6.670803

3.7.3 Multilevel Model using the Predicted values of the Lerner Index, allowing for Random Intercepts and Coefficients of the Lerner Index by Country and Bank and controlling for Country's Level of Development

Mixed-effects ML regression Number of obs = 5,120

Group Variable	No. of Groups	Observations per Group Minimum	Average	Maximum
country	86	1	39.7	504
bank	706	1	8	13

Wald chi2(23) = 251.88
Log likelihood = -3816.2646 Prob > chi2 = 0.0000

(Std. Err. adjusted for 86 clusters in country)

npl	Coef.	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
lernerindex_hat	-.1725131	.1311168	-1.64	0.012	-.7428388	-.033614
c.lernerindex_hat#c.lernerindex_hat	.0657981	.0237882	1.44	0.014	.0100411	.0888151
log_gdp						
--.	-.8411947	.1122417	-1.00	0.019	-1.080426	-.5319366
L1.	.4224647	.1066398	3.02	0.003	.287565	.64236441
roa	-.1040064	.0590074	-1.76	0.028	-.2196588	.0116461
fba	-.1614444	.0662684	-2.44	0.015	-.3315608	-.0913281
unem	.448617	.0115156	3.09	0.002	.3262951	.6634283
ldr	.0019725	.0009088	2.17	0.030	.0017537	.0051913
log_size	-.2420821	.2221187	-1.09	0.026	-.3932626	-.1774267
hdi	-.8054565	.5950376	-1.75	0.010	-1.485512	-.4484033
c.lernerindex_hat#c.hdi	.5028586	.0543434	0.48	0.031	.4647861	.9442144
c.lernerindex_hat#c.lernerindex_hat#c.hdi	-.208334	.0508344	-1.56	0.118	-.3787859	-.1258845
year						
2006	.2942274	.6177859	0.48	0.634	-.9166108	1.505066
2007	1.265375	.7656573	1.65	0.098	-.2352859	2.766036
2008	.8261163	.7326949	1.13	0.260	-.6099393	2.262172
2009	1.457254	.707224	2.06	0.039	.0711202	2.843387
2010	1.595106	.7070905	2.26	0.024	.2092342	2.980978
2011	1.084021	.6998877	1.55	0.021	-.2877341	2.455775
2012	.4065311	.7000277	0.58	0.061	-.9654979	1.77856
2013	1.772684	.693818	2.55	0.011	.4128254	3.132542
2014	1.401863	.730295	1.92	0.055	-.029489	2.833215
2015	1.319022	.8010934	1.65	0.100	-.2510927	2.889136
2016	.7266436	.8183559	0.89	0.025	-.8773046	2.330592
_cons	46.62909	30.92801	3.12	0.002	36.01131	57.24698

Random-effects Parameters	Estimate	Std. Err.	[95% Conf.	Interval]
country: Independent				
sd(lerner~t)	.6619354	.2318135	.3332115	1.314956
sd(_cons)	1.527512	1.162013	.3439188	6.784427
bank: Unstructured				
sd(lerner~t)	.9280226	.1239681	.7142537	1.20577
sd(_cons)	2.049856	.4171635	1.375614	3.054571
corr(lerner~t,_cons)	1	.0001555	-1	1
sd(Residual)	3.86628	.1026576	3.670221	4.072813

3.7.4 Multilevel Model using the Predicted values of the Lerner Index and allowing for Crossed Random Effects

```
Mixed-effects ML regression                     Number of obs       =     5,120
Group variable: _all                            Number of groups    =         1

                                                Obs per group:
                                                              min =     5,120
                                                              avg =   5,120.0
                                                              max =     5,120

                                                Wald chi2(23)       =    234.78
Log likelihood = -3842.1241                     Prob > chi2         =    0.0000

-----------------------------------------------------------------------------------------------
------
                                          |
                                      npl |       Coef.  Std. Err.       z  P>|z|     [95% Conf. Interval]
 -----------------------------------------+---------------------------------
                          lernerindex_hat |    -.1137275   .1541532   -3.83 0.000      -.4727399  -.0941512
                                          |
      c.lernerindex_hat#c.lernerindex_hat |     .0113316   .0244891    0.05 0.020       .0073221   .0286589
                                          |
                                  log_gdp |
                                      --. |    -.690157    .0399424   -0.49 0.022      -3.432978   2.052664
                                      L1. |     .3128036   .0530674    4.06 0.000       .2877034   .4803858
                                          |
                                      roa |    -.1162456   .0632008   -1.84 0.026      -.2401168   .0076257
                                      fba |    -.3319734   .0870653   -3.81 0.000      -.4613286  -.2026182
                                     unem |     .3131597   .0479905    4.14 0.000       .2231036   .5032157
                                      ldr |     .0043508   .0011987    3.63 0.000       .0037002   .0080015
                                 log_size |    -.6382717   .2790944   -2.29 0.022      -.8912066  -.5185287
                                      hdi |    -.8508973   .0385808   -1.53 0.025      -1.181097  -.6715156
                                          |
                    c.lernerindex_hat#c.hdi |     .3435551   .0932438    1.37 0.022       .1749228   .4253025
                                          |
 c.lernerindex_hat#c.lernerindex_hat#c.hdi |    -.2228718   .0310404   -0.07 0.021      -.3131252  -.1085509
                                          |
                                     year |
                                     2006 |     .5131302   .6424864    0.80 0.424      -.7461201   1.772381
                                     2007 |     1.417655   .8009588    1.77 0.077      -.1521952   2.987505
                                     2008 |     1.025141   .7699091    1.33 0.183      -.4838534   2.534135
                                     2009 |     1.594838    .745847    2.14 0.032       .1330045   3.056671
                                     2010 |     1.862106   .7453368    2.50 0.012       .4012723   3.322939
                                     2011 |     1.320045   .7422709    1.78 0.075      -.1347796   2.774869
                                     2012 |     .6136537   .7393423    0.83 0.007      -.8354307   2.062738
                                     2013 |     2.017667   .7344184    2.75 0.006       .5782333   3.457101
                                     2014 |     1.572033   .7721632    2.04 0.042       .0586212   3.085445
                                     2015 |     1.530957   .8477607    1.81 0.071      -.1306236   3.192537
                                     2016 |     .2125469   .8346271    0.25 0.799      -1.423292   1.848386
                                          |
                                    _cons |     47.51937   40.01524    4.44 0.000       39.09083   55.94773
-----------------------------------------------------------------------------------------------
---------

------------------------------------------------------------------------------
  Random-effects Parameters  |   Estimate   Std. Err.     [95% Conf. Interval]
-----------------------------+------------------------------------------------
_all: Identity               |
               sd(R.country) |   3.660819   .5922336      2.666086  5.026694
-----------------------------+------------------------------------------------
_all: Identity               |
                  sd(R.bank) |   5.384706   .2694339      4.881694  5.939549
-----------------------------+------------------------------------------------
                sd(Residual) |   4.115203   .1072614      3.910254  4.330894
```

3.7.5 Likelihood Ratio Test

```
Likelihood-ratio test                                 LR chi2(4)  =     178.75

(Assumption: complex_model nested in simpler_model)   Prob > chi2 =     0.0000
```

3.8 Robustness Checks

3.8.1 First Stage Regression of the Instrumental Variables to Predict the Boone Indicator

```
First-stage regression of booneindicator:

Statistics robust to heteroskedasticity and clustering on bankname
Number of obs =                                           5127
Number of clusters (bankname) =                            706

------------------------------------------------------------------------------------------

                             |                  Robust
               booneindicator |        Coef.  Std. Err.       t P>|t|     [95% Conf. Interval]
 ----------------------------+--------------------------------------------------------------
        regulatorytradebarriers |     .0544996   .0385016   -1.42 0.007     -.1300375  .0210382
 freedomtoentermarketsandcompete |    -.2932257   .1939246    1.51 0.001     -.0872429  .6736944
                       log_gdp |
                           --. |    -.0087265   .0470489   -0.19 0.853     -.1010338  .0835807
                           L1. |     .040928    .043206    0.95 0.344     -.0438397  .1256956
                               |
                           fba |    -.0086746   .005994   -1.45 0.148     -.0204344  .0030853
                           roa |    -.0306091   .021183   -1.44 0.149     -.0721689  .0109507
                           ldr |     8.32e-10   1.24e-09    0.67 0.501     -1.60e-09  3.26e-09
                      log_size |     .025778    .0156004    1.65 0.199     -.0048292  .0563851
                          unem |    -.0123528   .009315   -1.33 0.185     -.0306283  .0059227
                         _cons |    -2.173268   1.258881   -1.73 0.025     -4.643117  .2965818

------------------------------------------------------------------------------------------
F test of excluded instruments:
  F(     2, 705) =                                    11.15
  Prob > F      =   0.0000
Sanderson-Windmeijer multivariate F test of excluded instruments:
  F(     2, 705) =                                    11.15
  Prob > F      =   0.0000



 Summary results for first-stage regressions

-------------------------------------------

                                            (Underid)           (Weak id)
Variable      |F(   2,     705) P-val | SW Chi-sq(  2)  P-val |SW F(  2,    705)
booneindicat |          11.15 0.0000 |          52.32   0.0000|          11.15
```

3.8.2: Multilevel Model using the Predicted values of the Boone Indicator and allowing for Random Intercepts and Coefficients of the Boone Indicator by Country and Bank

```
Mixed-effects regression                            Number of obs =     4,820

        Grouping information
        -------------------------------------------------------------
                        |     No. of       Observations per group
         Group variable |     groups    Minimum    Average    Maximum
        ----------------+--------------------------------------------
              Country   |         86          1       35.7        503
             Bankname   |        706          1          8         13
        -------------------------------------------------------------

                                                    Wald chi2(18) =    175.94
Log pseudolikelihood = -4160.7767                   Prob > chi2   =    0.0000

                                (Std. err. adjusted for 86 clusters in country)
-------------------------------------------------------------------------------
             |               Robust
         npl | Coefficient  std. err.      z    P>|z|     [95% conf. interval]
-------------+-----------------------------------------------------------------
booneindicator_hat |  -1.05403    .017408    -0.63   0.001     -3.21049    -.231683
             |
          c. |
booneindicator_hat #|
          c. |
booneindicator_hat |   .508773    .0384494     0.60   0.007     .1147287    .8164833
             |
     Log_gdp |
         --. |  -.2390038     .04075    -0.13   0.005    -.4303728   -.1781736
         L1. |   .5629419    .396847     0.66   0.008     .4807548    1.148639
             |
         roa |  -.0332938   .0521574    -0.64   0.023    -.1355205    .0689329
         fba |  -.0070451   .0523628    -0.13   0.033    -.1096742     .005584
        unem |   .2037654   .1347367     1.94   0.012      .104106    .5085719
         ldr |    .072639   .0237175     1.10   0.031      .048207    .0942917
    log_size |  -.113906   .0151921    -1.28   0.021    -.1157413   -.0377601
             |
        year |
       2006  |   .2505416   .5390117    -0.46   0.742     .1306985    .8059019
       2007  |   .6371648   .6320734     1.01   0.013    -.6016763    1.876006
       2008  |   .2571687   .5435752     0.47   0.136    -.8082192    1.322557
       2009  |   .7065984   .7577907     0.93   0.021     -.778644    2.191841
       2010  |   .8496542   .6095015     1.39   0.033    -.3449467    2.044255
       2011  |     .47983   .5445575     0.88   0.038     -.587483    1.547143
       2012  |   .1732394   .6958055     0.25   0.053    -1.190514    1.536993
       2013  |   .8888609    .736085     1.21   0.227    -.5538393    2.331561
       2014  |   1.474675   .7170483     2.06   0.040      .069286    2.880064
             |
       _cons |   23.09988   15.66964     0.94   0.000     16.41097    32.56107
-------------------------------------------------------------------------------

------------------------------------------------------------------------------
                            |               Robust
  Random-effects parameters |   Estimate   std. err.     [95% conf. interval]
----------------------------+-------------------------------------------------
Country : Independent       |
      sd(booneindicator_hat) |   .6225521    .421338      .4766928     .827416
                  sd(_cons) |   1.278209    .702797       .862898     1.89935
----------------------------+-------------------------------------------------
Bankname : Unstructured     |
      sd(booneindicator_hat) |    .994517   .6220411      .6512938     1.64789
                  sd(_cons) |   1.854138   1.015008      1.221992     2.31307
corr(booneindicator_hat,_cons) |   .9280895    .104301      .6960988    1.684059
----------------------------+-------------------------------------------------
              sd(Residual) |   4.042484   .8443681      2.684447     6.08754
```

3.8.3 Multilevel Model using the Predicted values of the Boone Indicator, allowing for Random Intercepts and Coefficients of the Boone Indicator by Country and Bank and controlling for Country's Level of Development

```
Mixed-effects regression                             Number of obs =    5,120

        Grouping information
        -------------------------------------------------------------
                        |     No. of       Observations per group
         Group variable |     groups    Minimum    Average    Maximum
        ----------------+--------------------------------------------
                Country |         86          1       39.7        508
               Bankname |        706          1          8         13
        -------------------------------------------------------------

                                                     Wald chi2(21) = 225.84
Log pseudolikelihood = -4115.6602                    Prob > chi2   =   0.0000

                               (Std. err. adjusted for 86 clusters in country)
------------------------------------------------------------------------------
             |               Robust
         npl | Coefficient  std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
booneindicator_hat |  -1.57882    .0155128   -1.05   0.005    -1.98231    -.982392
          c. |
booneindicator_hat #|
          c. |
 booneindicator_hat |  .6297004    .020754     0.81    0.006    .526747      1.873466
             |
         hdi |   -.525891    .03098     -1.22   0.023    -.90714      -.33425
          c. |
booneindicator_hat #|
       c.hdi |   -.383031   .018298     -1.00   0.017    -.59336     -.173254
          c. |
booneindicator_hat #|
          c. |
booneindicator_hat #|
       c.hdi |   .872848    .034422    -0.80   0.012        .36172    1.153868
     Log_gdp |
         --. |  -.527503    .011284     -0.95   0.020    -.998853     4.133526
         L1. |   .2176042   .0293552     0.74   0.009    .1929562    .3577478
             |
         roa |  -.0055527   .0335866    -0.17   0.019    -.0602759    .0713813
         fba |   -.026569   .0182755    -1.45   0.036    -.0592502    .0623883
        unem |   .7259853   .1852998     3.92   0.000     .3628044    1.089166
         ldr |   .9230507   .0436009     2.20   0.000      .22639      2.64908
    log_size |  -.3909718   .01946259   -2.01   0.035    -.7724315    -.009512
        year |
       2006  |    .343412   .5240008     0.66   0.512    .2370435    .6836107
       2007  |   .4104851   .5914379     0.69   0.018    -.7487119    1.569682
       2008  |   .0107852   .5436271     0.02   0.384    -1.054704    1.076275
       2009  |   .0736638   .5260747     0.14   0.009    -.9574236    1.104751
       2010  |   .4140874   .5221953     0.79   0.038    -.6093967    1.437571
       2011  |   .0087871   .5109069     0.02   0.026     .000146     .9925719
       2012  |    .312452   .6901824     0.45   0.041    -1.665185    1.040281
       2013  |   .3196465   .6521372     0.49   0.024    -.9585189    1.597812
       2014  |   .9187884   .6122083     1.50   0.133    -.2811179    2.118695
             |
       _cons |   21.41394   12.56334     0.91   0.000     13.20976    36.03763
------------------------------------------------------------------------------

------------------------------------------------------------------------------
  Random-effects parameters  |   Estimate   Robust
                             |             std. err.     [95% conf. interval]
-----------------------------+------------------------------------------------
Country : Independent        |
      sd(booneindicator_hat) |   .5713513   .299786       .308311     1.38021
                   sd(_cons) |   1.238693   .6418609      .413904     1.93392
-----------------------------+------------------------------------------------
bankname : Unstructured      |
      sd(booneindicator_hat) |   1.01126    .503717        .627768     1.69492
                   sd(_cons) |   1.851609   1.004164      1.233762    3.278864
corr(booneindicator_hat,_cons) |  .9302481   .1020391      .696302     1.730634
-----------------------------+------------------------------------------------
               sd(Residual) |   4.042753   .8447637      2.684184    6.088947
------------------------------------------------------------------------------
```

3.8.4 Multilevel Model using the Predicted values of the Boone Indicator and allowing for Crossed Random Effects

Mixed-effects ML regression	Number of obs	=	5,120
Group variable: _all	Number of groups	=	1
	Obs per group:		
	min	=	5,120
	avg	=	5,120.0
	max	=	5,120
	Wald chi2(20)	=	214.42
Log likelihood = -4155.0545	Prob > chi2	=	0.0000

npl	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
booneindicator_hat	-1.010265	.036990	-1.12	0.003	-4.51454	-.535098
c.booneindicator_hat#c.booneindicator_hat	.5393195	.0336253	1.59	0.001	.203013	.7243739
hdi	-.6658846	.0553237	-1.60	0.020	-.865062	-3.24198
c.booneindicator_hat#c.hdi	-.3033013	.0341662	-1.14	0.024	-.5368944	.6623413
c.booneindicator_hat#c.booneindicator_hat#c.hdi	.7824869	.0457561	1.71	0.017	.18143175	.9692919
log_gdp						
--.	-.540824	.0496324	-2.21	0.027	-.7534867	-.2329784
L1.	.287265	.0141905	1.10	0.000	.1788546	.53385
roa	-.0003013	.0739273	-0.00	0.031	-.0045936	.0001961
fba	-.0830072	.0545051	-1.52	0.008	-.0938209	-.0698352
unem	.2208952	.0511247	0.43	0.006	-.7811309	1.222921
ldr	.0735958	.0075328	0.11	0.015	.0573928	.0950386
log_size	-.1534419	.0625240	-0.09	0.032	-1.27889	1.172006
year						
2006	.1258812	.6778763	0.19	0.853	-1.202732	1.454494
2007	.7188374	.8348829	0.86	0.059	-.917503	2.355178
2008	.4083641	.8175119	0.50	0.117	-1.19393	2.010658
2009	.8814534	.7998363	1.10	0.030	-.6861969	2.449104
2010	.8253082	.7858621	1.05	0.014	-.7149533	2.36557
2011	.4875976	.7761275	0.63	0.030	-1.033584	2.00878
2012	.2238758	.7568283	0.30	0.067	-1.25948	1.707232
2013	.7010398	.7581192	0.92	0.355	-.7848465	2.186926
2014	1.247626	.7641514	1.63	0.103	-.2500835	2.745335
2015	1.572033	.7721632	2.04	0.042	.0586212	3.085445
2016	1.530957	.8477607	1.81	0.071	-.1306236	3.192537
_cons	24.69001	16.89512	0.52	0.000	16.5128	37.31264

Random-effects Parameters	Estimate	Std. Err.	[95% Conf.	Interval]
_all: Identity				
sd(R.country)	3.26527	1.389404	2.873358	3.38383
_all: Identity				
sd(R.bankna~)	6.351312	.3336192	5.729963	7.040038
sd(Residual)	4.271687	.106538	4.067898	4.485685

3.8.5 First Stage Regression of the Instrumental Variables to Predict CR5

```
First-stage regression of cr5:

Statistics robust to heteroskedasticity and clustering on bankname
Number of obs =                                          5115
Number of clusters (bankname) =                           706

-------------------------------------------------------------------------------------------

                                |              Robust
                            cr5 |        Coef.Std. Err.         t  P>|t|      [95% Conf. Interval]
 -------------------------------+-----------------------
       regulatorytradebarriers |     .5926182.3727979       1.59  0.002       .3323793   .7385565
 freedomtoentermarketsandcompete |    -.7849332.6506111      -1.21  0.000      -.9911213  -.3910988
                                |
                        log_gdp |
                           --. |    -2.989207.8297302      -3.60  0.000      -4.616571  -1.361844
                           L1. |     2.485195.7358663       3.38  0.001       1.041929   3.928462
                                |
                            fba |    -.1024253.0321535      -3.19  0.001      -.1654886  -.0393621
                            roa |     .1899037.2220413       0.86  0.393      -.2455896    .625397
                            ldr |    -2.06e-073.96e-08      -5.20  0.000      -2.84e-07  -1.28e-07
                       log_size |       .55473.2883339       1.92  0.055       -.010784   1.120244
                           unem |     .2733621.2078213       1.32  0.189      -.1342412   .6809655
                          _cons |     3.743208 2.293266       8.85  0.000       2.716636   4.346978

-------------------------------------------------------------------------------------------
F test of excluded instruments:
  F(     2, 705) =                                   11.48
  Prob > F      =   0.0000
Sanderson-Windmeijer multivariate F test of excluded instruments:
  F(     2, 705) =                                   11.48
  Prob > F      =   0.0000


Summary results for first-stage regressions

-------------------------------------------

                                             (Underid)          (Weak id)
Variable      | F(   2,    705)  P-val | SW Chi-sq(  2)  P-val | SW F(     2, 705)
cr5           |          11.48  0.0000 |          2.99  0.0000 |          11.48
```

3.8.6 Multilevel Model using the Predicted values of the CR5 and allowing for Random Intercepts and Coefficients of the CR5 by Country and Bank

Mixed-effects regression   Number of obs =   5,120

Grouping information

Group variable	No. of groups	Observations per group Minimum	Average	Maximum
Country	86	1	37.4	508
Bankname	706	1	8	13

Wald chi2(20) = 227.55

Log pseudolikelihood = -6130.4706   Prob > chi2   =   0.0000

(Std. err. adjusted for 86 clusters in country)

npl	Coefficient	Robust std. err.	z	P>|z|	[95% conf.	interval]
cr5_hat	-.1556382	.0128411	-1.21	0.006	-.4073202	.0960438
c.cr5_hat #c.cr5_hat	.0011874	.0008091	1.47	0.012	-.0003984	.0027732
Log_gdp						
--.	-.333851	.0271751	-0.40	0.017	-.873787	-.255088
L1.	.5076427	.0643786	1.25	0.000	.409445	.9541598
roa	-.0630023	.0483653	-1.30	0.013	-.0817919	.1577966
fba	-.0181613	.0194213	-0.94	0.020	-.0562262	.0199037
unem	.5657132	.134965	4.19	0.030	.3011866	.8302398
ldr	.0539808	.047737	3.51	0.000	.258438	.8459352
log_size	-.4501311	.0164584	-2.73	0.006	-.7727103	-.127552
year						
2006	.5495553	.4686628	1.17	0.241	-.3690069	1.468117
2007	.583272	.7874582	0.74	0.009	-.9601177	2.126662
2008	.0998666	.8514098	0.12	0.907	-1.568866	1.768599
2009	.3769867	.8460663	0.45	0.006	-1.281273	2.035246
2010	1.039829	.9469022	1.10	0.032	-.8160648	2.895724
2011	.6849719	.6290875	1.09	0.026	-.5480169	1.917961
2012	.5603755	.7167805	0.78	0.004	-.8444884	1.96524
2013	1.137384	.741723	1.53	0.015	-.3163661	2.591135
2014	1.383272	.7570987	1.83	0.028	-.1006145	2.867158
2015	1.389502	.751837	1.85	0.035	-.0840713	2.863076
2016	1.333823	.9082146	1.47	0.142	-.4462449	3.113891
_cons	17.41127	7.54083	2.31	0.005	13.61509	32.19102

Random-effects parameters	Estimate	Robust std. err.	[95% conf.	interval]
country: Independent				
sd(cr5_hat)	.432074	.3734794	.2379394	.523513
sd(_cons)	.8348406	.6294453	.5493686	1.639277
bankname: Unstructured				
sd(cr5_hat)	1.2871465	.9556727	1.099228	1.830946
sd(_cons)	1.43303	.6176364	.6063447	2.34463
corr(cr5_hat,_cons)	.9701569	.5318335	.4996787	1.375419
sd(Residual)	4.554498	.7951921	3.234633	6.412922

3.8.7 Multilevel Model using the Predicted values of the CR5, allowing for Random Intercepts and Coefficients of the CR5 by Country and Bank and controlling for Country's Level of Development

```
Mixed-effects regression                              Number of obs =   5,223

        Grouping information
        -------------------------------------------------------------
                        |     No. of       Observations per group
         Group variable |     groups    Minimum    Average    Maximum
        ----------------+--------------------------------------------
                Country |         86          1       37.4        508
               Bankname |        706          1          8         13
        -------------------------------------------------------------

                                                      Wald chi2(23) =  206.58
Log pseudolikelihood = -6079.9285                     Prob > chi2   =  0.0000

                               (Std. err. adjusted for 86 clusters in country)
------------------------------------------------------------------------------
             |               Robust
         npl | Coefficient  std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
     cr5_hat |  -.3952625    .036192    -0.42   0.003     -.624546    -.134021
             |
  c.cr5_hat#|
   c.cr5_hat |   .0212602    .010489     0.10   0.014      .013811    .3912906
             |
         hdi |   -.745464    .014995    -0.77   0.020     -.978567    -.276659
  c.cr5_hat#|
       c.hdi |   -.449106    .032731    -0.29   0.023      -.89252    -.282341
             |
  c.cr5_hat#|
  c.cr5_hat#|
       c.hdi |    .547597   .0291387     0.19   0.031       .51635     .6258695
     log_gdp |
         --. |   -.313761    .054691    -1.13   0.000     -6.34088     1.713359
         L1. |   .4761741   .0425087     1.12   0.013      .309323     .6569747
             |
         roa |  -.0475005   .0550519    -1.59   0.012    -.0803992     .1954003
         fba |   -.023756   .0167397    -1.42   0.026    -.0565652     .0090533
        unem |   .5694247   .1118153    -5.09   0.000     .3502707     .7885787
         ldr |    .034623   .0821708     4.07   0.000     .0152807     .0532908
    log_size |   -.421687   .0169353    -2.49   0.013    -.7536133    -.0897607
             |
        year |
       2006  |   .3262371   .4109742     0.79   0.427    -.4792575     1.131732
       2007  |   .3693645   .7690795     0.48   0.011    -1.138004     1.876733
       2008  |   .0115383   .7382856     0.02   0.588    -1.435475     1.458551
       2009  |   .1809448   .7985986     0.23   0.021     -1.38428     1.746169
       2010  |   .7335037   .8101287     0.91   0.025    -.8543194     2.321327
       2011  |   .4031436   .5733594     0.70   0.022    -.7206201     1.526907
       2012  |   .2573885   .6532713     0.39   0.024       -1.023     1.537777
       2013  |   .6288974   .6849718     0.92   0.049    -.7136227     1.971417
       2014  |   .9832793   .6570418     1.50   0.035    -.3044991     2.271058
       2015  |   .8788202    .698545     1.26   0.038    -.4903028     2.247943
       2016  |   .9321763   .8384884     1.11   0.266    -.7112307     2.575583
             |
       _cons |   22.44954   7.402203     3.03   0.002      17.9414     26.95759
------------------------------------------------------------------------------
                             |              Robust
  Random-effects parameters  |   Estimate   std. err.     [95% conf. interval]
-----------------------------+------------------------------------------------
Country : Independent        |
                sd(cr5_hat)  |   .3611984   .6944376      .0083413    15.64084
                  sd(_cons)  |    1.23781   .8327824       .582813     2.98576
-----------------------------+------------------------------------------------
Bankname : Unstructured      |
                sd(cr5_hat)  |   1.484274   1.294939      .2684678    8.20608
                  sd(_cons)  |   1.961364    .405905      .8652397    3.00828
        corr(cr5_hat,_cons)  |   .6866454   .5964709      .5955558    1.87877
-----------------------------+------------------------------------------------
               sd(Residual)  |   4.687851   .8843295      3.238924    6.784954
```

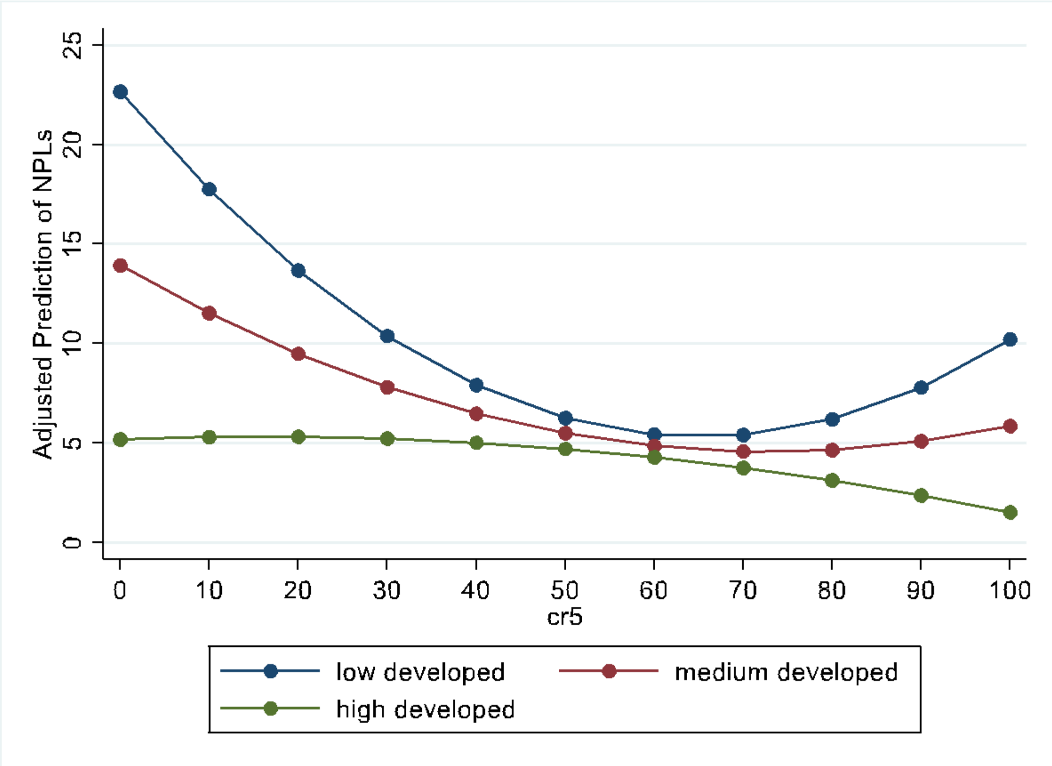
3.8.8 Multilevel Model using the Predicted values of CR5 and allowing for Crossed Random Effects

```
Mixed-effects ML regression                 Number of obs      =    5,127
Group variable: _all                        Number of groups   =        1

                                            Obs per group:
                                                         min =    5,127
                                                         avg =  5,127.0
                                                         max =    5,127

                                            Wald chi2(23)      =   215.71
Log likelihood = -6127.5797                 Prob > chi2        =   0.0000
```

npl	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
cr5_hat	-.5023184	.0376657	-0.21	0.003	-.160481	-.7155844
c.cr5_hat#c.cr5_hat	.1228346	.0173714	0.71	0.000	.0633085	.2176393
hdi	-.6433388	.0457119	-1.32	0.008	-.9738096	-.5404872
c.cr5_hat#c.hdi	-.3802925	.0195397	-0.13	0.001	-.4169973	.4509388
c.cr5_hat#c.cr5_hat#c.hdi	.2398707	.0226406	1.06	0.019	.16038768	.41836183
log_gdp						
--.	-.724568	.0456955	-1.87	0.021	-5.580147	.1310113
L1.	.5483775	.0347148	1.58	0.004	.3228776	.8320212
roa	-.0713707	.06688	-1.07	0.006	-.0997117	-.0124532
fba	-.0233104	.0203458	-1.15	0.032	-.0631875	.0165666
unem	.5831789	.1208479	4.83	0.000	.3463214	.8200364
ldr	.0802734	.0745295	0.65	0.013	.05830397	.09341745
log_size	-.5645991	.0147336	-3.83	0.000	-.8533741	-.2758241
year						
2006	.6457594	.9780865	0.66	0.509	-1.271255	2.562774
2007	.7127125	1.048225	0.68	0.497	-1.34177	2.767195
2008	.2059715	1.014843	0.20	0.039	-1.783085	2.195028
2009	.4192109	.9852428	0.43	0.030	-1.51183	2.350251
2010	1.000294	.9623985	1.04	0.029	-.8859723	2.886561
2011	.6885263	.925173	0.74	0.007	-1.124779	2.501832
2012	.632224	.8973683	0.70	0.001	-1.126585	2.391034
2013	1.002649	.8920341	1.12	0.051	-.7457059	2.751004
2014	1.233106	.8843166	1.39	0.033	-.5001224	2.966335
2015	1.302173	.8927097	1.46	0.045	-.4475061	3.051852
2016	1.095569	.9225892	1.19	0.235	-.7126723	2.903811
_cons	24.65767	9.18492	2.68	0.007	6.655552	42.65978

Random-effects Parameters	Estimate	Std. Err.	[95% Conf.	Interval]
_all: Identity				
sd(R.country)	4.722217	.7174339	3.506107	6.360141
_all: Identity				
sd(R.bankna~)	6.050821	.2624904	5.557614	6.587797
sd(Residual)	5.061408	.0973912	4.874079	5.255936

Figure 3.8.a: Adjusted Prediction of NPL against CR5 for Countries when Grouped according to their Level of Development



s

3.8.9 Multilevel Model using the Z-Score as a Measure of Financial Stability

```
                                           Number of
Mixed-effects ML regression                obs             =    5,111
Group variable: _all                       Number of groups =        1
                                           Obs per
                                           group:
                                                         min =    5,111
                                                         avg =  5,111.0
                                                         max =    5,111
                                           Wald
                                           chi2(23)        =   147.63
Log likelihood = -2923.7974                Prob > chi2     =   0.0000
-------------------------------------------------------------------------------------------
                                                                                  --------
                                                                               [95% Conf.
                         bankzscore |    Coef.  Std. Err.      z P>|z|          Interval]

                    lernerindex_hat | .7743073   .0202275   3.83 0.000    .3778552 1.170759
                                    |
  c.lernerindex_hat#c.lernerindex_hat | -.038838   .0030014  -1.29 0.003   -.0097665 .0019988
                                    |
                            loggdp  |
                                --. | .7670552    .038452   0.55 0.000   .54655377 1.480664
                                L1. | .0950236   .0345737   0.71 0.003   .03587825 .1687366
                                    |
                                roa |  .033343   .0280811   1.19 0.021   -.0216948 .0883809
                                fba |  .043349   .0107011   4.05 0.000    .0223752 .0643229
                               unem | -.361544   .0823876  -4.39 0.000   -.5230207-.2000672
                                ldr |-.0000304   .0000775  -0.39 0.032   -.0001216 .0001823
                            logsize | .0181417   .0413015   0.44 0.022   -.0628077 .0990912
                                hdi | .5323445   .0294055   1.36 0.005    .4304002 .7350891
                                    |
             c.lernerindex_hat#c.hdi | 1.125179   .0259063   4.34 0.000    1.0329331.6174247
c.lernerindex_hat#c.lernerindex_hat#c.h
                                 di |-.0058766   .0034805  -1.69 0.031   -.0099451 .0126983
                                    |
                              year  |
                             2006   |-.4287087   .3517876  -1.22 0.223     -1.1182 .2607824
                             2007   |-2.100045   .4364616  -4.81 0.000   -2.955494-1.244595
                             2008   |-1.696225   .4156455  -4.08 0.000   -2.510876-.8815754
                             2009   |-1.044247   .4053188  -2.58 0.010   -1.838657-.2498368
                             2010   |-.6975781   .4000401  -1.74 0.031   -1.481642 .0864861
                             2011   | .0074625   .3893111   0.02 0.085   -.7555732 .7704983
                             2012   | .1800464   .3853747   0.47 0.240   -.5752741  .935367
                             2013   | .0273673   .3795137   0.07 0.033   -.7164659 .7712005
                             2014   |-.4721067   .4069478  -1.16 0.246    -1.26971 .3254964
                             2015   | .1543735   .4347186   0.36 0.123   -.6976592 1.006406
                             2016   | .7759731   .4003671   1.94 0.053    -.008732 1.560678
                                    |
                             _cons | -3.486307   6.917003  -0.50 0.000   -17.04338 10.07077
-------------------------------------------------------------------------------------------
------------

------------------------------------------------------------------------------
  Random-effects
  Parameters                |  Estimate  Std. Err.    [95% Conf. Interval]
-------------------------   ----------------------------
----                        +         -----------------
_all: Identity              |
              sd(R.country) |  4.807054  .9252821     2.151337     6.799085
-------------------------   ----------------------------
----                        +         -----------------
_all: Identity              |
              sd(R.bankna~) |  7.7691479   .1442488   4.532564     9.1108297
-------------------------   ----------------------------
----                        +         -----------------
               sd(Residual) |  2.291202  .0579981     2.180302     2.407744
```

3.8.10 Estimations before the Global Financial Crisis

```
Mixed-effects ML regression                     Number of obs      =          2253
Group variable: _all                            Number of groups   =             1

                                                Obs per group:
                                                             min =          2253
                                                             avg =        2253.0
                                                             max =           253

                                                Wald chi2(14)      =         33.54
Log likelihood = -604.74953                     Prob > chi2        =        0.0024

------------------------------------------------------------------------------------------------------
                                   npl |      Coef.  Std. Err.       z   P>|z|      [95% Conf. Interval]

                      Lernerindex_hat |   .5543354   .0249696    2.14   0.032       .3556142   1.555275
                                       |
  c.lernerindex_hat#c.lernerindex_hat |  .07237427   .0049381      2.52  0.062      .05307499  .09236703
                                       |
                                   hdi |  -.6279771   .0369434   -1.72   0.036      -.8411037  -.4670646
                                       |
               c.lernerindex_hat#c.hdi |  -.5920428   .0529064   -1.52   0.039      -.7521137  -.2639597
                                       |
c.lernerindex_hat#c.lernerindex_hat#c.hdi |   -.0928507   .0096399   -2.19  0.059      -1.488866  -.0747578
                                       |
                             loggd
                            p     p|
                                  --. |   -.260725   .0819856   -2.34   0.019       -.827577  -.1938725
                                  L1. |   .0049114   .0160231    0.03   0.046       .0031896   .3091372
                                       |
                                  roa |  -.0208435   .0545954   -0.38   0.003      -.1278486   .0861615
                                  fba |  -.0204447   .0160524   -1.27   0.003      -.0410175   .0519069
                                 unem |   .1754998   .0192341    0.91   0.032      -.2014834   .5524831
                                  ldr |   .0006046   .0005026    1.20   0.029      -.0003804   .0015895
                              logsize |  -.1450049   .0142359   -1.02   0.008      -.4240246   .1340148
                                       |
                               year   |
                                2006  |   .1228056     .251113    0.49   0.025      -.3693668   .6149779
                                2007  |   .1511519   .3617121    0.42   0.676      -.8600945   .5577907
                                       |
                                _cons |    5.51564   .9824372    1.79   0.003       2.401528   8.643281
------------------------------------------------------------------------------------------------------

          ------------------------------------------------------------------------------
  Random-effects Parameters   |    Estimate   Std. Err.             [95% Conf. Interval]

_all: Identity                |
                sd(R.country) |2.398639    .218946       2.005709   2.868547

_all: Identity                |
               sd(R.bankna~)  |  5.307191        .8564419 3.868147              7.281593
----------------------------
                 sd(Residual) |1.341553          .091225 1.174158              1.532813
------------------------------------------------------------------------------
```

3.8.11 Estimations after the Global Financial Crisis

Mixed-effects ML regression		Number of obs	=	2795
Group variable: _all		Number of groups	=	1
		Obs per group:		
		min	=	2795
		avg	=	2795.0
		max	=	895
		Wald chi2(19)	=	63.26
Log likelihood = -2948.3132		Prob > chi2	=	0.0000

npl	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
Lernerindex_hat	-.0672107	.0742394	-1.78	0.004	-.0968705	-.1742832
c.lernerindex_hat#c.lernerindex_hat	.07712597	.033638	0.60	0.029	.03975306	1.686782
hdi	-.2473478	.09273503	-1.25	0.010	-.5297488	-.169053
c.lernerindex_hat#c.hdi	.4349594	.03589099	1.51	0.031	.2255387	1.20097
c.lernerindex_hat#c.lernerindex_hat#c.hdi	-.0590528	.0579797	-0.57	0.020	-.0982627	-.0174208
loggdp						
--.	-.5560904	.0149337	-0.48	0.029	-1.696568	-.3808749
L1.	.0861436	.04427437	3.65	0.000	.04842129	.2746605
roa	-.010115	.0808816	-0.13	0.000	-.14841	-.001686
fba	-.0274505	.0185165	-1.48	0.038	-.0637422	.0088411
unem	.2238133	.1026405	2.18	0.029	.0226417	.4249849
ldr	.00043	.0002169	1.98	0.037	-.087069	.0008551
logsize	-.3088981	.0166938	-1.85	0.024	-.6360862	.0182901
year						
2010	.2822429	.7802827	0.36	0.018	-1.247083	1.811569
2011	-.4628036	.7715282	-0.60	0.049	-1.974971	1.049364
2012	-1.273706	.7741915	-1.65	0.100	-2.791094	.2436811
2013	.1169896	.7670742	0.15	0.079	-1.386448	1.620428
2014	-.3643357	.8255531	-0.44	0.659	-1.98239	1.253719
2015	-.6447904	.9218636	-0.70	0.484	-2.45161	1.162029
2016	-2.110139	.9405182	-2.24	0.025	-3.953521	-.2667571
_cons	37.06059	8.010288	4.63	0.000	21.36072	42.76047

Random-effects Parameters	Estimate	Std. Err.	[95% Conf.	Interval]
_all: Identity				
sd(R.country)	1.91991	.7433102	.89894	4.100446
_all: Identity				
sd(R.bankna~)	5.840129	.3443631	5.202731	6.555616
sd(Residual)	4.793996	.1520286	4.505097	5.101422

Chapter 4

The Dynamic Relationship Between Bank Credit Ratings and Non-Performing Loans using Panel Vector Autoregressive Model

Studies in the literature have shown the importance of the banking system to the overall financial stability of an economy. Therefore, investigating those key factors that provide insight into the strength and financial soundness of the banking system is paramount. This chapter focuses on Bank credit ratings as existing studies show that Bank credit rating is one of those key factors (Gray et. at., 2006; Hassan, 2013; Klusak et. al., 2017). Bank credit ratings are said to be estimates that help to provide insight as to how likely a bank is to default on its debt payments or go out of business. They help to measure the bank's ability to meet its debt obligations as at when due and are considered an important factor when making financial and investment decisions. Hence, understanding the factors that significantly influence bank credit ratings is very crucial. In recent times, credit rating agencies consider changes in non-performing loans (NPLs) an important determinant of rating changes. Several studies have examined the impact of NPLs on credit ratings, however, many of these studies focus only on sovereign credit ratings. This study, using a total of 145 banks, examines the relationship between bank credit ratings and NPLs. Studies of this relationship have been seen to be very limited in literature with all of them focusing only on one direction of the relationship. This chapter, using the Panel VAR model as well as the Panel Granger causality test, contributes to the existing literature by investigating whether a two-way relationship exists between bank credit ratings and NPLs. The results reveal that, not only do NPLs affect banks credit ratings, but banks credit ratings also – through lending channels - affect NPLs.

4.1 Introduction

Studies such as (Hesse and Čihák, 2007; Douglas, 2008; Drigă and Dura, 2014; Aoki and Nikolov, 2015; Barra and Zotti, 2019; Allen et al., 2019; Iwanicz-Drozdowska et al., 2019) have shown that the importance of the banking system on the overall financial stability of an economy cannot be overemphasized. It is therefore important that those key parameters that provide insight into the strength and financial soundness of the banking system are investigated. Bank credit ratings have been seen to be one of those key parameters (Gray et. at., 2006; Hassan, 2013; Klusak et. al., 2017).

Bank credit ratings are said to be estimates that help to provide insight as to how likely a bank is to default on its debt payments or go out of business. They help to measure the bank's ability to meet its debt obligations as at when due. Three major credit rating agencies exist in the financial system. They are Standard & Poor's (S&P), Fitch Group and Moody's Investor Services. These rating agencies (CRAs) control a significant portion of the market, and they make use of several quantitative and qualitative variables in order to allocate a credit rating to an institution, company or organisation (Chee et. al., 2015).

According to previous studies (Ferri et. al., 1999; Jaramillo and Tejada, 2011) high credit ratings received by the CRAs imply that a bank has a lower probability of default in respect to another bank that receives low credit ratings. These ratings, given by these CRAs, are used by investors, borrowers and even the government to assess the reliability of financial institutions because credit ratings are considered an important factor when making financial and investment decisions (Grunert et. al., 2005; Poon and Firth, 2005). This key role that credit ratings play in the banking system and by extension, in the economy has led to a rise in its interest, especially after the global financial crisis.

Several studies such as (Bissoondoyal-Bheenick and Treepongkaruna, 2011; Hassan and Barrell, 2013; Chodnicka-Jaworska, 2014; Yıldız and Günsoy, 2017) have attempted investigating the impact of NPL on credit ratings. These studies highlight NPLs to be one of those key factors that affect bank credit ratings. In recent times, CRAs consider changes in NPLs as an important determinant of rating changes. These studies show that NPLs have a negative impact on credit ratings. They argue that high NPLs weaken the financial sector which in turn lead to an increase in the credit risk and a decrease in the credit ratings. However, these studies do not take into consideration the effect credit ratings might also have on NPLs. They focus their studies only on a unilateral directional effect and fail to account for a bilateral directional effect, with most of them paying more emphasis only on sovereign credit ratings even though several studies have shown that sovereign risk spills over to financial institutions through many channels (Panetta et. al., 2011; De Bruyckere et. al., 2013; Alsakka et. al., 2014).

Some studies go further to raise the issue of bias by CRAs in determining the sovereign ratings of countries. The study by Gültekin-Karakaş et. al., (2011) show that irrespective of the macroeconomic fundamentals of developed countries, CRAs tend to give these countries higher ratings. Reusens and Croux (2017) and Tennant et. al., (2020) also provide evidence in their studies to show that CRAs discriminate against developing and poor countries which makes it difficult for these countries to get an upgrade in ratings even when they have made positive changes in institutional and macroeconomic fundamentals.

It is important that the impact of banks credit ratings on NPLs is also investigated. Investigating this direction of the relationship is important because it gives a wholistic picture and better understanding of the relationship between banks credit ratings and NPLs. Even more importantly, it highlights how critical it is for credit rating agencies to eliminate any rating bias when rating banks as this might have an impact on NPLs which in turn plays a major role in the stability and health of the banking system. Mazreku et. al. (2018), Zhang (2018), Atoi (2018) and Khan et. al. (2020) provide evidence that show that NPLs significantly impacts the stability of the banking system. This study aims to contribute to the existing literature by addressing the gap raised above. This study using a Panel Vector Autoregressive Model (PVar), argues that banks credit ratings impact future NPLs of banks through lending channels. Several studies show the link between lending interest rate and probability of loan default (Khemraj and Pasha, 2009; Beck et. al., 2015; Bahruddin and Masih, 2018; Szarowska, 2018). They reveal that banks which have relatively higher lending interest rates tend to record higher levels of loan default by their customers, thereby leading to an increase in the banks' NPLs. Karam et. al. (2014) and Adelino and Ferreira (2016), show how credit ratings affect banks funding. Their studies reveal that a downgrade in a bank's credit rating leads to simultaneous and persistent decline in the bank's funding.

Based on this, this study argues that a downgrade in a bank's credit rating will lead to an increase in the borrowing interest rate of the bank as a result of an increase in the bank's supply-side constraints thereby leading to an increase in the bank's future lending interest rate to its customers. This in turn will lead to an increase in the probability of customers shifting into riskier projects and defaulting in their loan payment which will lead to an increase in future non-performing loans. Boumparis et. at. (2019), in his theoretical argument, briefly implied the possibility of this relationship using sovereign credit ratings.

This chapter makes three distinct contributions to literature. First, it focuses on the banking sector (banks' credit ratings) rather than sovereign credit ratings. Hence, this study adds to the very limited literature on the relationship between banks credit ratings and NPLs. Second, it allows for and focuses on a bilateral causality between banks credit ratings and NPLs. That is, it aims to investigate whether there is a two-way relationship between NPLs and credit ratings within the banking system. To the best of my knowledge, none of the studies have taken into consideration the effect NPLs and banks credit ratings have on each other. Finally, this study uses a dataset that covers the period before and after the global financial crisis. This allows for a broad range of datasets and the results from this dataset will provide more information regarding the relation between banks credit ratings and NPLs.

Previous studies (Hite and Warga, 1997; Kliger and Sarig, 2000; Norden and Weber, 2004) examined the static impacts of credit rating changes on various financial metrics (e.g., stock returns, bond spreads, and borrowing costs) without looking into the dynamic interrelationships. This research examines the dynamic relationship between bank credit ratings and non-performing loans (NPLs) using a Panel Vector Autoregressive (PVAR) model. By focusing on the temporal interactions and feedback mechanisms, it provides a more comprehensive understanding of how changes in one variable influence the other over time. Most existing literature (Holthausen, and Leftwich, 1986; Ferri, Liu, and Stiglitz, 1999; Kliger and Sarig, 2000; Norden and Weber, 2004) has focused on the unidirectional impact of credit rating changes on financial variables. This study investigates bidirectional causality, highlighting how NPLs can also affect bank credit ratings. This approach reveals the mutual influence and interconnectedness between credit ratings and loan performance, giving deeper insights into the risk dynamics within the banking sector.

Moreover, many previous studies (Altman and Saunders, 1998; Akhigbe and Madura, 2001; Hill, Brooks, and Faff, 2010) relied on cross-sectional or time-series data, limiting their ability to capture heterogeneity across banks or countries. By employing a panel data approach, this study accounts for both cross-sectional and time-series variations. This allows for more robust and generalizable findings, as it can control for individual bank-specific effects and common time effects. Lastly, the use of traditional econometric techniques such as Ordinary Least Squares (OLS) or simple Vector Autoregressive (VAR) models has been common in literature. The application of a PVAR model represents methodological advancement which enables the simultaneous analysis of multiple interrelated variables while addressing potential endogeneity issues. This enhances the accuracy and reliability of the findings.

In view of the foregoing, therefore, this study significantly advances the literature by providing a dynamic analysis of the relationship between bank credit ratings and non-performing loans using a sophisticated PVAR model. It offers novel insights into bidirectional causality, accounts for cross-sectional and time-series variations, and provides actionable policy recommendations to enhance banking sector stability. By addressing the limitations of previous studies, this research makes a substantial contribution to our understanding of the complex relationships between credit ratings and loan performance in the banking industry.

To explore the highlighted contribution of this study to existing literature, this study uses a dataset that covers over 140 banks across several countries between the period 2004 to 2016. The key variables which are banks credit ratings and banks non-performing loans were derived from S&P credit ratings report and bankscope database respectively. In other to investigate whether a two-way relationship exists between the variables of interest, the PVar model as well as the granger causality test were employed. Results from the investigation show that a two-way relationship does exist between banks credit rating ratings and NPLs. In addition, the results reveal that NPLs have an impact on current and future banks' credit ratings and vice versa. The results further reveal that past values of NPLs granger causes bank credit ratings while past values of banks credit ratings also granger causes NPLs. Finally, based on the empirical results, this chapter proposes a few policy suggestions for policy makers in order to help achieve a more stable banking system.

The rest of this chapter is organized as follows. Section 2 reviews the relevant literature on the relationship between credit ratings and NPLs. Section 3 introduces the data and describes the data in detail. Section 4 talks about the econometric model employed and gives an insight into Panel Vector Autoregressive Model. Section 5 puts forward the results from the empirical study and discusses the results. Finally, section 6 summarizes the study and puts forward policy suggestions based on the empirical results of this research while suggesting some possible avenues for future research.

4.2 Literature Review

Despite the heavy criticism and scrutiny credit rating agencies came under following the global financial crisis, the reliance on credit ratings has increased in recent years. This is as a result of revised/improved regulations in terms of rating methodologies, registration procedure, internal controls, governance requirements and disclosure rules. The determinants of credit ratings, particularly sovereign credit ratings, have been explored by a considerable body of literature. However, in the research on the determinants of sovereign credit ratings, the existing body of literature shows that the banking sector stability has been barely taken into consideration. The existing literature shows that macroeconomic variables such as per capital income, GDP growth, level of economic development, default history, external debt, inflation and unemployment have an impact on sovereign credit ratings (Mulder and Perrelli, 2001; Eliasson, 2002; Bissoondoyal-Bheenick, 2005).

Nevertheless, Caporale et. al. (2012) reveal that banks ratings are not only influenced by bank specific factors but are also influenced by the macroeconomic environment. They argue that banks that operate in a less stable economy tend to have lower ratings when compared to banks that operate in a more stable economy. Results from their study show that the macroeconomic condition of the country of origin is a key factor. Williams et. al. (2013) and Alsakka et. al. (2014), go further to show a direct link between sovereign ratings and bank ratings. They reveal that bank ratings are directly affected by sovereign ratings signals. Their study shows that the sovereign ratings of the banks' country of origin influences the rating of the banks. Klusak et. al. (2017), confirm these findings in their study. Their results reveal that sovereign status adversely impacts bank ratings through the rating channel. Their study confirms the presence of a link and reaffirms that a strong ceiling effect exists between sovereign and banks ratings.

Having seen the link established between banks ratings and sovereign ratings in previous literature, Brůha and Kočenda (2018), using EU countries over the period of 15 years (1999 to 2014), consider the impact of banking sector characteristics on sovereign credit ratings. Their study shows that the single most important bank-specific variable is NPLs. They show that an increase in NPLs will adversely affect sovereign risk assessment. Francisco et. al., (2019), using a group of emerging market economies, investigate the relationship between financial fragility and sovereign credit ratings. Results from their study show that there is a negative relationship between financial fragility and sovereign credit ratings. Stawasz-Grabowska (2020) also provides evidence that shows that NPL as well as GDP per Capital play important roles in the credit worthiness of EU countries. His study shows that an increase in NPL leads to a decrease in the credit rating of EU countries.

Amidst the limited literature that focuses on bank credit ratings, Bissoondoyal-Bheenick and Treepongkaruna (2011) using the S&P rating classification analyse the determinants of bank ratings for UK and Australian banks. Their study reveals that accounting variables tend to have more explanatory power than macroeconomic variables. The study by Chen (2012) also provided evidence to support this finding. It further shows that the most important factor for bank credit ratings is NPLs for banks with higher ratings while capital adequacy ratio tends to be the most important for banks with lower ratings. Hassan and Barrell (2013), using a sample of UK and US banks show that bank size, asset quality and return on equity are the key determinants of banks credit ratings.

Based on the limited literature review available on banks credit ratings, it can be observed that most studies on credit ratings focused only on sovereign credit ratings. This study aims to add to the existing literature by focusing only on bank credit ratings while taking into consideration the two-way effect of bank credit ratings and its key determinants with more attention given to NPLs. This is because, in previous literature, the NPL has been seen to be one of the most important sector-specific variables that is associated with increase in bank risk. In fact, the study by Brůha and Kočenda (2018), found it to be the most important of all variables. NPL has been shown to be a significant predictor of a decline in the cost structure of a bank, a decline in the bank efficiency, an increase in the banks' unwillingness to lend and in some cases a good predictor of banks failures (Balgova et. at., 2016).

4.3 Dataset and Variables

This study employs the use of the annual dataset of 140 banks covering the period 2004 to 2016. For the purpose of this study, two different datasets from different sources are combined (bankscope database and S&P report[1]). These two groups of datasets are merged using the bank names as both datasets contain data on similar banks. The dataset from bankscope provides data on banks NPLs and bank specific variables while the dataset from S&P report provides data on banks credit ratings, which is the key variable of interest. The reasons for using this rating agency are because S&P has been found to be the most effective and active rating agency among the big three in the industry which provides a larger and more reliable dataset for this study. In addition, the S&P ratings are also known to induce a stronger market reaction because their ratings are less foreseen by the market participants (Gande and Parsley, 2005; Christopher et. al., 2012; Ballester and González-Urteaga, 2017).

The S&P rating classification has a range of 58 possibly credit ratings that can be assigned to each bank. S&P uses four main credit rating scales: A, B, C and D. Each of these four main rating scales have subgroups which consist of ratings that fall under each alphabet. For instance, the rating scale group A has 7 subgroups under this category (AAA, AA+, AA, AA-, A+, A, A-) with AAA being the highest rating and A-being the lowest rating within the rating scale

[1] The S&P dataset, which provides the data on the key variable used in this study (banks credit ratings), was made available by Patrycja Klusak at Norwich Business school, University of East Anglia.

group A. Rating grades under group A imply that a bank has a high capacity to meet its financial commitments while rating grades under group D implies that a bank has failed to meet all its financial commitments in a timely manner. Grade D is also used when a bankruptcy petition has been filed. Comparing the different subgroups across all main alphabets in regard to how substantially proven the investment environment of a bank is, a rating grade between AAA and BBB- shows a substantially good investment environment while any rating grade between BB+ and D is speculative.

Table 4.1 shows the score that is assigned to each rating grade. The rating grades across all main groups and subgroups are transformed to a rating score using a 3-point scale of 1 to 58. The rating grades that take the rating score 1 are rating grades that imply that the bank is currently in default, or the bank is currently highly vulnerable, and its debt is at high risk of not being paid. In addition to the rating grades assigned by S&P, S&P also uses an outlook or watch action in its evaluation of potential changes to credit ratings over a short or long period. There cannot be two actions at the same time. That is, aside from the different rating subgroups that exist in each main rating group, S&P also provides an additional measure to evaluate the probability that a bank which has maintained a particular grade of rating over a short or long time period, will experience a change in credit rating. Watch action status lasts up to 90 days. That is, it gives information on what a potential change in rating might be within the next 90 days while outlook action status lasts up to 2 years for investment grades and 1 year for speculative grades. These actions attempt to project what the ratings will be within the given period, compared to what the current rating is. That is, they highlight the potential direction of rating. For this study, the actions are not accounted for as this study focuses only on the actual ratings of banks and not the projections.

Table 4.1: The Linear Transformation of S&P Credit Ratings

Category	Rating Grade	Rating Score
Investment Grade	AAA	58
Investment Grade	AA+	55
Investment Grade	AA	52
Investment Grade	AA-	49
Investment Grade	A+	46
Investment Grade	A	43
Investment Grade	A-	40
Investment Grade	BBB+	37
Investment Grade	BBB	34
Investment Grade	BBB-	31
Speculative Grade	BB+	28
Speculative Grade	BB	25
Speculative Grade	BB-	22
Speculative Grade	B+	19
Speculative Grade	B	16
Speculative Grade	B-	13
Speculative Grade	CCC+	10
Speculative Grade	CCC	7
Speculative Grade	CCC-	4
Speculative Grade	C	1
Speculative Grade	SD	1
Speculative Grade	CC	1
Speculative Grade	D	1

Studies discussed in literature show that the major bank specific factors that affect bank credit ratings are NPLs, Bank Total Assets, Return on Equity (ROE) and Capital Adequacy Ratio (CAR). These studies argue that these variables represent the financial health of a bank and as such, a significant change in these variables will have an impact on the bank's credit rating. Using GDP Per Capita as a macroeconomic variable, they also argue that the condition of the macroeconomic environment in which the banks operate significantly has an impact on the banks credit ratings. Building on this evidence, the listed variables are also used in this study with an addition of the Loan Loss Provision (LLP) variable.

Chen (2012) and Bissoondoyal-Bheenick and Treepongkaruna (2011) show that bank specific variables tend to have more impact on banks credit ratings than macroeconomic variables. This is expected as rating agencies tend to consider an in-depth and broad range of financial and business attributes of a bank when assigning credit ratings. As a result, bank specific variables that give insight into the financial health of a bank (NPLs, Bank Size, ROE and CAR) are thoroughly taken into consideration. A bank's NPLs measure the percentage of the defaulting loans to total gross loans of the bank. Therefore, high NPLs imply that the bank has a high number of loans that has passed its due date and is in default. This in turn increases the bank's risk of profit loss and even bankruptcy if measures are not taken to reduce the high levels of NPLs. Hence, an increase in a bank's risk of profit loss or bankruptcy is expected to lead to an increase in the risk of the bank being unable and unwilling to meet its own financial obligations as at when due and in full.

Bank Size is also a key bank specific variable that has been seen to have an impact on banks credit ratings (Hassan and Barrell, 2013). It is a measure of a bank's total assets. Ideally, banks with bigger total assets tend to have a higher ability and willingness to meet their financial obligations on time and in full. Thus, an increase in the bank's size is expected to lead to an increase in the bank's credit rating.

ROE measures the rate of return received from the equity invested by the bank. That is, it measures managerial efficiency, financial leverage as well as the income generated with the money invested by shareholders. It is also considered as a measure of profitability in the banking system. Studies show that banks with lower ROE tend to indulge in more risk in other to boost their profit margin thereby leading to higher risk of loan default on the part of the bank's customers (Shigjerji, 2013; Ahmed and Bashir, 2013; Makri et al., 2014). This in turn will lead to a higher probability of the bank being unable to meet up with its own financial obligation, hence, leading to a decline in the bank's credit rating.

CAR is a measure of a bank's available capital in respect to its total assets. This is the percentage of a bank's risk weighted exposure. It is a measure that shows whether a bank has enough capital on reserve to handle a certain amount of risk before being at the risk of becoming insolvent. Thus, a high CAR implies that a bank has a low exposure to risk and the ability to meet its own financial obligations as at when due and in full. Therefore, an increase in a bank's CAR is expected to lead to an increase in the bank's credit rating (Chen, 2012).

This study introduces Loan Loss Provision (LLP) to the already established bank specific variables in the existing literature. It also includes GDP Per Capital which controls for the macroeconomic conditions of the country in which the banks operate. It is expected that banks that operate within a country with better economic conditions will perform better than banks that operate within a country with lower economic conditions (Caporale et. al., 2012). As an account of this, an increase in GDP Per Capital is expected to lead to an increase in the banks' credit rating.

LLP is an income statement expense set aside as an allowance for default loans. A bank that has a higher level of LLP tends to have a higher ability to cover up for losses as a result of loan defaults, thereby reducing the risk associated with loan losses. However, this study argues that an increase in LLP will lead to a drop in the bank's rating as a result of the decrease in the bank's profitability that is associated with an increase in LLP. Alhadab and Alsahawneh (2016) and Hamza (2017) in their studies, show that LLP tend to have a negative relationship with the bank's profitability because the bank uses its capital to absorb the default loans. This study provides empirical evidence that shows the relationship between LLP and banks credit ratings.

Loan loss provisions (LLP) are reserves set aside by banks to cover potential losses from defaulted loans. They reflect the bank's assessment of credit risk and its risk management practices. Higher loan loss provisions indicate a bank's proactive approach to managing credit risk, potentially leading to lower future NPLs. Conversely, insufficient provisions may result in higher NPLs as unanticipated defaults materialize. Thus, including LLP in the model helps to capture the bank's internal risk assessment and preparedness to absorb losses, which is critical for understanding the true credit risk and stability of the bank. A study by Hasan and Wall (2004) reveals the positive relationship between loan loss provisions and bank risk management, indicating their significance in predicting NPLs. Loan loss provisions serve as an early warning indicator of potential future NPLs, reflecting the bank's risk management and credit assessment capabilities. Regulatory frameworks often require banks to maintain adequate provisions, making them a critical component of financial stability analysis.

Similarly, Lending interest rates represent the cost of borrowing for customers. They are influenced by the bank's credit risk, market conditions, and monetary policy. Higher lending rates may increase the burden on borrowers, potentially leading to higher default rates and NPLs. Lower rates might stimulate borrowing but also entail risks if the lending standards are relaxed. Therefore, including lending interest rates in the model captures the cost of borrowing and the economic environment's influence on borrowers' repayment capacity, directly affecting the level of NPLs. This is in line with the findings of Louzis, Vouldis, and Metaxas (2012) who analyzed the determinants of NPLs in the Greek banking sector and revealed the impact of lending rates on NPLs.

Table 4.2: Variables: Definition, Source, and the Expected Sign of their Impact on Banks Credit Ratings

Variable	Definition	Source	Sign
NPLs	Non-performing loans	Bankscope, Bureau van Dijk (BvD)	-
CAR	Capital Adequacy Ratio	Bankscope, Bureau van Dijk (BvD)	+
Bank Size	Total assets	Bankscope Bureau vanDijk (BvD)	+
ROE	Return on Equity	Bankscope ,Bureau van Dijk (BvD)	+
LLP	Loan Loss Provision	Bankscope, Bureau van Dijk (BvD)	-
Log_GDP	GDP Per Capita	Bankscope, Bureau van Dijk (BvD)	

In order to investigate the other direction of the relationship between Banks Credit Ratings (BCRs) and NPLs, this study also uses NPLs as a dependent variable. The Pvar model allows for the simultaneous use of BCRs and NPLs as endogenous variables while the other variables discussed are represented as exogenous variables. In addition to the exogenous variables listed, the Lending Interest Rate is also included as an explanatory variable for NPLs. As discussed, and investigated in previous chapters of this thesis, these variables have been observed to have an impact on NPLs. Table 4.3 shows the sources of these variables and the expected sign of the effect on NPLs while table 4.4 shows the summary statistics of all the variables discussed and used in this study.

Table 4.3: Variables: Definition, Source, and the Expected Sign of their Impact on Non-Performing Loans

Variable	Definition	Source	Sign
BCRs	Bank Credit Ratings	S&P database	-
CAR	Capital Adequacy Ratio	Bankscope, Bureau van Dijk (BvD)	+
Bank Size	Total assets	Bankscope Bureau vanDijk (BvD)	-
ROE	Return on Equity	Bankscope Bureau van Dijk (BvD)	-
LLP	Loan Loss Provision	Bankscope, Bureau van Dijk (BvD)	+
Log_GDP	GDP Per Capita	Bankscope, Bureau van Dijk (BvD)	+
LIR	Lending Interest Rate	Bankscope, Bureau van Dijk (BvD	+

Table 4.4: Summary Statistics of Variables Used in the Model

Variable	Mean	Std. Dev.	Min	Max
BCRs	36.476	10.9035	1	58
NPLs	6.0855	11.2019	0	96.22
ROE	7.2095	26.7835	-745.3	99.75
LLP	18.706	59.3346	-4.32	8.94
Log_Bank Size	30.07	29.2552	8.056	21.592
LIR	10.001	5.5505	0.5	33.544
Log_GDP	9.1262	1.3448	5.9955	11.247
CAR	21.963	17.1447	8.13	28.7

As seen in table 4.4, the values of bank ratings (BCRs) range from 1 to 58, which shows that in the data set some banks were observed to either be in default or were highly vulnerable and their debts were at high risk of not being paid while some banks were seen to have extremely strong capacity to meet their financial commitments. NPLs range from 0% to 96.22%, showing that there are some banks who within the time frame lost almost all their loans to bad debts and there are some banks whose loans were all performing. Return on Equity (ROE) shows a minimum of -745.3% and maximum of 99.75%, indicating that some banks experienced losses and bad managerial efficiency while others experienced more banking profitability, better managerial efficiency, and more financial leverage. Loan Loss Provision (LLP) has a minimum of -4.32% and a maximum of 8.94%, indicating that during the time frame, some banks did not set aside any expense to cover for loans that might stop performing while some other banks made provisions for loans that might stop performing/bad loans. Log_Bank Size which represents the bank size/total assets of the bank has a minimum of 8.06 and a maximum of 21.59. This shows that some banks have a stronger net-worth than others hence placing them in a higher tier/ranking than their counterparts. The Lending Interest rate (LIR) can be observed to have a minimum of 0.5% and a maximum of 33.54%. This shows that some banks give out loans with a higher interest rate than others. log_GDP presents a minimum of 5.96 and a maximum of 11.25, indicating that over the period of 2004 to 2016, some banks experienced a better business economy than others. Finally, CAR has a minimum of 8.13% and a maximum of 28.7%, indicating that some banks have a lower ability to absorb unexpected losses while some countries have a higher ability to absorb unexpected losses.

In addition to the summary statistics given in table 4.1, Table 4.5 shows a more detailed descriptive statistics of the variables of interest (BCRs and NPLs). From the table it can observed that the within variation of banks credit rating is lower than the between variation. This implies that the changes in a bank's credit ratings over time are lower than the changes that occur across banks. Figure 4.1 gives a rough image of how credit rating changes over time for a few banks used in the study.

Table 4.5: Descriptive Statistics of BCRs and NPLs Showing the Between and Within Variations

Variables		Mean	Std. Dev	Min	Max	Observations
BCRs	overall	36.475	10.903	1	58	1882
	between		8.296	16	51.076	145
	within		7.099	3.244	62.783	
NPLs	overall	6.084	11.202	0	96.22	1876
	between		7.477	0	61.434	145
	within		8.348	0	80.922	

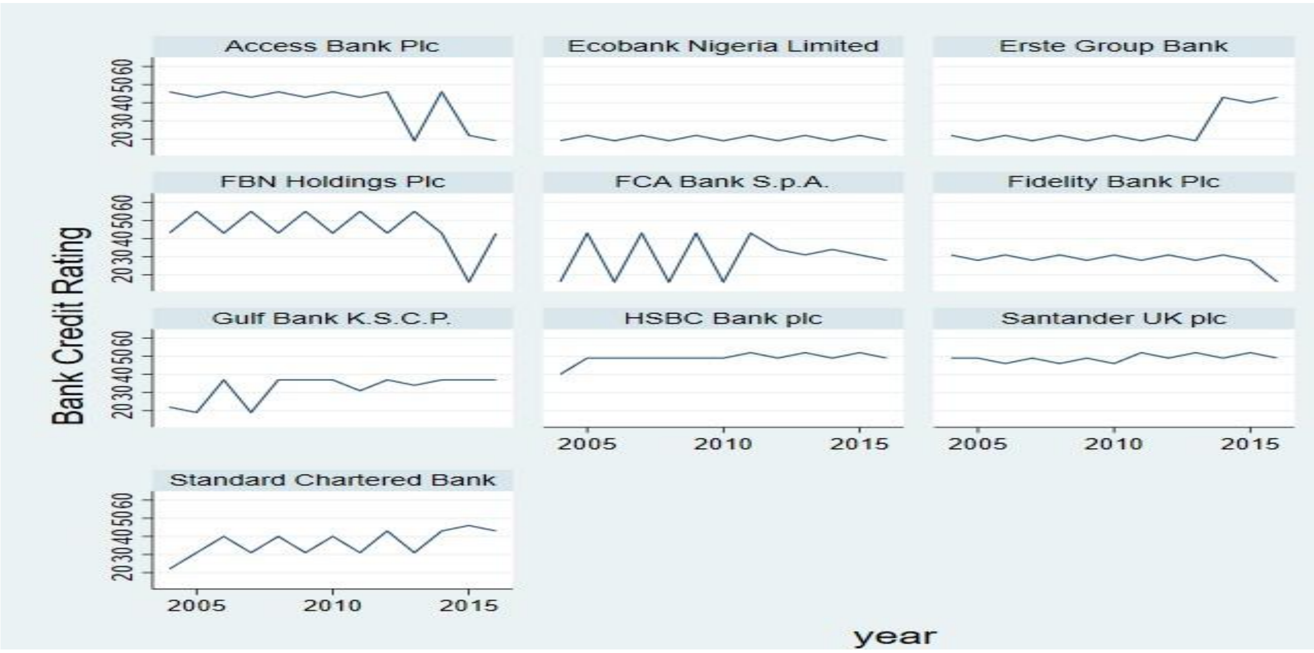


Figure 4.1: Graph Showing Bank Credit Ratings Over Time for Some Banks

4.4 Econometric Model: Panel Vector Autoregressive Model (PVar)

This study employs the use of the PVar model and Granger Causality test. This is because, unlike previous studies, this study does not only investigate the impact of the key bank specific variables on bank credit ratings, but it also identifies whether a two-way relationship exists between banks' credit ratings and NPLs. The study focuses on identifying the complex relationships between the relevant bank specific variables, namely NPLs and bank credit ratings and to use PVar model and the Granger Causality test to determine the interactions between the relevant variables. Many previous empirical studies have been devoted to analyzing such concepts as profitability, capital adequacy, and asset quality as factors defining the credit ratings. But, these studies have paid scant attention to the question of reciprocal causality, especially which exists between NPLs and credit ratings. This study is especially beneficial from a PVar model as it permits the documentation of the direct impacts of the variables on credit ratings, as well as the feedback mechanisms that may exist within this market segment of the banking subsystem. In so doing, this study hopes to offer a better perspective into how adjustments in NPL levels may not only impact, but could in turn be impacted upon, by variations in credit ratings, to help address the current research's identified knowledge gap.

Furthermore, the use of the Granger causality test in this case to examine whether NPLs can be used to explain variations in credit ratings or credit ratings can be used to explain variations in NPLs to determine the causality test. This research questions the one-way impact model of risk and instead contributes towards a better understanding of the prevalence of two-loop causal relationships in banking. Knowledge of these relationships is especially important for regulators, investors and policy makers who want to improve, via enlightened choice, the resilience of financial systems and who need to make balanced judgments based on prospective and retrospective indicators of risk. Therefore, it enriches not only the theoretical system of banking risk but also has theoretical and practical concerns for credit rating agencies and financial institutions.

We employ the PVar model for the following main reasons: First, the Pvar model allows for the endogenous interaction between banks' credit ratings and NPLs. That is, it allows us to investigate whether a change in NPLs helps in predicting a change in banks' credit ratings and vice versa. Second, it also allows us to identify the direction of the relationship between banks credit ratings and NPLs through the application of the granger causality test which in turn allows for the possibility of bidirectional causalities. Finally, the application of the Pvar model allows us to evaluate the dynamic links among banks' credit ratings and NPLs using the impulse response functions (IRF).

This study argues that a downgrade in a bank's credit rating will lead to an increase in the borrowing interest rate of the bank as a result of an increase in the bank's supply-side constraints thereby leading to an increase in the bank's future lending interest rate to its customers which will lead to an increase in the probability of customers shifting into riskier projects and defaulting in their loan payment, hence lead to an increase in future non-performing loans. The application of the PVar model and the granger causality test will help to explain the dynamic links between banks credit ratings and NPLs.

This PVar model uses the traditional vector autoregressive model but in a panel structure to investigate the dynamic interrelationship between multiple variables. It allows us to treat more than one variable as an endogenous variable and takes each endogenous variable as a function of the lag value of other endogenous variable in the model while also accounting for exogenous (predetermined) variables. This helps to capture more characteristics of the data and provides a rich structure. The PVar model also helps to solve the problem of heteroscedasticity while fully considering individual and time effects.

The economic justification for the choice of empirical model is that credit ratings are an important indicator of a bank's financial health and creditworthiness. Higher credit ratings indicate lower credit risk and better financial stability. Conversely, lower credit ratings signal higher risk. This is in line with the Information Asymmetry Theory, which suggests that credit ratings reduce information asymmetry between borrowers and lenders, thereby influencing the lending behavior and risk management practices of banks. Cantor and Packer (1997) discuss how credit ratings help reduce information asymmetry in the financial markets, influencing borrowing costs and lending standards. Furthermore, banks with higher credit ratings are likely to attract better-quality borrowers and secure lower-cost funding, leading to more prudent lending practices and lower levels of NPLs. On the other hand, banks with lower ratings may engage in riskier lending to maintain profitability, resulting in higher NPLs. This is supported by the Adverse Selection and Moral Hazard concepts. Bannier and Hirsch (2010) highlight how credit ratings affect banks' lending behavior and risk management, influencing the level of NPLs. The autoregressive component of the model captures the persistence of NPLs over time, reflecting the tendency of loan quality to exhibit temporal correlation due to economic cycles and bank-specific factors. This dynamic relationship is essential for understanding how past levels of NPLs influence current levels. Also, the contemporaneous effect as shown in the model captures the immediate impact of credit ratings on NPLs, emphasizing the role of credit ratings as a real-time indicator of a bank's financial health. Jorion, Liu, and Shi (2005) discuss the dynamic nature of credit ratings and their impact on financial indicators, emphasizing the importance of temporal effects.

Additionally, the time-specific effect accounts for macroeconomic shocks and other external factors affecting all banks at a given time, such as changes in economic conditions, regulatory policies, or market-wide events. This ensures that the model captures broader economic influences on NPLs and credit ratings. This is in line with the study of Ferri, Liu, and Stiglitz (1999) who highlight the role of macroeconomic factors in influencing credit ratings and bank performance during financial crises, demonstrating the importance of accounting for time-specific effects.

Thus, the PVAR model provides a comprehensive framework for analyzing the dynamic relationship between bank credit ratings and non-performing loans. By incorporating both autoregressive and contemporaneous components, as well as bank-specific and time-specific effects, the model captures the complex relationships between these variables. The economic motivation is grounded in theories of information asymmetry, adverse selection, moral hazard, and the impact of macroeconomic factors, supported by relevant literature.

The theory used to form the theoretical basis for the choice of variables in the model is the Information Asymmetry Theory. This theory posits that asymmetric information between borrowers and lenders can lead to adverse selection and moral hazard, which in turn affect credit risk and loan performance. The theory suggests that bank credit ratings, which reflect the creditworthiness and financial stability of banks, can impact the levels of NPLs. According to financial theory, credit ratings affect a bank's cost of capital, risk management strategies, and overall risk profile, which in turn impact the occurrence and management of NPLs. For instance, better-rated banks might have stricter credit risk management practices, leading to lower NPLs. Therefore, the choice as to which variables enter y and x was guided by some assumptions.

First, it is assumed that past values of NPLs are likely to influence current values due to the persistence of loan performance trends and the time it takes for credit quality issues to manifest fully. Thus, including lagged values helps capture the temporal dynamics and potential inertia in the levels of NPLs, reflecting the gradual adjustment process of loan portfolios. Secondly, the study assumes bank credit ratings to be exogenous even though they might be influenced by past NPLs, indicating potential endogeneity problems. However, studies (Beck et. al., 2015; Bahruddin and Masih, 2018; Szarowska, 2018) have established the link between bank credit ratings and NPLs. Thirdly, the study assumes there are unobserved, time-invariant factors specific to each bank that influence NPLs, such as management quality, business model, and operational practices. As such, accounting for these fixed effects helps isolate the impact of credit ratings on NPLs from these bank-specific characteristics. Similarly, it is assumed that there are time-specific factors affecting all banks, such as economic cycles, regulatory changes, and industry-wide shocks. However, including time effects controls for these common influences, ensuring that the analysis captures the direct relationship between credit ratings and NPLs. The study assumes that the variables are stationary to avoid spurious results and where variables are non-stationary, differencing was done to ensure validity of the model. Lastly, the study assumes the error term should be white noise, having a mean of zero, constant variance, and no autocorrelation. This ensures that the residuals are well-behaved, leading to unbiased and consistent parameter estimates.

This study considers a PVar model with fixed effects which helps in capturing unobservable time-invariant factors at the bank level. We assume that the data generating process is the same for all the cross-sectional units. Hence, systematic cross- sectional heteroscedasticity is modelled as panel-specific fixed effects.

It follows the estimation approach of Binder et. al. (2005) as well as the implementation and extension by Sigmund and Ferstl (2021):

$$\boldsymbol{y_{it}} = \boldsymbol{\mu i} + \sum_{l=1}^{p} \boldsymbol{A_l y_{i,t-1}} + \boldsymbol{B x_{i,t}} + \boldsymbol{\theta_t} + \boldsymbol{\epsilon}_{it} \qquad (1)$$

Where $y_{i,t} \in R^m$ denotes an (m x 1) vector endogenous variables for the i-th cross- sectional unit (l = 1, 2, …, N) at time t (t = 1, 2, …, T), $y_{i,t-1} \in R^m$ denotes an (m x 1) vector of lagged endogenous variables, $Bx_{i,t} \in R^m$ denotes an (k x 1) vector denotes the exogeneous variables for the i-th cross-sectional unit (l = 1, 2, …, N) at time t (t = 1, 2, …, T), $\varepsilon_{i,t} \in R^m$ is an (n x 1) vector of disturbances which are independently and identically distributed for all i and t with $E[\varepsilon_{i,t}] = 0$ and $Var\ [\varepsilon_{i,t}] = \Sigma_\varepsilon$ (where Σ_ε is a non-singular matrix). Let μ_i be an (m x 1) vector of individual specific effects, θ_t represent the time effect and p be the lag length of the PVar model. The specification in Eq. (1) assumes parameter homogeneity for A_l (m x m) and (m x k) for all i. To assure co-variance stationarity, the model in Eq. (1) assumes that all unit roots fall inside the unit circle. A PVar model is therefore a combination of a single equation dynamic panel model (DPM) and a vector autoregressive model (VAR).

Taking the first difference of equation (1), we get:

$$\Delta \boldsymbol{y_{it}} = \sum_{l=1}^{p} \boldsymbol{A_l} \Delta \boldsymbol{y_{i,t-1}} + \boldsymbol{B} \Delta \boldsymbol{x_{i,t}} + \Delta \boldsymbol{\theta_t} + \Delta \boldsymbol{\epsilon}_{it} \qquad (2)$$

Where Δ is the first difference operator.

Following Binder et. al. (2005), the lagged endogenous and predetermined moment conditions are:

$$[\Delta * \boldsymbol{\epsilon}_{it} y | i, j] = 0 \quad j \in \{1, \dots, \mathrm{T}-2\} and\ t \in T_\Delta * \qquad (3)$$

Stacking over t, we can re-write equation (2) as:

$$\Delta \boldsymbol{y_i} = \sum_{l=1}^{p} \Delta \boldsymbol{Y_i} \boldsymbol{A_l^T} + \Delta \mathrm{B} \boldsymbol{x_{i,t}} + \Delta \boldsymbol{\epsilon}_i \qquad (4)$$

Where ΔY_i, Δ $_i$, and $\Delta \boldsymbol{\epsilon}_i$ are ((T – 1 p) x m) matrices. Therefore, the stacked moment conditions for each i is:

$$[Q^T{}_i(\Delta E_i)] = 0 \qquad (5)$$

Where Q_i is the stacked form of q_i, and $q_{i,t} = (y_i, t^T = p - 1^T, y_{i,}, \dots, y_i, l^T)$ for $t \epsilon \{p + 1, \dots, T\}$.

The minimization problem based on the moment condition in equation (5) is:

$$\min \{\sum_{i=1}^{N} Z_T(\Delta \boldsymbol{Y_i} - (\Delta \mathrm{Y}_{i-1})\Phi_T \Lambda^{-1} \sum_{i=1}^{N} Z_T(\Delta \boldsymbol{Y_i} - (\Delta \mathrm{Y}_{i-1})\Phi)\} \qquad (6)$$

Where Φ gives the GMM (General Method of Moments) estimates of model (2) and based on step estimation of Binder et. al., (2005) Λ is the weighing matrix.

Using the Pvar approach, the stationarity of the key variables is first analysed using the Im-Pesaran-Shin (IPS) test which allows for unbalanced data where T is fixed, and N is large. The Im-Pesaran-Shin (IPS) test is suitable for unbalanced panels as N is large and T is fixed, which helps in establishing the stationarity of variables. This is critical, especially before conducting a PVAR model. Equally significant is the choice of appropriate lag length, since it affects the consistency of parameters' estimates, IRFs, and variance decompositions.

Results from the test show that the variables are stationary. It is also important to choose the right number of lags when using the PVar model. This is because estimates from a PVar regression whose lag length differs from the true lag length are inconsistent as well as the impulse response functions (IRFs) and variance decompositions derived from the estimated PVar (Braun and Mittnik, 1993). This implies that the orthogonalized IRFs (through the Choleski decomposition) may change depending on how the variables are ordered.

Impulse Response Functions (IRFs) are, inter alia, one of the critical instruments in time series analysis, in particular, the analysis of vector autoregressive (VAR) models. Those are the outgrowing characteristics describing how the endogenous variables in the system evolve over time after a one-shot change to one of the variables, while other changes are left unchanged. Put more simply, IRFs demonstrate the change being induced in each of the variables due to unit shock (rise) in any single variable over a set period. As stated by Lütkepohl (2005), the basic assumptions (IRFs) are important since they assist in the exploration of dynamic features in VAR models by demonstrating how shocks proliferate within the structure. They assist scholars in determining the initial and long-term ramifications of the shocks with respect to the endogenous variables of the system. As per Hamilton (1994), IRFs help in ascertaining causal relations through the clear illustration of how individual shock of one exogenous variable affects other variables of the system at particular periods.

Cholesky decomposition allows a symmetric positive definite matrix to be factored into a lower triangular matrix and its transpose. In econometrics, it is commonly employed to orthogonalize shocks in VAR models. It assumes that structural shocks can be defined by writing out the shocks, enabling the achievement of orthogonalization through an explanation of the residual covariance structure using Cholesky decomposition. As Lütkepohl (2005) explains, in the context of VAR models, rather than stating that there are additional residuals that are unobservable, Cholesky decomposition is used to find the appropriate ordering of the variables in a VAR system that will be required for formulating impulse response functions. However, as noted by Kilian and Lütkepohl (2017), the ordering of variables is important in determining which structural attributes are stripped from the data synthesis and which may have distinct interpretations of the structural impulse innovations when reversed and applied in different strategies.

The Cholesky decomposition is often used to identify structural shocks by imposing restrictions on the covariance matrix of residuals. This approach assumes that the covariance matrix of the reduced-form errors is symmetric, positive definite, and can be decomposed into a lower triangular matrix and its transpose. These properties ensure that the matrix can be uniquely broken down into components that allow sequential ordering of the variables to identify the impact of shocks. The Cholesky decomposition creates a very specific structure in the system by assuming causal orderings of the variables. More specifically, it restricts the contemporaneous associations among the variables to be lower triangular, thus allowing a variable to respond only to the shocks of the variables that have been ordered before it and not to affect them at the same time. This assumption also strengthens the orthogonality of the residuals, making it easier to define structural shocks. Lütkepohl (2005) and Kilian and Lütkepohl (2017) pointed out that it is Cholesky decomposition that assumes the causal hierarchy among the variables and that there is a certain predetermined pathway in which the shocks are spread.

The most important one is that the first variable in the ordering does not contemporaneously respond to any of the other variables, while the last variable in the ordering is expected to respond to shocks from all these variables. This type of identification is often referred to as a "short-run restriction," which has very far-reaching consequences where the underlined structure of the shocks influences the resulting impulse response functions (IRFs) and their subsequent variance decompositions. Hence, under Cholesky's restrictions different orderings lead to different interpretations of the shocks and their dynamic impacts on the variables.

IRFs plot the response of one endogenous variable in a model that has been subjected to a one-time shock in another variable, holding other shocks constant. These IRFs give further insight into the dynamic interaction among the endogenous variables of the system. Typical identification of the shocks in a PVAR model is done through orthogonalized IRFs, utilizing Cholesky decomposition so as to simplify the problem of the variance-covariance matrix of residuals. Essentially, Cholesky decomposition allows for the identification and the analysis of structural variances in a PVAR model. This orthogonalizes the shocks by retransforming the residuals into a new set of uncorrelated variables whose variances are unity. This helps in making the interpretation of IRFs easier because it ensures that the shocks that strike the system are independent from one another.

However, it should be emphasized that the outcome of the Cholesky decomposition is sensitive to the ordering of variables, irrespective of the stability of the system. The ordering determines the recursive structure through which the orthogonalization of shocks is conducted, and different orderings will result in different IRFs. The first variable in the ordering is assumed to be contemporaneously unaffected by any others, while the last variable is affected by shocks to all prior variables. For that reason, the relative positioning of the variables significantly influences the decomposition of shocks, and the resulting dynamic patterns captured through IRFs. That is, the ordering of the variables always matters, even when one refers to stable models, for which the system does not run the risk of explosive behavior.

This study employs the three model selection criteria by Andrews and Lu (2001) to determine the right number of lags for PVar models. Their study reveals that the preferred model should be the model that has the smallest MBIC, MAIC and MQIC. The results in Table 4.6 indicate that for lag 1, the criteria MBIC, MAIC, and MQIC all suggest that this is the best model fit compared to higher lags. The highly significant J p-value indicates that the model may have some issues with over-identifying restrictions that need to be considered. For lag 2, the J-statistic's p-value is not significant, indicating that the over-identifying restrictions are acceptable. However, MBIC, MAIC, and MQIC values are higher than those for lag 1, suggesting that lag 1 is a better fit. For lag 3, the J-statistics' p-value is also not significant, indicating that the over-identifying restrictions are acceptable. However, the MBIC, MAIC, and MQIC values are higher than those for lag 1, again suggesting that lag 1 is a better fit.

Based on the selection criteria (MBIC, MAIC, and MQIC), lag 1 appears to be the most appropriate choice for the panel VAR model. It provides the lowest values for these criteria, indicating a better fit compared to higher lags. The significant J-statistic p-value for lag 1 suggests potential issues with over-identifying restrictions, which should be examined further. However, the overall evidence points to lag 1 as the optimal lag length for this panel VAR model, balancing model fit and complexity.

Table 4.6: Results from panel Var Lag Order Selection

lag	CD	J	J pvalue	MBIC	MAIC	MQIC
1	- 0.8769	49.4591	0.1740	-45.132*	- 6.4591*	- 25.890*
2	- 0.9015	11.9569	0.1531	- 34.437	-4.0430	-19.289
3	- 0.8833	2.7098	0.6074	- 25.487	-5.2901	-12.913

For each criterion, the preferred value is marked with a *****

Certain assumptions underline banks credit ratings reaction to NPLs shocks. One of these is information lag. Credit rating agencies update their ratings based on financial information that becomes available periodically, often quarterly or annually. Hence, there is a natural delay in the reflection of recent financial performance, such as an increase in NPLs, in credit ratings. The major economic reasoning behind this assumption is that financial statements and other relevant data are released on a quarterly or annual basis, causing a lag in the availability of updated information. Rating agencies rely on audited financial statements, which may take time to produce and verify. According to Cantor and Packer (1997), rating agencies tend to smooth ratings change over time to avoid frequent reversals and provide stability. This smoothing behavior can result in delayed reactions to new information such as increases in NPLs.

The second assumption is that rating agencies follow a thorough and methodical process for updating ratings, which includes extensive analysis and review. This process can take several months. The reasoning behind this is that the comprehensive nature of the credit rating process, which includes qualitative and quantitative assessments, meetings with bank management, and internal review procedures, necessitates a time lag. Ratings are not adjusted instantaneously but are based on observed trends and confirmed data. A study by Jorion, Liu, and Shi (2005) found that rating agencies often lag behind market indicators in adjusting ratings. This lag is attributed to the need for thorough analysis and the availability of audited financial information.

In addition, it is also assumed that rating agencies may allow a period for market stabilization to see if the increase in NPLs is temporary or part of a more sustained trend. This is because temporary shocks or short-term increases in NPLs may not warrant an immediate rating change if the agency expects the bank to manage the issue effectively. Agencies might wait to see if the bank's management can stabilize and mitigate the rise in NPLs. Lastly, banks report NPLs and other financial metrics to regulators and the public with a certain delay. There is often a lag between the occurrence of financial events and their reporting due to the regulatory schedule, internal data consolidation, and auditing processes. Bannier and Hirsch (2010) discuss how the credit rating process involves extensive data analysis, meetings with bank executives, and consideration of market conditions, all contributing to the delay in rating adjustments. Ferri, Liu, and Stiglitz (1999) highlight that markets often react more swiftly to changes in NPLs compared to rating agencies, which take a more cautious approach to avoid overreacting to temporary market conditions.

In summary, the assumption that bank credit ratings react to NPL shocks with a delay of one year is well-supported by the need for comprehensive data analysis, regulatory reporting lags, and the desire for rating stability. These assumptions are corroborated by empirical findings in the literature (Cantor and Packer, 1997; Ferri, Liu, and Stiglitz, 1999; Ferri, Liu, and Stiglitz, 1999; Jorion, Liu, and Shi, 2005; Bannier and Hirsch, 2010) which highlight the methodical and cautious approach rating agencies take in updating their assessments, thereby explaining the delayed response to changes in NPLs.

4.4.1 Granger Causality Test

The Granger Causality helps in determining whether one time period is useful in determining another time period. That is, it helps in achieving better forecast of an expected effect because it can measure whether previous values of a variable can be used in predicting its future values. A Variable (Y) is said to granger cause another variable (X) if the future values of variable X which is influenced by the past values of variable X as well as the past values of variable Y, are more significant than when only the past values of variable X are used to predict variable Y. Hence, for this study, the Granger Causality test will help to provide a better insight into the estimation results gotten from the PVar regression thereby identifying whether NPLs granger causes banks credit ratings or Banks credit ratings granger causes NPLs.

4.5 Empirical Results

Table 4.7 reports the regression result from the PVar model specified in equation (6). It reports on the relationship that exists between the variables of interest and shows the effect of the exogenous variables on the variables of interest.

Table 4.7: Results of the PVAR Model Using Bank Credit Ratings and NPLs as Endogenous Variables

Variables	Bank Credit Rating$_{(t-1)}$	NPLs$_{(t-1)}$	ROE	LLP	Bank Size	CAR	LIR	GDP
Bank Credit Rating$_{(t-1)}$	0.369*** (0.070)	-0.13*** (0.049)	0.02** (0.025)	-0.05*** (0.018)	0.124** (0.051)	0.024** (0.030)	-0.793* (0.03)	3.643** (1.89)
NPLs$_{(t-1)}$	-0.130** (0.051)	0.929*** (0.081)	-0.06** (0.026)	0.025*** (0.009)	-0.03** (0.047)	0.055 (0.033)	0.075** (0.212)	-0.04** (0.047)

Note: The PVAR model is estimated by GMM. Reported numbers show the coefficients of the column variables. That is, they show the response of the row variables to an impulse in the column variables. Coefficients asterisked are significant, where ***, **and * indicates significance at 1%, 5% and 10% level, respectively. The values in the bracket are the standard errors from the regression.

Using Bank Credit Ratings as an endogenous variable, results from table 4.7 and appendix 4.8.1 seem to infer that, changes in Banks Credit Ratings and NPLs in year t, have an impact on Banks Credit Ratings in year t+1 at 1% level of significance. The results show that an increase in the current credit rating grade of a bank will lead to an increase in the bank's credit rating grade in the next year. It also shows that an increase in a bank's current NPLs will lead to a downgrade in the bank's credit rating in the next year. From the results, it is observed that ROE, LLP, Bank Size, CAR and GDP all have a significant effect on Bank credit ratings at 5%, 1%, 5%, 5%, 10% and 5% respectively. The result shows that an increase in a bank's ROE, Bank Size, CAR and GDP will lead to an upgrade in the bank's credit rating while an increase in LLP and LIR will lead to a downgrade in the bank's credit ratings. These results are in line with the results by Bissoondoyal-Bheenick and Treepongkaruna (2011), Caporale et. al. (2012), Chen (2012), Hassan and Barrell (2013), and Balgova et. at. (2016).

On the other hand, table 4.7 and appendix 4.8.1 provide results also using NPLs as an endogenous variable. The results answer the main question of this study; Do banks credit ratings also impact NPLs? The results reveal that not only do NPLs affect banks credit ratings, but banks credit ratings also affect NPLs. They show that changes in NPLs and Banks Credit Ratings in year t, have an impact on NPLs in year t+1 at 5% and 1% level of significance respectively. It reveals that a downgrade in a bank's current credit rating will lead to a significant increase in the bank's NPLs in year t+1. This result answers the main question of this study and contributes to the existing literature by providing empirical evidence that shows that a two-way relationship exists between Banks Credit Ratings and Non-Performing Loans.

To further provide evidence that supports the result presented in table 4.7 and to identify the direction of causality between Banks credit ratings and NPLs, the results of the granger causality test are presented in table 4.8 and appendix 4.8.2. The results show the presence of a bidirectional granger causality between Bank credit ratings and NPLs. Hence, the evidence from the result proves that past values of NPLs granger causes bank credit ratings while past values of banks credit ratings also granger causes NPLs.

Table 4.8: Results from the Granger Causality Test

Equation/Excluded	Chi2	df	Prob>chi2
NPLs			
Credit Ratings	6.539	1	0.011
All	6.539	1	0.011
Credit Ratings			
NPLs	7.666	1	0.006
All	7.666	1	0.006

After confirming the presence of a bidirectional granger causality between banks credit ratings and NPLs, this study uses the implied forecast error variance decompositions (FEVD) and the orthogonalized Impulse Response Function (IRF) to examine the response of bank credit ratings to an impulse NPLs and vice versa. The FEVD and IRF are important in understanding the dynamic interactions in a PVar model. The FEVD dissects the contribution of each shock to the forecast error variance of a variable over different horizons. Essentially, FEVD quantifies the extent to which each structural shock contributes to the uncertainty in the forecast of a variable at future time points. It also shows how the influence of different shocks evolves over time. It is important to state that the FEVD are more sensitive to the ordering of the variables even in a stable system. This is because unlike IRFs, FEVD are directly influenced by the order of variables because the Cholesky decomposition affects the contribution of each variable to the forecast errors. Overall, the FEVD provides valuable insights to researchers by identifying the relative importance of each shock in explaining the fluctuations of a variable over time (Canova and Ciccarelli, 2013; Abrigo et. Al., 2016).

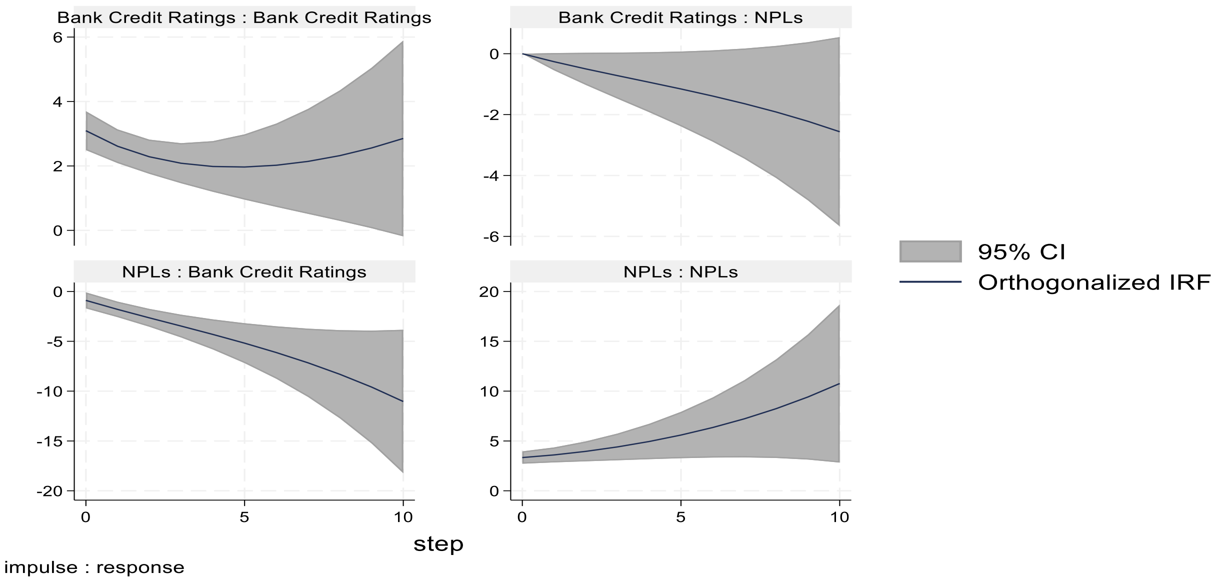
The IRFs (as seen in Figure 4.2), help to visualize the effects of a shock to banks credit ratings on NPLs as well as the effects of a shock to NPLs on banks credit ratings while the FEVDs (as seen in Table 4.9) provide information about the relative importance of each state disturbance in affecting the forecast error variance of all measurements of the key variables in the model.

The IRF for a period after the shock is given by:

$$\phi_i = \sum_{j=1}^{i} \phi_{i-j} A_{j,}$$

With $\phi_0 = I_k$ an $A_j = 0$ fo j > p, where p is the lag order of the model, and the number of endogenous variables is K. We also impose zero restrictions to the shock.

Figure 4.2: Graph Showing the Impulse Response Functions (IRF)



Note: Shaded areas refer to the 95% confidence interval

Table 4.9: Forecast-error variance decomposition (FEVD)

Response Variable	Impulse Variable (NPLs)	Impulse Variable (Bank Credit Ratings)
NPLs		
0	0	0
1	1	0
2	0.9971581	0.002842
3	0.9920973	0.0079027
4	0.9860888	0.0139112
5	0.9799405	0.0200595
6	0.9741259	0.0258741
7	0.9688913	0.0311087
8	0.9643357	0.0356644
9	0.9604677	0.0395323
10	0.957245	0.042755
Bank Credit Ratings		
0	0	0
1	0.076935	0.923065
2	0.1974391	0.8025609
3	0.3378861	0.6621139
4	0.4706646	0.5293354
5	0.5821481	0.4178518
6	0.6699686	0.3300314
7	0.7370272	0.2629728
8	0.7875763	0.2124237
9	0.8255521	0.1744479
10	0.8541148	0.1458852

The results in table 4.9 indicate that changes or shocks in banks' credit ratings account for 4.3% of the forecast error variance in future non-performing loans (NPLs). In other words, credit ratings have a modest but noticeable influence on future levels of NPLs. The finding that credit ratings explain 4.3% of the variation in future NPLs implies that credit ratings serve as a modest predictor of future loan performance. This indicates that while credit ratings are useful, they are not the dominant factor influencing NPLs. Banks should consider additional factors and more comprehensive risk assessments to predict and manage NPLs effectively.

On the other hand, the result shows that shocks in NPLs account for 14.6% of the forecast error variance in future credit ratings. It suggests that NPLs have a more substantial impact on the future credit ratings of banks compared to the reverse relationship. Therefore, the fact that NPLs explain 14.6% of the variation in future credit ratings highlights the significant role that loan performance plays in determining credit ratings. High levels of NPLs can negatively impact credit ratings, reflecting increased risk and financial instability. This underscores the importance for banks to maintain stringent credit risk management practices to keep NPLs at manageable levels and safeguard their credit ratings.

The FEVD results demonstrate a bi-directional relationship between banks' credit ratings and NPLs, with NPLs exerting a stronger influence on future credit ratings. These findings have significant implications for banks, regulators, investors, and researchers, emphasizing the importance of managing NPLs and considering credit ratings as part of a broader risk assessment framework. The FEVD results also show that when NPLs are ordered first, a shock to NPLs will immediately affect credit ratings. That is, changes in NPLs have a contemporaneous effect on banks' credit ratings when NPLs are ordered first. On the other hand, the result further shows that when banks' credit ratings are ordered second, a shock to banks credit ratings will not immediately affect NPLs. That is, a shock to banks credit ratings will not have an impact on NPLs in the current period. Instead, the effect on NPLs will only be observed in the future periods. Figure 4.2, which shows that a downward shock is observed in NPLs and Bank Credit Ratings, also gives a graphical presentation of the effect of these shocks when NPLs are ordered first.

To test the stability of our model, the stability test is applied. A stable model ensures that the forecast errors remain within a reasonable range thereby enhancing the accuracy of our predictions. It ensures that our model produces consistent and reliable forecasts over time, which is crucial for making informed decisions based on future expectations. Results from the stability check as seen in figure 4.3 show that our model is stable because the roots of the companion matrix are all inside the unit circle.

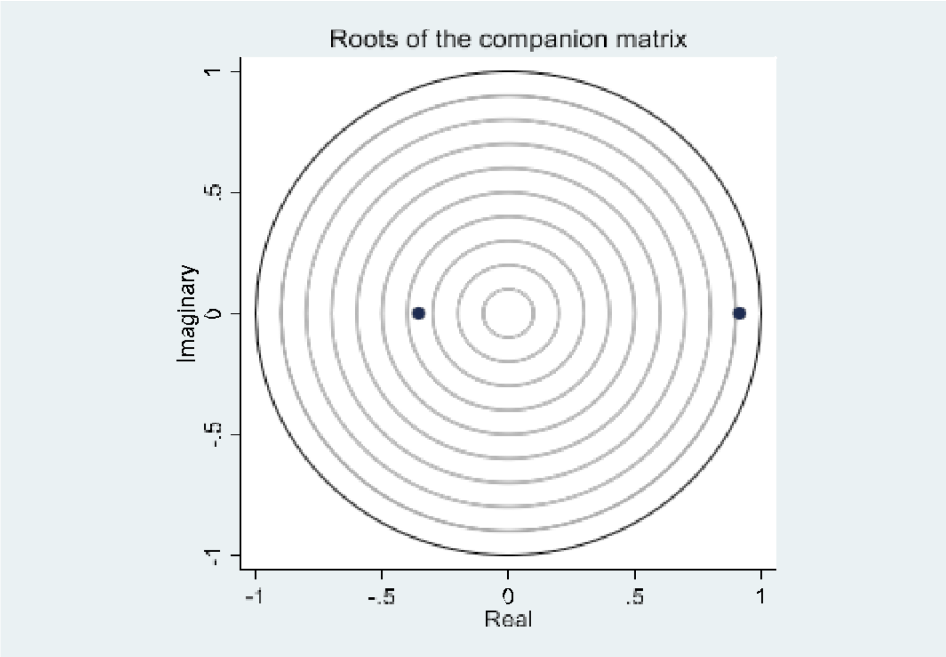


Figure 4.3: Graph Showing the Stability of the Estimates

The stability of a model is determined by the location of its roots in the complex plane within the companion matrix. The roots of the companion matrix, which are the eigenvalues of the matrix, determine the behavior of the system represented by the matrix. The rule is that for a stable system, all roots must lie inside the unit circle and if any root lies outside the unit circle, the system is considered unstable.

In a Roots of companion matrix for stability check, the vertical axis represents imaginary while the horizontal axis represents real in a dynamic system. In figure 4.3, the points within the circle meet at the intersection of imaginary and real axes. The graph shows that our companion matrix has all its roots inside the unit circle. Therefore, the predictions of our overtime forecast are consistent and reliable.

4.6 Robustness Checks

To check the sensitivity of our results, we carry out a robustness check by changing the order of the variables in our PVar model. This process helps to ensure that our conclusions are not unduly influenced by the ordering of the variables. By systematically varying the order of our variables, our study provides a more comprehensive and reliable analysis of the dynamic relationship in our model. Results from our Pvar estimations when the variable ordering is inverted as seen in appendix 4.8.3 show that changes in NPLs and Banks Credit Ratings in year t, have an impact on NPLs in year t+1 at 1% and 5% level of significance respectively. It reveals that a downgrade in a bank's current credit rating will lead to a significant increase in the bank's NPLs in year t+1. On the other hand, the results also show that changes in Banks Credit Ratings and NPLs in Year t, have an impact on Banks Credit Ratings in year t+1 at 1% level of significance. The results show that an increase in a bank's current NPLs will lead to a downgrade in the bank's credit rating in the next year.

To identify the direction of causality between Banks credit ratings and NPLs when the ordering of our variables is inverted, the granger causality test is applied. The results of the granger causality test as seen in appendix 4.8.4 show the presence of a bidirectional granger causality between Bank credit ratings and NPLs. These results are in line with our main findings in appendices 4.8.1 and 4.8.2.

To truly identify whether the results in our main findings are sensitive to the ordering of the variables, this study further applies the implied forecast error variance decompositions (FEVD) and the orthogonalized Impulse Response Function (IRF) to examine the response of bank credit ratings to an impulse NPLs and vice-versa when the variable ordering is inverted. The results of the IRFs and FEVD as seen in figure 4.4 and table 4.10 respectively help to visualize the effects of a shock to banks credit ratings on NPLs as well as the effects of a shock to NPLs on banks credit ratings when the ordering of the variables is inverted.

Figure 4.4: Graph Showing the Impulse Response Functions (IRF) when the Variable ordering is Inverted

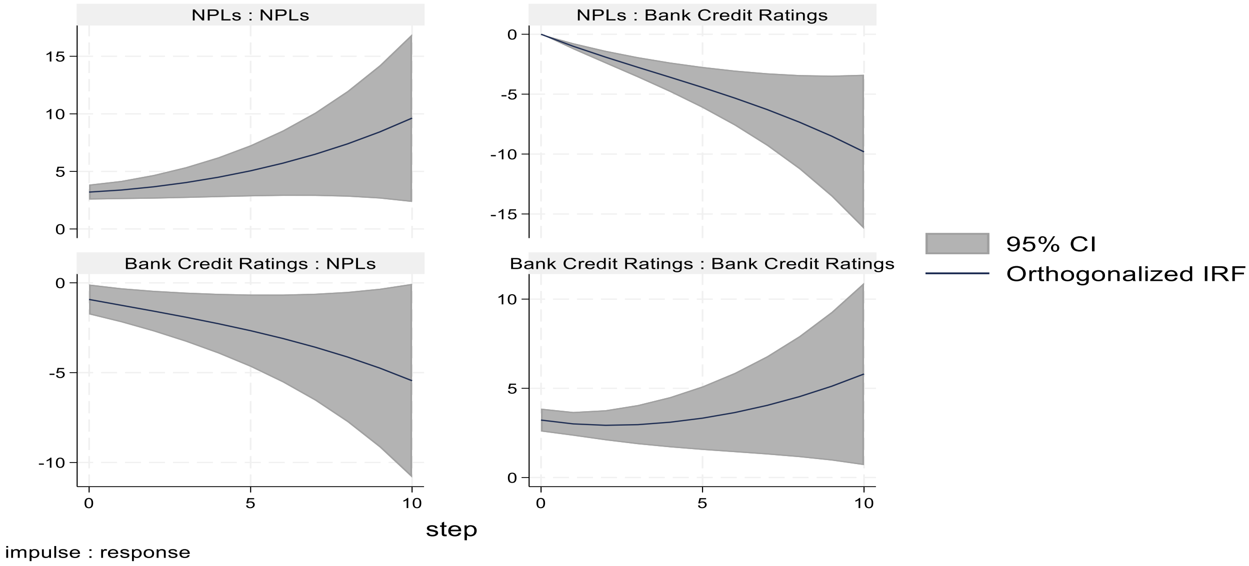


Table 4.10: Forecast-error variance decomposition (FEVD) when the Variable Ordering is Inverted

Response Variable		Impulse Variable (Bank Credit Ratings)	Impulse Variable (NPLs)
Bank Credit Ratings			
	0	0	0
	1	1	0
	2	0.9506718	0.0493282
	3	0.8576564	0.1423437
	4	0.7502231	0.2497769
	5	0.6486754	0.3513246
	6	0.5619054	0.4380946
	7	0.4915393	0.5084607
	8	0.435978	0.564022
	9	0.3926799	0.6073202
	10	0.3591446	0.6408554
NPLs			
	0	0	0
	1	0.076935	0.923065
	2	0.1001532	0.8998469
	3	0.1223848	0.8776152
	4	0.1427611	0.8572389
	5	0.1608483	0.8391517
	6	0.1765128	0.8234872
	7	0.1898152	0.8101848
	8	0.2009318	0.7990682
	9	0.2100986	0.7899014
	10	0.2175732	0.7824268

The results show that when the ordering of variables is inverted, the response of NPLs to a shock in banks credit ratings changes. That is, they show that when banks credit ratings are ordered first, a shock to banks credit ratings will immediately have an effect on NPLs in the current period. The results also show that when the ordering of the variables is inverted, the response of banks credit ratings to a shock in NPLs changes. That is, they show that when banks' credit ratings are ordered first, a shock to NPLs will not have an immediate effect on banks credit ratings in the current period. Instead, the effect on banks credit ratings will only be observed in future periods.

These results provide evidence in support of the restrictions implied by the Cholesky decomposition on the contemporaneous relationship between variables. They show that changing the ordering of the variables shifts the direction of the causality implied by the ordering.

4.7 Conclusion

The purpose of this study was to investigate the relationship between bank credit ratings and NPLs but more specifically, to investigate whether a two-way relationship exists between bank credit ratings and NPLs. This study has been able to achieve this. The results from this study contribute to the existing literature by showing that a two-way relationship exists between NPLs and banks credit ratings. The results reveal that NPLs have an impact on current and future bank credit ratings while bank credit ratings also have an impact on current and future non-performing loans. The results show that not only do NPLs affect bank credit ratings (as seen in past literature), but bank credit ratings also affect NPLs. These results provide empirical evidence that backs up the theoretical argument by Boumparis et. at., (2019) where he suggested that a downgrade in sovereign credit ratings might lead to a downgrade in banks credit ratings which might trigger an increase in banks NPLs.

In conclusion and based on the existing results from this study, it is paramount that policy makers take into consideration the effect banks credit ratings have on NPLs when forming policies that address the high rate of NPLs in the banking sector. It is also important that attention is given to both banks' loan performance and banks' credit ratings as one has an impact on the other and an unfavourable change in either of them, if not properly managed, can have an impact on the overall stability of the bank.

4.8 Appendix

4.8.1 Pvar Model Estimation

Panel vector autoregresssion

GMM Estimation

Final GMM Criterion Q(b) = .107
Initial weight matrix: Identity
GMM weight matrix: Robust

No. of obs = 1292
No. of panels = 140
Ave. no. of T = 9.229

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
NPLs						
NPLs L1.	.9285194	.0815135	11.39	0.000	.768756	1.088283
Bcr L1.	-.1303329	.0509673	-2.56	0.011	-.230227	-.0304389
ROE	-.0621452	.0263344	-2.36	0.018	-.1137597	-.0105307
LoanLossProvision	.024688	.0087647	2.82	0.005	.0075094	.0418665
Size	-.0285828	.0468184	0.61	0.042	-.0631795	.1203452
lir	.0757235	.212278	0.36	0.048	-.3403337	.4917807
GDP	-.0390687	1.101333	0.04	0.042	-2.119504	2.197641
Car	.0551731	.033094	1.67	0.095	-.0096899	.1200361
Bcr						
NPLs L1.	-.1369882	.0494752	2.77	0.006	-.400185	-.033957
Bcr L1.	.3691168	.070168	-5.26	0.000	.2506643	.623159
ROE	.0220361	.0250075	0.88	0.018	-.0269777	.07105
LoanLossProvision	-.0503271	.0177979	-2.83	0.005	-.0852102	-.0154439
Size	.1241261	.0510963	2.43	0.015	.0239792	.224273
lir	-.7931478	.3584483	-2.21	0.057	-1.495694	-.0906019
GDP	3.642635	1.895545	-1.92	0.055	-7.357836	.0725657
Car	.0247163	.0302919	0.82	0.015	-.0346548	.0840874

4.8.2 Granger-Causality Test

panel VAR-Granger causality Wald test
Ho: Excluded variable does not Granger-cause Equation variable
Ha: Excluded variable Granger-causes Equation variable

Equation \ Excluded		chi2	df	Prob > chi2
NPLs				
	Bcr	6.539	1	0.011
	ALL	6.539	1	0.011
Bcr				
	NPLs	7.666	1	0.006
	ALL	7.666	1	0.006

4.8.3 Pvar Model Estimation when the Variable ordering is Inverted

Panel vector autoregresssion

GMM Estimation

Final GMM Criterion Q(b) = .107
Initial weight matrix: Identity
GMM weight matrix: Robust

No. of obs = 1292
No. of panels = 140
Ave. no. of T = 9.229

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
Bcr						
Bcr L1.	.3691168	.070168	-5.26	0.000	.2506643	.623159
NPLs L1.	-.1369882	.0494752	2.77	0.006	-.400185	-.033957
ROE	.0220361	.0250075	0.88	0.018	-.0269777	.07105
LoanLossProvision	-.0503271	.0177979	-2.83	0.005	-.0852102	-.0154439
Size	.1241261	.0510963	2.43	0.015	.0239792	.224273
lir	-.7931478	.3584483	-2.21	0.057	-1.495694	-.0906019
GDP	3.642635	1.895545	-1.92	0.055	-7.357836	.0725657
Car	.0247163	.0302919	0.82	0.015	-.0346548	.0840874
NPLs						
Bcr L1.	-.1303329	.0509673	-2.56	0.011	-.230227	-.0304389
NPLs L1.	.9285194	.0815135	11.39	0.000	.768756	1.088283
ROE	-.0621452	.0263344	-2.36	0.018	-.1137597	-.0105307
LoanLossProvision	.024688	.0087647	2.82	0.005	.0075094	.0418665
Size	-.0285828	.0468184	0.61	0.042	-.0631795	.1203452
lir	.0757235	.212278	0.36	0.048	-.3403337	.4917807
GDP	-.0390687	1.101333	0.04	0.042	-2.119504	2.197641
Car	.0551731	.033094	1.67	0.095	-.0096899	.1200361

4.8.4 Granger-Causality Test when the Variable ordering is Inverted

```
panel VAR-Granger causality Wald test
    Ho: Excluded variable does not Granger-cause Equation variable
    Ha: Excluded variable Granger-causes Equation variable
```

Equation \ Excluded		chi2	df	Prob > chi2
Bcr				
	NPLs	7.666	1	0.006
	ALL	7.666	1	0.006
NPLs				
	Bcr	6.539	1	0.011
	ALL	6.539	1	0.011

Chapter 5

Concluding Remarks

Non-performing loans (NPLs) have been seen to have a huge impact on the strength and financial health of the banking industry. Consistent high rate of NPLs does not only threaten the banking industry. It also threatens the economy and the growth of potentially profitable businesses by significantly limiting their access to enough credit facilities as a result of the banks' huge losses due to high rates of NPLs. Therefore, in order to ensure the strength, growth and stability of the banking industry as well as the overall economy, it is important that the factors that influence NPLs are investigated. This thesis focused on banking competition as being one of those factors. This thesis comprised of three independent but related empirical essays that examine the effect of banking competition on NPLs at the country-level and at the bank-level. It also investigated the relationship between NPLs and banks' credit ratings.

The first essay in this thesis focused on the effect competition in the banking industry has on NPLs at the country level. Having tested both the competition-fragility and the competition-stability hypotheses, the results showed a non-linear relationship exists between banking competition and NPLs. The results revealed that there is an optimal level of competition in the banking industry that allows predicted NPLs to be at their minimum, hence, improving the financial strength of banks. It is therefore important that regulatory authorities in charge of banking competition policies take into consideration the optimal level of banking competition that allows NPLs to be at their minimum. This includes ensuring that the competition policies made and implemented allow for a conducive environment that is not too competitive and is also not too hostile to competition in the banking industry.

The second essay investigated the same relationship but at the bank level. It also controlled for the country's level of development in which the banks operate. This allowed us to properly examine whether the level of competition in which the banks operate has an impact on the effect we see in the first part of the thesis. The results showed that a non-linear relationship still exists for low developed and medium developed countries while highly developed countries tend to respond differently to banking competition. The results revealed that for highly developed countries, a banking market that is not so competitive tends to improve banks' loan performance in these countries. The result from this chapter will aid policy makers in making more informed decisions regarding banking competition. This includes understanding that it is important to take into consideration the level of development of the country in which they intend to implement certain banking competition policies.

The last essay focused on banks' credit rating and their relationship with NPLs. We build on existing literature that reveals that NPLs impacts banks' credit ratings. However, this thesis adds to the existing literature by arguing that NPLs also affect banks' credit ratings. We argued that a two-way relationship exists between banks' credit ratings and NPLs. The empirical results revealed that, in as much as NPLs affect banks' credit ratings, banks' credit ratings also affect NPLs through the lending channels. This implies that in addressing the issue of future high NPLs, it is important that the authorities at the bank level take into consideration the effect the current credit ratings might have on future NPLs.

Notwithstanding the strengths of these, certain limitations are worth noting. In the first and second parts of this thesis, we measure banking competition using the Lerner index due to data availability. I believe future research could include other measurements of banking competition such as the Boone indicator and H-statistics. In the final part of this thesis that focuses on only S&P credit ratings on banks due to data availability, I believe future research could include ratings from other rating agencies. Finally, future research may consider examining the issue of bias by CRAs in determining banks credit ratings and how this may vary across banks and countries based on the bank size and the country's level of development respectively.

Bibliography

Abrigo, M.R. and Love, I., 2016. Estimation of panel vector autoregression in Stata. *The Stata Journal*, 16(3), pp.778–804.

Abro, Q.M.M., 2012. *Advanced econometrics*. Pearson Education, India.

Adelino, M. and Ferreira, M.A., 2016. Bank ratings and lending supply: Evidence from sovereign downgrades. *The Review of Financial Studies*, 29(7), pp.1709–1746.

Adjei-Frimpong, K., Gan, C. and Hu, B., 2016. Competition in the banking industry: Empirical evidence from Ghana. *Journal of Banking Regulation*, 17(3), pp.159–175.

Ahmad, F. and Bashir, T., 2013. Explanatory power of macroeconomic variables as determinants of non-performing loans: Evidence from Pakistan. *World Applied Sciences Journal*, 22(2), pp.243–255.

Ahmad, N.H. and Ariff, M., 2007. Multi-country study of bank credit risk determinants. *International Journal of Banking and Finance*, 5(1), pp.135–152.

Ahmed, A.S., Takeda, C. and Thomas, S., 1999. Bank loan loss provisions: A reexamination of capital management, earnings management and signaling effects. *Journal of Accounting and Economics*, 28(1), pp.1–25.

Aiello, F. and Ricotta, F., 2014. Firm heterogeneity in productivity across Europe. What explains what? Presented at the 54th Congress of the European Regional Science Association, St. Petersburg, Russia.

Aiello, F. and Ricotta, F., 2016. Firm heterogeneity in productivity across Europe: Evidence from multilevel models. *Economics of Innovation and New Technology*, 25(1), pp.57–89.

Akhigbe, A. and Madura, J., 2001. Intra-industry effects of bank stock prices on bank holding company returns. *Journal of Banking & Finance*, 25(2), pp.311–330.

Alhadab, M. and Alsahawneh, S., 2016. Loan loss provision and the profitability of commercial banks: Evidence from Jordan. *International Journal of Business and Management*, 11(12), pp.106–116.

Allen, F. and Gale, D., 2004. Competition and financial stability. *Journal of Money, Credit and Banking*, 36(3), pp.453–480.

Allen, F., Carletti, E. and Gu, X., 2019. The roles of banks in financial systems. In: A.N. Berger, P. Molyneux and J.O. Wilson, eds., *The Oxford handbook of banking*. 3rd ed. Oxford: Oxford University Press, pp.37–64.

Alsakka, R. and Ap Gwilym, O., 2013. The impact of sovereign rating actions on bank ratings in emerging markets. *Journal of Banking & Finance*, 37(2), pp.563–577.

Alsakka, R., Ap Gwilym, O. and Vu, T.N., 2014. The sovereign-bank rating channel and rating agencies' downgrades during the European debt crisis. *Journal of International Money and Finance*, 49, pp.235–255.

Altman, E.I. and Saunders, A., 1998. Credit risk measurement: Developments over the last 20 years. *Journal of Banking & Finance*, 21(11–12), pp.1721–1742.

Amidu, M. and Wolfe, S., 2013. Does bank competition and diversification lead to greater stability? Evidence from emerging markets. *Review of Development Finance*, 3(3), pp.152–166.

Amoroso, L., Forrest, G. and Shepherd, W.M., 2012. The static supply curve. *Giornale degli Economisti e Annali di Economia*, 71(2/3), pp.201–230.

Anastasiou, D., Louri, H. and Tsionas, M., 2019. Nonperforming loans in the euro area: Are core–periphery banking markets fragmented? *International Journal of Finance & Economics*, 24(1), pp.97–112.

Andrews, D.W. and Lu, B., 2001. Consistent model and moment selection procedures for GMM estimation with application to dynamic panel data models. *Journal of Econometrics*, 101(1), pp.123–164.

Anjom, W. and Karim, A.M., 2016. Relationship between non-performing loans and macroeconomic factors with bank-specific factors: A case study on loan portfolios–SAARC countries perspective. *ELK Asia Pacific Journal of Finance and Risk Management*, 7(2), pp.1–29.

Aoki, K. and Nikolov, K., 2015. Bubbles, banks and financial stability. *Journal of Monetary Economics*, 74, pp.33–51.

Arellano, M., 1987. Computing robust standard errors for within-groups estimators. *Oxford Bulletin of Economics and Statistics*, 49(4), pp.431–434.

Arellano, M. and Bond, S., 1991. Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *The Review of Economic Studies*, 58(2), pp.277–297.

Arellano, M. and Bover, O., 1995. Another look at the instrumental variable estimation of error-components models. *Journal of Econometrics*, 68(1), pp.29–51.

Atoi, N.V., 2018. Non-performing loan and its effects on banking stability: Evidence from national and international licensed banks in Nigeria. *CBN Journal of Applied Statistics*, 9(2), pp.43–74.

Bahruddin, W.A. and Masih, M., 2018. Is the relation between lending interest rate and non-performing loans symmetric or asymmetric? Evidence from ARDL and NARDL. *Munich Personal RePEc Archive*. Available at: https://mpra.ub.uni-muenchen.de/91565/ [Accessed 23 November 2024].

Bain, J.S., 1959. *Industrial organization*. 2nd ed., 1967. New York: John Wiley & Sons, Inc.

Ballester Miquel, L. and González-Urteaga, A., 2017. How credit ratings affect sovereign credit risk: Cross-border evidence in Latin American emerging markets. *Emerging Markets Review*, 30, pp.200–214.

Balgova, M., Nies, M. and Plekhanov, A., 2016. The economic impact of reducing non-performing loans. *Munich Personal RePEc Archive*. Available at: https://elischolar.library.yale.edu/ypfs-documents/10870 [Accessed 23 November 2024].

BankScope, 2007. Bureau Van Dijk.

Barra, C. and Zotti, R., 2019. Bank performance, financial stability and market concentration: Evidence from cooperative and non-cooperative banks. *Annals of Public and Cooperative Economics*, 90(1), pp.103–139.

Barseghyan, L., 2010. Non-performing loans, prospective bailouts, and Japan's slowdown. *Journal of Monetary Economics*, 57(7), pp.873–890.

Bashir, U., Yu, Y., Hussain, M., Wang, X. and Ali, A., 2017. Do banking system transparency and competition affect nonperforming loans in the Chinese banking sector? *Applied Economics Letters*, 24(21), pp.1519–1525.

Baum, C.F., Schaffer, M.E. and Stillman, S., 2003. Instrumental variables and GMM: Estimation and testing. *Stata Journal*, 3(1), pp.1–31.

Beck, R., Jakubik, P. and Piloiu, A., 2015. Key determinants of non-performing loans: New evidence from a global sample. *Open Economies Review*, 26, pp.525–550.

Beck, T., De Jonghe, O. and Schepens, G., 2013. Bank competition and stability: Cross-country heterogeneity. *Journal of Financial Intermediation*, 22(2), pp.218–244.

Ben Ali, M.S., Intissar, T. and Zeitun, R., 2018. Banking concentration and financial stability: New evidence from developed and developing countries. *Eastern Economic Journal*, 44, pp.117–134.

Berger, A.N. and DeYoung, R., 1997. Problem loans and cost efficiency in commercial banks. *Journal of Banking & Finance*, 21(6), pp.849–870.

Berger, A.N., Klapper, L.F. and Turk-Ariss, R., 2017. Bank competition and financial stability. In: A.N. Berger, P. Molyneux and J.O.S. Wilson, eds. *Handbook of competition in banking and finance*. Cheltenham: Edward Elgar Publishing, pp.185–204.

Bikker, J.A., Spierdijk, L. and Finnie, P., 2007. The impact of market structure, contestability and institutional environment on banking competition. *Discussion Paper Series/Tjalling C. Koopmans Research Institute*, 7(29), pp.1–25.

Binder, M., Hsiao, C. and Pesaran, M.H., 2005. Estimation and inference in short panel vector autoregressions with unit roots and cointegration. *Econometric Theory*, 21(4), pp.795–837.

Bissoondoyal-Bheenick, E. and Treepongkaruna, S., 2011. An analysis of the determinants of bank ratings: Comparison across ratings agencies. *Australian Journal of Management*, 36(3), pp.405–424.

Bissoondoyal-Bheenick, E., 2005. An analysis of the determinants of sovereign ratings. *Global Finance Journal*, 15(3), pp.251–280.

Blaug, M., 2001. Is competition such a good thing? Static efficiency versus dynamic efficiency. *Review of Industrial Organization*, 19, pp.37–48.

Blinder, A.S., 2013. *After the music stopped: The financial crisis, the response, and the work ahead*. London: Penguin Classics.

Bolt, W. and Tieman, A.F., 2004. Banking competition, risk and regulation. *Scandinavian Journal of Economics*, 106(4), pp.783–804.

Bond, S.R., 2002. Dynamic panel data models: A guide to micro data methods and practice. *The Institute for Fiscal Studies*.

Boudriga, A., Taktak, N.B. and Jellouli, S., 2010. Bank-specific, business and institutional environment determinants of banks' nonperforming loans: Evidence from MENA countries. *Economic Research Forum, Working Paper*, 547, pp.1–28.

Boumparis, P., Milas, C. and Panagiotidis, T., 2019. Non-performing loans and sovereign credit ratings. *International Review of Financial Analysis*, 64, pp.301–314.

Boyd, J.H. and De Nicolo, G., 2005. The theory of bank risk-taking and competition revisited. *The Journal of Finance*, 60(3), pp.1329–1343.

Bozic, V. and Magazzino, C., 2013. Credit rating agencies: The importance of fundamentals in the assessment of sovereign ratings. *Economic Analysis and Policy*, 43(2), pp.157–176.

Braun, P.A. and Mittnik, S., 1993. Misspecifications in vector autoregressions and their effects on impulse responses and variance decompositions. *Journal of Econometrics*, 59(3), pp.319–341.

Brůha, J. and Kočenda, E., 2018. Financial stability in Europe: Banking and sovereign risk. *Journal of Financial Stability*, 36, pp.305–321.

Caminal, R. and Matutes, C., 2002. Market power and bank failures. *International Journal of Industrial Organisation*, 20(9), pp.1341–1361.

Canova, F. and Ciccarelli, M., 2013. Panel vector autoregressive models: A survey. *ECB Working Paper*, No. 1507.

Cantor, R. and Packer, F., 1995. Sovereign credit ratings. *Current Issues in Economics and Finance*, 1(3), pp.1–6.

Caporale, G.M., Matousek, R. and Stewart, C., 2012. Ratings assignments: Lessons from international banks. *Journal of International Money and Finance*, 31(6), pp.1593–1606.

Carruthers, B.G., 2013. From uncertainty toward risk: The case of credit ratings. *Socio-Comparisons*, 39(1), pp.129–152.

Casu, B. and Girardone, C., 2009. Testing the relationship between competition and efficiency in banking: A panel data analysis. *Economics Letters*, 105(1), pp.134–137.

Cetorelli, N., 2001. Competition among banks: Good or bad? *Economic Perspectives-Federal Reserve Bank of Chicago*, 25(2), pp.38–48.

Cetorelli, N., 2004. Real effects of bank competition. *Journal of Money, Credit and Banking*, 36(3), pp.543–558.

Čihák, M. & Schaeck, K., 2007. How well do aggregate bank ratios identify banking problems? *International Monetary Fund*.

Čihák, M. & Schaeck, K., 2010. How well do aggregate prudential ratios identify banking system problems? *Journal of Financial Stability*, 6(3), pp.130–144.

Claessens, S. & Laeven, L., 2004. What drives bank competition? Some international evidence. *Journal of Money, Credit and Banking*, 36(3), pp.563–583. https://doi.org/10.1353/mcb.2004.0044

Claessens, S., Law, A. & Wang, T., 2018. How do credit ratings affect bank lending under capital constraints? *Bank for International Settlements*. Available at: <www.bis.org>

Cogley, T. & Sargent, T.J., 2005. Drifts and volatilities: Monetary policies and outcomes in the post WWII US. *Review of Economic Dynamics*, 8(2), pp.262–302.

Comin, D. & Gertler, M., 2006. Medium-term business cycles. *American Economic Review*, 96(3), pp.523–551.

Cotugno, M., Stefanelli, V. & Torluccio, G., 2010. Bank intermediation models and portfolio default rates: What's the relation? In: *23rd Australasian Finance and Banking Conference*, August.

Cournot, A., 1838. *Recherches sur les principes mathématiques de la théorie des richesses*. Paris: Hachette. Euvres complètes de A.-A. Cournot, 8.

Cucinelli, D., 2015. The impact of non-performing loans on bank lending behavior: Evidence from the Italian banking sector. *Eurasian Journal of Business and Economics*, 8(16), pp.59–71.

Curak, M., Pepur, S. & Poposki, K., 2013. Determinants of non-performing loans–Evidence from Southeastern European banking systems. *Banks & Bank Systems*, 8(1), pp.45–53.

Curry, T.J., Fissel, G.S. & Hanweck, G.A., 2008. Is there cyclical bias in bank holding company risk ratings? *Journal of Banking & Finance*, 32(7), pp.1297–1309.

Dash, M.K. & Kabra, G., 2010. The determinants of non-performing assets in Indian commercial bank: An econometric study. *Middle Eastern Finance and Economics*, 7(2), pp.94–106.

De Bock, R. & Demyanets, M.A., 2012. Bank asset quality in emerging markets: Determinants and spillovers (No. 12-71). *International Monetary Fund*.

De Bruyckere, V., Gerhardt, M., Schepens, G. & Vander Vennet, R., 2013. Bank/sovereign risk spillovers in the European debt crisis. *Journal of Banking & Finance*, 37(12), pp.4793–4809.

De Nicoló, M.G. & Loukoianova, E., 2007. Bank ownership, market structure and risk. *International Monetary Fund*.

Delis, M.D., 2012. Bank competition, financial reform, and institutions: The importance of being developed. *Journal of Development Economics*, 97(2), pp.450–465.

Demirgüç-Kunt, A. & Maksimovic, V., 1998. Law, finance, and firm growth. *The Journal of Finance*, 53(6), pp.2107–2137.

Demirguc-Kunt, A. & Martínez Pería, M.S., 2010. A framework for analyzing competition in the banking sector: An application to the case of Jordan. *The World Bank*.

Di Patti, E.B. & Dell'Ariccia, G., 2000. Bank competition and firm creation. In: *Proceedings, Federal Reserve Bank of Chicago*, May, pp.132–161.

Douglas, J.L., 2008. The role of a banking system in nation-building. *Maine Law Review*, 60, pp.511–525.

Drigă, I. & Dura, C., 2014. The financial sector and the role of banks in economic development. *Economic Review*, 11(3), pp.525–551.

Eliasson, A.C., 2002. Sovereign credit ratings (No. 02-1). *Research Notes*.

Espinoza, R.A. & Prasad, A., 2010. Nonperforming loans in the GCC banking system and their macroeconomic effects (No. 10-224). *International Monetary Fund*.

European Commission, 2017. *Quarterly report on the Euro area (QREA), Vol. 16, No. 1*. Federal Reserve Bank of San Francisco.

Ferri, M.G., Liu, L. & Stiglitz, J.E., 1999. The procyclical role of rating agencies: Evidence from the East Asian crisis. *Economic Notes*, 28(3), pp.335–355.

Fernandez de Guevara, J., Maudos, J. & Perez, F., 2005. Market power in European banking sectors. *Journal of Financial Services Research*, 27(2), pp.109–137.

Fernández, R.O. & Garza-García, J.G., 2015. The relationship between bank competition and financial stability: A case study of the Mexican banking industry. *Ensayos Revista de Economía (Ensayos Journal of Economics)*, 34(1), pp.103–120.

Fofack, H.L., 2005. Nonperforming loans in Sub-Saharan Africa: Causal analysis and macroeconomic implications. *The World Bank*.

Francisco, A.C.F.G.J. & Valenzuela, M.P., 2019. Sovereign credit risk, financial fragility, and global factors. *Working Paper*.

Fungáčová, Z. & Weill, L., 2013. Does competition influence bank failures? *Economics of Transition*, 21(2), pp.301–322.

Gande, A. & Parsley, D.C., 2005. News spillovers in the sovereign debt market. *Journal of Financial Economics*, 75(3), pp.691–734.

García-Marco, T. & Robles-Fernández, M.D., 2008. Risk-taking behaviour and ownership in the banking industry: The Spanish evidence. *Journal of Economics and Business*, 60(4), pp.332–354.

Gelman, A. & Hill, J., 2006. *Data analysis using regression and multilevel/hierarchical models*. Cambridge University Press.

Ghosh, A., 2015. Banking-industry specific and regional economic determinants of non-performing loans: Evidence from US states. *Journal of Financial Stability*, 20, pp.93–104.

Ghosh, A., 2018. What drives banking industry competition in developing countries? *Journal of Economic Development*, 43(4), pp.1–23.

Giocoli, N., 2012. Who invented the Lerner index? Luigi Amoroso, the dominant firm model, and the measurement of market power. *Review of Industrial Organization*, 41, pp.181–191.

Goddard, J. & Wilson, J.O., 2009. Competition in banking: A disequilibrium approach. *Journal of Banking & Finance*, 33(12), pp.2282–2292.

Godlewski, C.J., 2004. Capital regulation and credit risk taking: Empirical evidence from banks in emerging market economies. *SSRN*.

Goldstein, H., 2011. *Multilevel statistical models*. Wiley.

Golub, G.H. & Van Loan, C.F., 2013. *Matrix computations* (4th ed.). Johns Hopkins University Press.

Gray, S., Mirkovic, A. & Ragunathan, V., 2006. The determinants of credit ratings: Australian evidence. *Australian Journal of Management*, 31(2), pp.333–354.

Greene, W.H., 2012. *Econometric analysis* (7th ed.). Pearson Education.

Grunert, J., Norden, L. & Weber, M., 2005. The role of non-financial factors in internal credit ratings. *Journal of Banking & Finance*, 29(2), pp.509–531.

Gültekin-Karakaş, D., Hisarcıklılar, M. & Öztürk, H., 2011. Sovereign risk ratings: Biased toward developed countries? *Emerging Markets Finance and Trade*, 47(sup2), pp.69–87.

Hafeez, B., Li, X., Kabir, M.H. & Tripe, D., 2022. Measuring bank risk: Forward-looking z-score. *International Review of Financial Analysis*, 80, 102039.

Hamilton, J.D., 1994. *Time series analysis*. Princeton University Press.

Hamza, S.M., 2017. Impact of credit risk management on banks' performance: A case study in Pakistan banks. *European Journal of Business and Management*, 9(1), pp.57–64.

Harutiyansari, A.G., 2018. Pengaruh faktor internal bank terhadap non-performing loan dengan metode generalized method of moment. *Jurnal Manajemen Bisnis Indonesia (JMBI)*, 7(1), pp.27–36.

Hassan, I. & Wall, L.D., 2004. Determinants of the loan loss allowance: Some cross-country issues. *Journal of Banking & Finance*, 28(4), pp.615–620.

Hassan, O.A. & Barrell, R., 2013. Accounting for the determinants of banks' credit ratings. *Economics and Finance Working Series*. Available at: http://www.brunel.ac.uk/economics

Hausman, J.A., 1978. Specification tests in econometrics. *Econometrica: Journal of the Econometric Society*, 46(6), pp.1251–1271.

Herring, R.J., 1999. Credit risk and financial instability. *Oxford Review of Economic Policy*, 15(3), pp.63–79.

Hesse, H. & Čihák, M., 2007. Cooperative banks and financial stability. *IMF Working Paper*.

Hill, J., Brooks, R. & Faff, R., 2010. Variations in sovereign credit quality assessments across rating agencies. *Journal of Banking & Finance*, 34(6), pp.1327–1343.

Hite, G.L. & Warga, A., 1997. Detecting long-run relations in cointegrated systems. *Journal of Financial and Quantitative Analysis*, 32(4), pp.467–484.

Hoggarth, G., Reis, R. & Saporta, V., 2002. Costs of banking system instability: Some empirical evidence. *Journal of Banking & Finance*, 26(5), pp.825–855.

Holthausen, R.W. & Leftwich, R.W., 1986. The effect of bond rating agency announcements on bond and stock prices. *Journal of Finance*, 41(4), pp.1019–1034.

Hoshi, T., Kashyap, A. & Scharfstein, D., 1990. The role of banks in reducing the costs of financial distress in Japan. *Journal of Financial Economics*, 27(1), pp.67–88.

Hsiao, C., Appelbe, T.W. & Dineen, C.R., 1993. A general framework for panel data models with an application to Canadian customer-dialed long distance telephone service. *Journal of Econometrics*, 59(1–2), pp.63–86.

Hsiao, C., Mountain, D.C. & Illman, K.H., 1995. A Bayesian integration of end-use metering and conditional-demand analysis. *Journal of Business & Economic Statistics*, 13(3), pp.315–326.

Huizinga, H. & Laeven, L., 2008. International profit shifting within multinationals: A multi-country perspective. *Journal of Public Economics*, 92(5–6), pp.1164–1182.

Iwanicz-Drozdowska, M., Bongini, P., Smaga, P. & Witkowski, B., 2019. The role of banks in CESEE countries: Exploring non-standard determinants of economic growth. *Post-Communist Economies*, 31(3), pp.349–382.

Jaramillo, L. & Tejada, M., 2011. Sovereign credit ratings and spreads in emerging markets: Does investment grade matter? *International Monetary Fund*.

Jiménez, G., Lopez, J.A. & Saurina, J., 2013. How does competition affect bank risk-taking? *Journal of Financial Stability*, 9(2), pp.185–195.

Jimenez, G. & Saurina, J., 2006. Credit cycles, credit risk, and prudential regulation. *International Journal of Central Banking*, 2(2), pp.65–98.

Jovanovic, B. & Nyarko, Y., 1994. Learning by doing and the choice of technology. *Econometrica*, 62(6), pp.1293–1310.

Kashkari, N., 2016. Lessons from the crisis: Ending too big to fail. Remarks at the Brookings Institution, Washington, DC.

Kasman, S. & Kasman, A., 2015. Bank competition, concentration and financial stability in the Turkish banking industry. *Economic Systems*, 39(3), pp.502–517.

Kaufman, G.G., 2014. Too big to fail in banking: What does it mean? *Journal of Financial Stability*, 13, pp.214–223.

Keeley, M.C., 1990. Deposit insurance, risk, and market power in banking. *The American Economic Review*, 80(5), pp.1183–1200.

Khan, M.A., Siddique, A. & Sarwar, Z., 2020. Determinants of non-performing loans in the banking sector in developing states. *Asian Journal of Accounting Research*, 5(1), pp.135–145.

Khemraj, T. & Pasha, S., 2009. The determinants of non-performing loans: An econometric case study of Guyana. *MPRA Paper No. 53128*. Available at: https://mpra.ub.uni-muenchen.de/53128/

Kick, T. & Prieto, E., 2015. Bank risk and competition: Evidence from regional banking markets. *Review of Finance*, 19(3), pp.1185–1222.

Kilian, L. & Lütkepohl, H., 2017. *Structural vector autoregressive analysis*. Cambridge University Press.

King, R.G. & Levine, R., 1993. Finance and growth: Schumpeter might be right. *The Quarterly Journal of Economics*, 108(3), pp.717–737.

Klacek, J. & Vopravil, J., 2008. Total factor productivity in Czech manufacturing industry: KLEM framework. *Statistika*, 5, pp.414–428.

Kliger, D. & Sarig, O., 2000. The information value of bond ratings. *Journal of Finance*, 55(6), pp.2879–2902.

Klusak, P., Alsakka, R. & Ap Gwilym, O., 2017. Does the disclosure of unsolicited sovereign rating status affect bank ratings? *The British Accounting Review*, 49(2), pp.194–210.

Leadership, 2019. Banks and non-performing loans. *Leadership*. Available at: https://leadership.ng/2019/03/12/banks-and-non-performing-loans/ [Accessed 29 June 2019].

Leon, F., 2015. Measuring competition in banking: A critical review of methods. *HAL*.

Lerner, A.P., 1934. The concept of monopoly and the measurement of monopoly powers. *The Review of Economic Studies*, 1(3), pp.157–175.

Levine, R. & Zervos, S., 1998. Stock markets, banks, and economic growth. *American Economic Review*, 88(3), pp.537–558.

Levine, R., 1997. Financial development and economic growth: Views and agenda. *Journal of Economic Literature*, 35(2), pp.688–726.

Levine, R., Loayza, N. & Beck, T., 2000. Financial intermediation and growth: Causality and causes. *Journal of Monetary Economics*, 46(1), pp.31–77.

Lin, X. & Zhang, Y., 2009. Bank ownership reform and bank performance in China. *Journal of Banking & Finance*, 33(1), pp.20–29.

Liu, H., Molyneux, P. & Wilson, J.O., 2013. Competition and stability in European banking: A regional analysis. *The Manchester School*, 81(2), pp.176–201.

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), pp.1012–1027.

Love, I. & Martínez Pería, M.S., 2015. How bank competition affects firms' access to finance. *The World Bank Economic Review*, 29(3), pp.413–448.

Lowe, P., 2009. Competition policy and the economic crisis. *CPI Journal*, 5, pp.1–4.

Lu, W. & Whidbee, D.A., 2013. Bank structure and failure during the financial crisis. *Journal of Financial Economic Policy*, 5(3), pp.281–299.

Lütkepohl, H., 2005. *New introduction to multiple time series analysis* (Ch. 7). Springer-Verlag Berlin Heidelberg.

Maggi, B. & Guida, M., 2011. Modelling non-performing loans probability in the commercial banking system: Efficiency and effectiveness related to credit risk in Italy. *Empirical Economics*, 41(2), pp.269–291.

Makri, V., Tsagkanos, A. & Bellas, A., 2014. Determinants of non-performing loans: The case of Eurozone. *Panoeconomicus*, 61(2), pp.193–206.

Marcus, A.J., 1984. Deregulation and bank financial policy. *Journal of Banking & Finance*, 8(4), pp.557–565.

Martinez-Miera, D. & Repullo, R., 2010. Does competition reduce the risk of bank failure? *The Review of Financial Studies*, 23(10), pp.3638–3664.

Mazreku, I., Morina, F., Misiri, V., Spiteri, J.V. & Grima, S., 2018. Determinants of the level of non-performing loans in commercial banks of transition countries. *European Research Studies Journal*, 21(3), pp.3–13.

McNulty, P.J., 1967. A note on the history of perfect competition. *Journal of Political Economy*, 75(4), pp.395–399.

Mentari, S.H., 2017. Pengaruh CAR, LDR dan BOPO terhadap non-performing loan bank umum di Indonesia [Doctoral dissertation, STIE PERBANAS Surabaya].

Messai, A. S. & Jouini, F., 2013. Micro and macro determinants of non-performing loans. *International Journal of Economics and Financial Issues*, 3(4), pp.852–860.

Miller, S. M. & Noulas, A. G., 1996. The technical efficiency of large bank production. *Journal of Banking & Finance*, 20(3), pp.495–509.

Morrison, A. D., 2011. Systemic risks and the ‘too-big-to-fail’ problem. *Oxford Review of Economic Policy*, 27(3), pp.498–516.

Mulder, C. & Perrelli, R., 2001. Foreign currency credit ratings for emerging market economies. *IMF Working Paper No WP/01/191*.

Naudé, W., 2009. The financial crisis of 2008 and the developing countries. *United Nations University - World Institute for Development Economics Research*, No. 2009/01.

Ng’etich, J. C. & Wanjira, K. W., 2011. The effects of interest rate spread on the level of non-performing assets: A case of commercial banks in Kenya. *International Journal of Business and Public Management*, 1(1), pp.58–65.

Nkusu, M. M., 2011. Nonperforming loans and macrofinancial vulnerabilities in advanced economies. *International Monetary Fund*, No. 11-161.

Norden, L. & Weber, M., 2004. The comovement of credit default swap, bond and stock markets: An empirical analysis. *European Financial Management*, 10(1), pp.109–141.

Noman, A.H.M., Gee, C.S. & Isa, C.R., 2017. Does competition improve financial stability of the banking sector in ASEAN countries? An empirical analysis. *PloS one*, 12(5), p.0176546.

Okpala, G., 2019. The relationship between non-performing loans (NPLs) and level of competition in the banking industry: Evidence from panel data. *University of East Anglia* [Unpublished manuscript].

Orhangazi, Ö., 2015. Financial deregulation and the 2007–08 US financial crisis. In *The demise of finance-dominated capitalism*, pp.68–91. Edward Elgar Publishing.

Oshchepkov, A. Y. & Shirokanova, A., 2020. Multilevel modeling for economists: Why, when and how. *Higher School of Economics Research Paper No. WP BRP, 233.*

Ozili, P. K., 2018. Banking stability determinants in Africa. *International Journal of Managerial Finance*, 14(4), pp.464–476.

Ozili, P. K., 2019a. Determinants of banking stability in Nigeria. *CBN Bullion*, 43(2), pp.15–27.

Ozili, P. K., 2019b. non-performing loans and financial development: New evidence. *The Journal of Risk Finance*, 20(1), pp.59–81.

Panetta, F., Correa, R., Davies, M., Di Cesare, A., Marques, J. M., Nadal de Simone, F., Signoretti, F., Vespro, C., Vildo, S., Wieland, M. & Zaghini, A., 2011. The impact of sovereign credit risk on bank funding conditions. *MPRA Paper No. 32581*. Available at: https://mpra.ub.uni-muenchen.de/32581/.

Panzar, J. C. & Rosse, J. N., 1982. Structure, conduct, and comparative statistics. *Bell Telephone Laboratories*.

Pastory, D. & Mutaju, M., 2013. The influence of capital adequacy on asset quality position of banks in Tanzania. *International Journal of Economics and Finance*, 5(2), pp.179–194.

Petersen, M. A. & Rajan, R. G., 1995. The effect of credit market competition on lending relationships. *The Quarterly Journal of Economics*, 110(2), pp.407–443.

Pettigrew, T. F., 1996. *How to think like a social scientist*. HarperCollins College Division.

Poon, W. P. & Firth, M., 2005. Are unsolicited credit ratings lower? International evidence from bank ratings. *Journal of Business Finance & Accounting*, 32(9–10), pp.1741–1771.

Rajan, R. & Dhal, S. C., 2003. Non-performing loans and terms of credit of public sector banks in India: An empirical assessment. *Reserve Bank of India Occasional Papers*, 24(3), pp.81–121.

Rajan, R. & Zingales, L., 1998. Financial development and growth. *American Economic Review*, 88(3), pp.559–586.

Raudenbush, S. W. & Bryk, A. S., 2002. *Hierarchical linear models: Applications and data analysis methods*. Sage Publications.

Renda Gonzalez-Hermosillo, B., 1999. Developing indicators to provide early warnings of banking crises. *IMF Working Papers*, 36.

Repullo, R., 2004. Capital requirements, market power, and risk-taking in banking. *Journal of Financial Intermediation*, 13(2), pp.156–182.

Reusens, P. & Croux, C., 2017. Sovereign credit rating determinants: A comparison before and after the European debt crisis. *Journal of Banking & Finance*, 77, pp.108–121.

Riley, R. D., Lambert, P. C. & Abo-Zaid, G., 2010. Meta-analysis of individual participant data: Rationale, conduct, and reporting. *BMJ*, 340, c221.

Riyadi, S., Iqbal, M. & Lauren, N., 2015. Strategi pengelolaan non-performing loan bank umum yang go public. *Jurnal Manajemen Bisnis Indonesia*, 4(2), pp.115–130.

Robinson, J., 1969. *The economics of imperfect competition*. Springer.

Rokhim, R. & Susanto, A. P., 2011. The increase of foreign ownership and its impact on performance, competition & risk in Indonesian banking industry. *Competition & Risk in Indonesian Banking Industry*, pp.1–28.

Saba, I., Kouser, R. & Azeem, M., 2012. Determinants of non-performing loans: Case of US banking sector. *The Romanian Economic Journal*, 44(6), pp.125–136.

Saif-Alyousfi, A. Y., Saha, A. & Md-Rus, R., 2020. The impact of bank competition and concentration on bank risk-taking behavior and stability: Evidence from GCC countries. *The North American Journal of Economics and Finance*, 51, p.100867.

Salas, V. & Saurina, J., 2002. Credit risk in two institutional regimes: Spanish commercial and savings banks. *Journal of Financial Services Research*, 22(3), pp.203–224.

Sarno, L. & Zinna, G., 2019. Risky bank guarantees. *Bank of Italy, Economic Research and International Relations Area*, No. 1232.

Saurina Salas, J., Jimenez, G. & Lopez, J. A., 2007. How does competition impact bank risk-taking? *EFA 2007 Ljubljana Meetings Paper*, FRB of San Francisco Working Paper (No. 2007-23).

Schaeck, K. & Čihák, M., 2012. Banking competition and capital ratios. *European Financial Management*, 18(5), pp.836–866.

Schaeck, K., Čihák, M. & Wolfe, S., 2009. Are competitive banking systems more stable? *Journal of Money, Credit and Banking*, 41(4), pp.711–734.

Selma, M. A. & Jouini, F., 2013. Micro and macro determinants of non-performing loans. *International Journal of Economics and Financial Issues*, 3(4), pp.852–860.

Shaban, M. & James, G. A., 2018. The effects of ownership change on bank performance and risk exposure: Evidence from Indonesia. *Journal of Banking & Finance*, 88, pp.483–497.

Shingjerji, A., 2013. Impact of bank-specific variables on the nonperforming loans ratio. *European Scientific Journal*, 9(1), pp.289–305.

Sigmund, M. & Ferstl, R., 2021. Panel vector autoregression in R with the package SIMPRO. *ResearchGate*, pp.10–11.

Simkovic, M., 2013. Competition and crisis in mortgage securitization. *Indiana Law Journal*, 88, pp.213–262.

Škarica, B., 2014. Determinants of non-performing loans in Central and Eastern European countries. *Financial Theory and Practice*, 38(1), pp.37–59.

Smith, A., 1776. *An inquiry into the nature and causes of the wealth of nations*. R. H. Campbell & A. S. Skinner (eds.), Oxford: Oxford University Press.

Soedarmono, W., Machrouh, F. & Tarazi, A., 2013. Bank competition, crisis and risk taking: Evidence from emerging markets in Asia. *Journal of International Financial Markets, Institutions and Money*, 23, pp.196–221.

Staff W., 2019. Banking sector to face further increase in non-performing loan: Rusirupala Tennakoon. *News First*. Available at: https://www.newsfirst.lk/2019/06/28/banking-sector-to-face-further-increase-in-non-performing-loans-rusirupala-tennakoon/ [Accessed: 29 June 2019].

StataCorp, 2021. *Stata: Release 17*. College Station, TX: StataCorp LLC.

Stawasz-Grabowska, E., 2020. Sovereign credit rating determinants of the EU countries: The role of the euro area crisis and its legacy. *Entrepreneurial Business and Economics Review*, 8(2), pp.47–69.

Szarowska, I., 2018. Effect of macroeconomic determinants on non-performing loans in Central and Eastern European countries. *International Journal of Monetary Economics and Finance*, 11(1), pp.20–35.

Tanasković, S. & Jandrić, M., 2015. Macroeconomic and institutional determinants of non-performing loans. *Journal of Central Banking Theory and Practice*, 4(1), pp.47–62.

Tennant, D. F., Tracey, M. R. & King, D. W., 2020. Sovereign credit rating: Evidence of bias against poor countries. *The North American Journal of Economics and Finance*, 51, p.100877.

Trevino, L. & Thomas, S., 2000. Systematic differences in the determinants of foreign currency sovereign ratings by rating agency. *International Journal of Economics and Financial Issues*, 3(1), pp.852–860.

Uhde, A. & Heimeshoff, U., 2009. Consolidation in banking and financial stability in Europe: Empirical evidence. *Journal of Banking & Finance*, 33(7), pp.1299–1311.

Van Oort, F. G., Burger, M. J., Knoben, J. & Raspe, O., 2012. Multilevel approaches and the firm-agglomeration ambiguity in economic growth studies. *Journal of Economic Surveys*, 26(3), pp.468–491.

Vatansever, M. & Hepsen, A., 2013. Determining impacts on non-performing loan ratio in Turkey. *Journal of Finance and Investment Analysis*, 2(4), pp.119–129.

Verdict, S., 2019. Tanzania relaxes bank reserve requirements to boost lending. *Retail Banker International*. Available at: https://www.verdict.co.uk/retail-banker-international/news/tanzania-relaxes-bank-reserve-requirements-to-boost-lending/ [Accessed: 29 June 2019].

Vickers, J., 1995. Concepts of competition. *Oxford Economic Papers*, 47(1), pp.1–23.

Vives, X., 2001. Competition in the changing world of banking. *Oxford Review of Economic Policy*, 17(4), pp.535–547.

Vives, X., 2008. Innovation and competitive pressure. *The Journal of Industrial Economics*, 56(3), pp.419–469.

Williams, G., 2009. *WIDER discussion paper*.

Wooldridge, J.M., 2010. *Econometric analysis of cross section and panel data*. 2nd ed. Cambridge, MA: MIT Press.

World Bank, 2018. *World development indicators (WDI)*. World Bank Database.

World Bank, 2016. *Global financial development report on financial stability*. Available at: https://www.worldbank.org/en/publication/gfdr/gfdr-2016/background/financial-stability [Accessed: 29 June 2019].

Yalta, A. T. & Yalta, A. Y., 2018. Are credit rating agencies regionally biased? *Economic Systems*, 42(4), pp.682–694.

Yeh, T. L., 2010. Bank loan loss provision decisions: Empirical analysis of Taiwanese banks. *Journal of Financial Services Marketing*, 14(4), pp.278–289.

Yildiz, Ü. & Günsoy, B., 2017. Macroeconomic determinants of sovereign credit ratings: Panel data analysis. *International Journal of Business and Social Science*, 8(11), pp.118–125.

Yulianti, E., Aliamin, A. & Ibrahim, R., 2018. The effect of capital adequacy and bank size on non-performing loans in Indonesian public banks. *Journal of Accounting Research, Organization and Economics*, 1(2), pp.205–214.

Zaghdoudi, K., Hamdi, H., Dkhili, H. & Hakimi, A., 2016. Bank competition and risk appetite: Evidence from Tunisia. *Global Journal of Business Research*, 10(1), pp.85–93.

Zeng, S., 2012. Bank non-performing loans (NPLs): A dynamic model and analysis in China. *Modern Economy*, 3(01), pp.100–110.

Zhang, D., Cai, J., Liu, J. & Kutan, A. M., 2018. Real estate investments and financial stability: Evidence from regional commercial banks in China. *The European Journal of Finance*, 24(16), pp.1388–1408.