The Impact of Corruption on Commercial Banks' Credit Risk

Ezuldeen Alhadi Alshareef

Submitted to the
Institute of Graduate Studies and Research
in partial fulfillment of the requirements for the degree of

Doctor of Philosophy
in
Finance

Eastern Mediterranean University
September 2021
Gazimağusa, North Cyprus

Approval of the Institute of Graduate Studies and Research

Prof. Dr. Ali Hakan Ulusoy
Director

I certify that this thesis satisfies all the requirements as a thesis for the degree of Doctor of Philosophy in Finance.

Prof. Dr. Nesrin Özataç
Chair, Department of Banking and Finance

We certify that we have read this thesis and that in our opinion it is fully adequate in scope and quality as a thesis for the degree of Doctor of Philosophy in Finance.

Prof. Dr. Hatice Jenkins
Supervisor

Examining Committee

1. Prof. Dr. Hatice Doğukanlı
2. Prof. Dr. Mübeccel Banu Durukan Salı
3. Prof. Dr. Glenn Paul Jenkins
4. Prof. Dr. Hatice Jenkins
5. Assoc. Prof. Dr. Hasan Ulaş Altıok

ABSTRACT

This research explores the influence of country wide corruption on the commercial banks' credit risk. It applies the quantile regression (QR) estimation method for a panel data of 191 commercial banks from 18 MENAP nations, between the years 2011-2018. The research finding indicates that corruption significantly exacerbates the problem of bad loans of commercial banks. Furthermore, the QR results reveal that corruption does not affect all commercial banks at the same level. Commercial banks in higher quantiles (i.e. higher credit risk banks) appear to be affected more than the ones in lower quantiles (i.e. lower credit risk banks). Commercial banks with a high credit risk tend to be more vulnerable to corruption than commercial banks with low credit risk.

Keywords: corruption, MENAP countries, credit risk, quantile regression, commercial banks.

ÖZ

Bu araştırma, ülke çapındaki yolsuzluğun ticari bankaların kredi riski üzerindeki etkisini araştırmaktadır. 2011-2018 yılları arasında 18 MENAP ülkesinden 191 ticari bankanın panel verilerini kullanarak kantil regresyon tahmin yöntemini uygulamıştır. Araştırma bulguları, yolsuzluğun ticari bankaların sorunlu kredilerini önemli ölçüde artırdığını göstermektedir. Ayrıca, kantil regresyon sonuçları yolsuzluğun tüm ticari bankaları aynı düzeyde etkilemediğini ortaya koymaktadır. Daha yüksek kantillerdeki ticari bankalar, yani daha yüksek kredi riski taşıyan bankalar, düşük kantillerdekilerden, yani daha düşük kredi riskli bankalardan daha fazla etkilenmiş görünmektedir. Yüksek kredi riskine sahip ticari bankalar, düşük kredi riskine sahip ticari bankalara göre yolsuzluğa karşı daha savunmasız olma eğilimindedir.

Anahtar Kelimeler: yolsuzluk, MENAP ülkeleri, kredi riski, kantil regresyon, ticari bankalar.

DEDICATION

To all of

The memory of My late Parents,

My Wife and Children,

My Brothers and Sisters,

My Lovely Family in Libya

ACKNOWLEDGMENT

I would like to appreciate Allah Almighty for providing me the motivation to finish this project.

Then, I would like to take this time to thank everyone who have supported me in many ways over the course of my PhD education and research. First of all, I would like extend my heartfelt appreciation to my advisor, Prof. Dr. Hatice Jenkins, for her unwavering encouragement of my Ph.D work and empirical research, as well as her courage, inspiration, and vast expertise. Her advice was invaluable in the study and writing of this thesis. I really couldn't have imagined having a better instructor and advisor during my Ph.D. study.

Finally, and above all, I am very grateful to my family: my brothers and sisters, as well as my wife and children, for their spiritual support in the writing of this thesis.

PREFACE

A part of this thesis has been published as Jenkins, H., Alshareef, E., & Mohamad, A. (2021). The impact of corruption on commercial banks' credit risk: Evidence from a panel quantile regression. International Journal of Finance & Economics. DOI: 10.1002/ijfe.2481. Also The Effect of Corruption on Banks' Credit Risk: A Comparative Study Between Conventional and Islamic Banks has been presented at the 2nd International Conference on Banking and Finance Perspectives"(ICBFP). April 21, 2017, Famagusta, North Cyprus.

TABLE OF CONTENTS

LIST OF TABLES

Chapter 1

INTRODUCTION

It is widely agreed that credit risk is the most serious threat to commercial banks and other financial institutions. A high percentage of non-performing loans (NPLs) can jeopardize banks' capital and lead to insolvency. The Basel Committee on Banking Supervision reported that poor credit risk management techniques continue to be the major causes of banking crises worldwide (Ariffin *et al.*, 2009). Accordingly, commercial banks and their controllers should know about the factors that escalate credit risk. One of the primary factors affecting commercial banks' credit risk, and one that has received relatively little attention in previous research, is the level of corruption in the countries. The aim of this research is to investigate the association between the level of countrywide corruption and commercial banks' credit risk.

The connection between corruption and banks' NPLs is not straightforward, however a number of studies showed that corruption affects banks' NPLs through various channels (Agarwal et al,2015; Toader et al 2018). Among these channels, affecting the decisions of the loan officers through political connections or using bribery are the most common practices. Such corruptive behaviors prevent loan officers from performing accurate credit analysis hence they may lend to loan applicants who do not qualify for a loan. Furthermore, corrupt practices may encourage borrowers not to repay their loans, even if they have the financial capacity to do so. Thus, causing the NPLs in commercial banks to increase.

The endemic problem of corruption, alongside improvements in the availability of data, has provoked numerous analysts to research the impact of corruption on commercial banks' lending activity (Weill, 2011; Toader et al., 2018; Bahoo, 2020). These studies are summarized by Bahoo (2020) in a bibliometric review of articles that investigate corruption in banks. However, empirical research investigating the impact of corruption on banks' credit risk still remains limited to a small number of studies (Goel and Hasan, 2011; Park, 2012; Şan, 2018; Anastasiou *et al.*, 2019, Son et al., 2020). By applying a new methodology to data from a broad sample of commercial banks in the MENAP area, the current research aims to fill this gap in the literature.

The influence of countrywide corruption on commercial banks' credit risk merits more attention particularly among less developed countries, where commercial banks are struggling with high NPLs and societies are riddled with corruption. Olken and Pande (2012) showed that, in developing countries, the anticorruption policies are often weakened as officials find alternative strategies to pursue rents. The prevailing bureaucratic systems in these countries, along with the public sector's hegemony and a lack of transparency, make the influence of corruption on the financial sector highly likely. Our research will investigate the impact of corruption on commercial banks' credit risk in a sample of 18 emerging countries in the MENAP area.

The model employed in this research includes both macroeconomic and bank-specific data from 2011 to 2018, and it involves annual data from 191 commercial banks operating in 18 MENAP countries. This research period was chosen for two reasons, the first being that it removes the skewed impact of the worldwide financial crisis of 2007–2010, and the second is that to avoid data limitations that exist for some countries for pre-global financial crises period.

Furthermore, unlike previous studies, which have employed traditional methodologies to deal with the mean function of the dependent variable, this research applies a panel quantile regression (QR) estimation method. The QR is more robust to outliers and enables exploration of whether corruption has different effects on the conditional distribution of credit risk while controlling for unobserved country heterogeneity. The empirical findings of our research provide robust evidence suggesting a strong positive association between corruption and credit risk of commercial banks, indicating that the higher the corruption levels, the higher the credit risk of commercial banks. In addition, the QR findings show that corruption has a stronger effect on the higher quantiles than the lower ones, meaning that increased corruption level has a stronger impact on commercial banks with higher credit risk than commercial banks with lower credit risk.

This research adds to the body of knowledge by demonstrating that corruption increases bank credit risk, and that high credit risk banks are more susceptible to countrywide corruption than low credit risk banks. Hence, in countries where the countrywide corruption increases, we expect that commercial banks, particularly commercial banks with high credit risk, will suffer bigger losses in their loan portfolios.

The remainder of the paper is organized in the following manner. The related literature is reviewed in Chapter 2. The sample, data, and methodology are all described in Chapter 3. The analytical findings are presented in Chapter 4, and the research conclusions are presented in Chapter 5.

Chapter 2

LITERATURE REVIEW

2.1 Credit Risk in The Banking Sector

In the banking sector, credit risk is the risk of default on a debt and it is considered as being one of the most significant forms of risk facing commercial banks (Atakelt et al., 2015). Commercial banks are especially susceptible to credit risk, which arises from the issuance of loans to borrowers who are not creditworthy and their commitments to repay credit on time is very low (Altıntaş, 2012). The Basel Banking Oversight Committee describes credit risk as the possibility of a partial or total loss of outstanding credit. Furthermore, the Bank for International Settlements (BIS), emphasized that the credit risk is a major source of financial uncertainty in the financial sector.

In recent years, commercial banks are increasingly experiencing credit risk in a variety of financial transactions, such as interbank transactions, acceptances, foreign exchange deals, financial derivatives, bonds, equities, options, contract extensions and transaction settlements (Thalassinos et al, 2018). Credit policies of commercial banks are used to protect banks from extreme risk. In the literature three explanations are used for the volatility of bank credit policies. First, is the agent problem, making profit from supplying loans can lead to activities that do not always maximize the investors wealth, hence managers can begin to embrace high risk (Williamson, 1963). Second, high bank competition can lead to lower earnings, and by selling more and more loans to make more money, managers can increase risk. That is consistent with the findings of Norton and Olive (1996) that, due to excessive competition in the banking sector, commercial banks may offer loans without properly assessing creditworthiness of the loan applicants in order to maximize the amount of loans made to customers. However, this can result in a state of high credit risk in banks. Also, lax payment policies, and low collateral standards play a role in occurrence of bad loans.

Several studies have long shown that commercial banks could also face bad debts due to economic events. Jimenez and Saurina (2006) confirmed that weakening economic growth can cause a decline of borrowers cash balances that makes it difficult for them to fulfill their credit obligations. The recent subprime mortgage crises in the USA and the following global financial crises of 2007-2010 stimulated interest in academic research in this area. Reinhart and Rogoff (2011) suggested that elevated levels of NPLs mark the beginning of a financial crisis which result in a slowdown in the USA economy and eventually spread to rest of the world.

In the literature factors that affect bank credit risk are classified into two as internal factors, i.e. bank-specific factors (unsystematic credit risk) and external factors i.e. non-bank related factors (systematic risk) (Radivojević et al., 2019). Bank internal risk management can partially mitigate the unsystematic credit risks, with various risk management tools such as asset allocation, diversification, and adjusting the evaluation time. Systematic risk, i.e. non-bank specific risks represent the effect of economic and political factors, is inherent in the whole market. This form of risk is distinct from unsystematic risk affecting the whole banking sector. Both systematic and unsystematic risks are threats to the financial markets and the economy, but there are different reasons and strategies for handling these hazards.

2.2 Determinants of Credit Risk

Loan-loss provisions (LLP) and non-performing loans (NPLs) ratios are most often used as credit risk indicators in the current literature. Due to data availability, the majority of studies used NPLs as a credit risk indicator. In several former studies (Bhatti et al., 2019; Al Rahahleh et al., 2019; Alandejani et al., 2017; Misman et al. 2015, and Rahman et al., 2010), credit risk is measured as the percentage of non-performing loans to overall gross loans (NPLs). According to Bloem & Freeman (2005), a loan is considered non-performing whether interest and/or principal payments are 90 days or more past due, or interest payments equal to 90 days or more have been capitalized, refinanced, or deferred by agreement, or payments are less than 90 days past due, although there are other good reasons to believe the payments will be made in full—such as a trustee filing for bankruptcy. When a loan is listed as non-performing, it will remain so until it is written down or interest and/or principal payments are made.

In the literature, two key line of research discussed the determinants of credit risk. First one supports the view that credit risk is determined by the macro-economic variables. The other one holds that bank specific factors influence credit risk. According to the countries investigated, methodologies applied and variables considered, the empirical literature differs considerably. Instead of examining individual cases, a large majority of studies concentrate on groups of countries. Some consider only macro variables, while others depend on precise credit risk modeling for both macro and micro-economic indicators. Recent empirical analysis demonstrates the role of bank specific and macro-economic factors, as well as other influences relevant to the legal and regulatory system, in understanding the nature of credit risk. Many analyses have been conducted to examine the effect of various bank specific and macro-economic factors on credit risk. Such researchers analyzed their findings independently, while others did so collaboratively. This research uses the latest literature to determine the independent variables for this research.

2.2.1 Macroeconomic Factors

The main macro-economic factors that may affect the credit risk of banks are listed in the literature as inflation rate, employment or unemployment rate, GDP growth rate, interest rate, and foreign exchange rate (Nkusu, 2011; Beck et al., 2015). It is also stated by many empirical research on credit risk that the macro-economic determinants of NPLs are countercyclical (Klein 2013). Specifically, when an economy grows and real GDP grows, income rises, this increases the borrower's ability to repay a loan obligation. During an economic downturn, on the other hand, the unemployment rate tends to rise, causing borrowers with less funds not being able to meet their obligations.

Beck et al.(2013) used dynamic panel estimation method to demonstrate that the GDP growth rate stands out as the most significant factor reducing the level of NPLs of commercial banks. In countries such as Greece (Louzis et al., 2012), Spain (Salas et al., 2002), Italy (Quagliariello, 2009) and Mexico (Blavy et al., 2009), studies have identified substantial relations between asset quality of banks and the macroeconomic environment. Numerous studies using different methodologies have investigated the linkage between NPLs and the macroeconomic indicators. Some of the major studies on this subject are listed below.

Nkusu (2011) used only macro-economic variables to analyze the relationship between NPLs and the macro-economic output of 26 developing nations from 1998 to 2009. The GDP growth, unemployment, inflation, the change in the housing price, the change in the stock market index, the exchange rate, the policy interest rate, and private sector credit are used in this research as the major macroeconomic factors that affect banks NPLs. The findings of this study indicates that poor macro-economic performance in emerging regions such as slower GDP growth, higher unemployment, or lower asset prices is linked to increasing NPLs.

In a similar study, Skarica (2014) investigated european economies from 2007 to 2012. The findings revealed an adverse association between GDP growth and the unemployment rate and credit risk. Endut et al. (2013) utilized the random effects of the GLS model to investigate board panel data including Australia, and 12 Asian countries. The outcomes revealed that interest rate, inflation rate, and GDP growth rate affected NPLs ratios in Asia. In addition, Islamoğlu (2015) used VAR technique to examine the effect of macro-economic variables (business credit, lending rate, and government debt-to-GDP ratios) on NPLs with data from 13 banks in Borsa, Istanbul from 2002 to 2013. According to the study, declines in interest rate trigger long-term unsustainable credit growth and increase NPLs. The study also found a positive connection between NPLs and Sovereign debt.

Roman et al. (2015) examined the relationship between credit risk and macro-economic variables in 28 European countries from 2000 to 2015. According to these researchers, economic indicators had a substantial impact on credit quality. For example, if the rate of economic growth increases and unemployment rate falls, the number of NPLs also falls. The general reason is that high GDP growth typically translates into more revenue, which increases borrowers' debt serviceability. The general explanation is that high GDP growth usually transforms into more income, which increases the debt serviceability of borrowers.

Syed et al. (2020) used an adjusted OLS method to examine the effect of macro-economic conditions on NPLs in the banking sectors of Brazil, Russia, India, China, and South Africa from 2000 to 2016. According to the findings, the unemployment rate had a substantial positive effect on the NPLs ratio, in other words increase in the unemployment rate increased the NPLs of banks while an increase in gross domestic saving of households had a significant adverse impact on NPLs. In other words, the increase in gross domestic savings reduced the NPLs of banks.

2.2.2 Bank Specific Factors

Recent research have also investigated the relationship between bank specific variables and credit risk of banks. Various studies in the literature like Angbazo (1997), Cebenoyan et al. (2004) and Gallo et al. (1996) have considered the bank management and activities of banks to investigate the association between bank specific variables and credit risk. The literature indicated that many internal factors affect banks' need and ability to enhance their management of credit risk. Since an effective and risk averse bank management is required to eliminate aggressive lending in a volatile macroeconomic environment, the influence of bank management on credit risk has been studied more thoroughly than any other aspect in credit risk management (Berger and DeYoung et al., 1997; Peristiani, 1996; Shi et al., 2018). Ineffective bank management results in cost inefficiency, reduced performance, and the generation of bad debts, both of which can lead to bank collapse.

Berger et al. (1997) used multiple theories to explain the association between bank-specific variables and credit risk. These authors developed the Bad Management Hypothesis with inefficiency and the Moral Hazard Hypothesis with capital adequacy variables. To shape possible theories, the authors examined the association between capital adequacy, inefficiency, and NPLs, especially the Bad Luck, Skimping, Moral Hazard, and Bad Management hypotheses. Similarly, Klein (2013) used the Bad Management, Skimping , Moral Hazard, and Excess Lending Hypotheses to explain the connection between internal factors and NPLs.

Skimping theory states that significant cost reduction in the credit department may lead higher NPLs because of insufficient numbers of personnel and shortage of investment in information technology for loan monitoring may contribute in higher NPL rates in banks. Additionally, the principal-agent concept, known as agency theory, points to the conflict of interest between the owners, known as principals, and the managers, known as agents (Jensen et al., 1976). The Agency theory illustrates the low-quality insider lending issue, which was the essential driver of financial institutions crisis in the banking system. Moral hazard a specific type of asymmetry of information that deals with risk. A Moral hazard can emerge under asymmetric information in which risk-taking party to a transaction is more aware of its motivations than the party paying the risk consequences.

Other bank specific factors that previous research analyzed are the bank size, performance, capital adequacy ratio, management efficiency ratio, liquidity ratio, and loan growth. An empirical investigation on the Indonesian banking sector was performed by Chaibia et al. (2014) considering a provision of loan losses, performance, financial leverage, banks noninterest income, size of bank, and return on equity as explanatory variables. They used the GMM modeling approach to study the effect of bank-specific indicators on the NPLs ratio in two European countries (German and France) from 2005 to 2011. The findings from France showed a statistically significant positive effect of the provision of loan losses, efficiency, and non-interest income on the NPLs. On the other hand, Germany's results showed a positive direct impact of leverage and bank size on the NPLs, while the return on equity ratio had a significant negative impact on the NPLs.

To discover bank specific factors that may affect NPLs, Laryea et al. (2016) used a linear approach to evaluate data from 22 Ghanaian Commercial banks from 2005 to 2010, using the loan-to-deposit ratio, capital adequacy ratio, and asset size as independent variables and the NPLs ratio as the dependent variable. The authors found that the loan to deposit and the capital adequacy ratio positively and significantly affects non-performing loans. Also, they found the asset size had a substantial adverse influence.

In Turkey, Us (2016) used a survey of 21 banks to analyze the determinants of the NPLs ratio using the GMM approach for the pre crises (2002-2008) and post crises (2008-2015) periods. Study findings have shown that the loan growth and bank inefficiency ratios have a significantly positive impact on the NPLs ratio while the remaining estimated coefficients are found insignificant. Similarly, from 1995 to 2011, Bardhan et al. (2019) looked into the bank specific, i.e. internal variables that influence NPLs in 82 Indian Commercial banks. As explanatory variables for NPLs, they looked at capital adequacy ratio, credit expansion, operating expenses to assets ratio, market share, net profit to total assets ratio, and deposit growth rate. The research findings showed that the net profit margin and capital adequacy ratio both had a substantial adverse effect on NPLs, while market share and operating expenses had a positive and significant effect. On the other hand, the rate of deposit growth was negligible.

Furthermore, Khan et al. (2020) used panel data analysis of listed Commercial banks operating in Pakistan to investigate the variables that influencing the NPLs from 2005 to 2017. Profitability, operational performance, capital adequacy, and revenue diversification are used as the explanatory variables. According to the findings operating efficiency and profitability had an substantial adverse effect on NPLs, whereas capital adequacy ratio and income diversification had an insignificant influence.

2.2.3 Countrywide Corruption

In addition to the macroeconomic and bank specific factors, the countrywide corruption is viewed as one of the factors that affect banks' credit risk. Corruption is often described in literature as the use of public services and resources for personal benefit (Vishny et al., 1993; Klitgaard, 1991; Transparency International, 1995). Corruption occurs when those in positions of authority, such as officers or government officials, act in a dishonest manner to create personal benefits.

In order to quantify the level of countrywide corruption , Transparency International (TI), a non-profit organization developed the Corruption Perception Index (CPI) which is the most commonly used measure of corruption throughout the world. The CPI reflects professional opinion since it is based on the averages of numerous structured expert surveys, such as the Control of Corruption (COC) indicator developed by the World Bank. CPI and the COC are the two most widely used corruption indicators that are calculated annually for every country.

It is often argued that corruption stifles development and cause instability by manipulating economic production, and preventing institutions from working efficiently (Sequeira, 2012). The pioneering work of Leff (1964) was the first to examine corruption. The findings clarified a significant correlation between corruption and economic development. Since then, numerous articles such as Baylay (1966) and Kaufmann (1997) have been published to determine the impacts of corruption.

2.3 Corruption and Banks' Non-Performing Loans

The information asymmetry between commercial banks and borrowers has two possible outcomes: adverse selection and reverse incentives (Stiglitz & Weiss, 1981). If borrowing rate increases, the adverse selection effect occurs, meaning that safe borrowers stop from entering the financial system, while the risky borrowers who are willing to invest in higher risk projects are willing to borrow at any cost.

Credit rationing, implies that some borrowers are willing to pay a higher interest rate than the market rate in order to obtain loans therefore, they have an opportunity to bribe bank officials to secure the loan. However, only risky borrowers act in this manner because borrowers who are considered secure, or less risky, are unwilling to borrow at a higher interest rate. Based on the adverse selection theory, low-quality companies with small financing opportunities are more likely to pay bribes to obtain bank loans than high-quality companies. Consequently, Commercial banks also formulate more stringent company lending terms in order to avoid adverse selection and moral hazard. Nevertheless, this in turn may increase credit costs and expose businesses to higher risk.

Corruption, on the other hand, can be like greasing the wheels of economic activity. Based on the "Grease the Wheels" hypothesis, corruption can accelerate economic growth when governance structures are weak and there is high bureaucracy (Aidt, 2009; Méon and Sekkat, 2005). In other words, corruption can give a push to the economy, reducing transactions costs, and capital costs. However, owing to a lack of empirical evidence, the efficiency-enhancing view of corruption has increasingly fallen out of favor (Aidt, 2003). On the contrary, the recent research pointed to a common conclusion that corruption triggers a rise in NPLs and a decline in the commercial banks' soundness (Barth et al., 2004; Goel & Hasan, 2011).

Over the past decade the relationship between corruption and banks' lending behavior attracted the attention of many researchers. Boudriga, et al. (2010) analyzed the components of NPLs using a survey of 46 banks from twelve diverse MENA economies. The study concluded that the high NPL rates of banks could be mitigated by controlling corruption and enhancing the quality of law and regulations. In a broader study, Goel and Hasan (2011) investigated the effect of corruption throughout the economy on banks' NPLs in a survey of 100 nations in a larger analysis. Using an ordinary least squares (OLS) technique, The results indicated a positive and significantly meaningful association between corruption and bank NPL levels across the sample.

Similarly, Park (2012) looked at the impact of corruption on the banking sector's soundness and economic growth across a large panel of countries. This report, as in earlier research, found that corruption slowed economic development and exacerbated the problem of nonperforming loans across the sample. The study asserted that through the distribution funds to poor ventures, corruption decreases the value of capital funding and therefore has a detrimental effect on economic development.

Ahmed (2013) used macro and institution-level data and the OLS method to research the impact of corruption, information symmetry, GDP, and lending rate as predictor factors on NPLs for the entire Pakistani banking sector, for the period 2001-2010. To understand the rise or decrease in the bad loans, the author looked at the corruption at the country level, organization level, and information symmetry. Even though early literature has found that corruption exacerbates the problem of bad debts of banks, this study found that corruption and information symmetry do not affect NPLs.

Chen et al. (2015) used evidence from 1,200 banks based in 35 emerging market economies between 2000 and 2012 to examine the effect of corruption on banks' risk-taking activity. The authors found consistent evidence that higher levels scores of corruption are linked to increased bank risk-taking behavior of banks. Furthermore, this research provided indication that the indirect influence of corruption has an influence on bank risk, and that fiscal policy has a significant impact on bank risk-taking activity as corruption becomes more serious.

Another study by Bougatef (2016) analyzed the impact of wide corruption on banks' asset quality in the emerging market economies, applying a simple and multiple regression analysis on dataset of banks working in 22 countries during the period 2008–2012. The study found robust evidence supporting the hypothesis that corruption worsens the problem of credit risk. It also shown how misappropriation of bank lending hampered the development of economic growth in emerging markets.

Furthermore, in a recent study in Indonesia, Murharsito et al. (2017) studied the role of corruption on the performance and credit quality of local development banks. This study used a corruption variable obtained from the National Forum for Indonesian Transparency Agency. Running a cross-sectional regression on data collected from 26 local development banks for 2012 and 2013, the study found that corruption has no effect on credit risk of local development banks. However, the additional results showed that corruption has an adverse and statistically significant influence on the financial performance of the same banks.

While most previous studies have been based on secondary data, a recent study by Şan (2018) utilized primary data alongside secondary data to analyze the reasons for high NPLs in the Albanian banking sector. The research concluded that financing unrealistic projects and making bad lending decisions due to external influences have been among the main causes of the high NPLs in Albania. Moreover, 86% of the bank officials who participated in this study indicated that the most effective way to deal with the high credit risk in Albania would be to introduce better credit analysis methods and to reduce the level of corruption in the country.

A recent study by Murshed and Saadat (2018) also provided similar results for three South Asian countries, namely Bangladesh, India, and Pakistan. The authors performed several estimation techniques, such as OLS, FE, and random effects panel data, to investigate the impact of governance indicators on NPLs patterns across these three countries. To determine the long and short run causality between governance and NPL, as well as the path of causality between variables, the researchers used a vector error correction model and a Granger test. The causality tests found robust evidence suggesting long-run causal associations between the governance indicators and NPLs in Bangladesh, India, and Pakistan.

The most recent study by Anastasiou et al. (2019) sought to determine the effect of the worldwide governance Indicators on banks' NPLs in in Greece's Commercial banks. The research applied principal component analysis (PCA) on Commercial banks' annual data for the period 1996–2016. PCA is a method for reducing the dimensionality of large datasets, increasing interpretability while decreasing information loss. This research showed that when Greece has better governance (i.e., high accountability, high transparency, government strength, administrative quality, stable political situation and corruption control), it has a more stable financial sector, with less bad loans.

Son et al. (2020) investigated the influence of corruption on the financial system and economic development. They used the 3SLS regressions to analyze composite data from the World Bank representing 120 nations from 2004 to 2017. According to the findings, there is a positive correlation between corruption and credit risk. They also discovered that the banking sector acts as a conduit for the transition of corruption's effect on the economy. Higher credit risk in the financial sector is argued to be the product of corruption, which slows economic growth.

Mohamad et al. (2020) examined the effect of corruption on credit risk in 16 economies in the Middle East and North Africa (MENA) area over the period 2011–2019. For this, they used a model of macroeconomic and bank-specific metrics, as well as data from 197 Commercial banks, and the hierarchical fixed impact regression methodology. The outcomes showed a direct and substantial association between country-wide corruption and NPLs.

Ali et al. (2020) analyzed the influence of corruption on the incidence of financial crises using credit data from 38 countries from 2000 to 2017. They looked at both direct and indirect ways that corruption might influence the frequency of financial disasters. Overall, the outcomes introduced that corruption raises the likelihood of a banking crisis. The indirect effect revealed that corruption harmed bank lending by raising risk rather than increasing profitability.

Rehmana et al. (2020) used a panel data of 18 Pakistani commercial banks from 2000 to 2017 and ordinary least square, fixed effect, and random effect models are used to explore the connection between corruption and NPLs. The findings showed that Control of Corruption Index has a strong and adverse association with NPLs, implying that tighter control of corruption would result in fewer NPLs.

Thus, previous research have attempted to analyze the impact of corruption on banks' credit risk by using multiple methodologies in various context. These previous studies are based on traditional methodologies that deal with the mean function of the dependent variable (Lee & Li, 2012). Unlike previous studies however, the current research applies a panel QR estimation method. The QR estimation method is more robust to outliers and it enables an exploration of whether corruption has different effects on banks with different credit risk, as conditional distribution of credit risk, while controlling for unobserved country heterogeneity.

Chapter 3

SAMPLE, DATA, AND METHODOLOGY

3.1 Sample and Data

This research uses a sample of 191 commercial banks from 18 MENAP countries. Table 1 shows the number of commercial banks by country and the average corruption scores of these countries between the period 2011–2018.

Table 1: Sample of Commercial Banks by Country

NO.	Country	Commercial Banks	Average CPI Score 2011- 2018
1	The United Arab Emirates	17	3.10
2	Kuwait	5	5.67
3	Bahrain	7	5.43
4	Saudi	7	5.26
5	Qatar	6	3.36
6	Oman	6	5.33
7	Yemen	4	8.21
8	Egypt	22	6.66
9	Jordan	10	5.18
10	Lebanon	27	7.22
11	Iraq	2	8.28
12	Tunis	10	5.96
13	Morocco	5	5.23
14	Mauritania	4	5.65
15	Algeria	5	6.58
16	Turkey	23	5.62
17	Pakistan	21	7.06
18	Syria	10	8.15
	Total	191	

Source: Transparency International, CPI annual reports, 2011–2018. CPI original index ranges from 100 to 0, here it is converted into a range from 0 to 10, where 0 indicates the cleanest and 10 indicates the most corrupt country. A score above 5 indicates a severe national corruption problem.

The International Monetary Fund (IMF) defines this analytical region, i.e. MENAP, as Middle East, North Africa, Afghanistan and Pakistan. Despite having some diversity in their economic environments and legal systems, these 18 countries appear to have similar cultural values, political environments, and the bureaucratic systems that leave opportunities for corrupt activities in multiple sectors, including banking. In order to create a single community of banks, just commercial banks are included in the sample. Table 2 shows the ownership structure of the sample banks for each country. As presented, the majority of banks in the sample are private banks.

Table 2: Sample of Commercial Banks by Ownership Structure

NO	Countries	Public	Private
1	The United Arab Emirates	0	17
2	Kuwait	0	5
3	Bahrain	0	7
4	Saudi	2	5
5	Qatar	0	6
6	Oman	0	6
7	Yemen	1	3
8	Egypt	3	19
9	Jurdan	0	10
10	Lebanon	0	27
11	Iraq	0	2
12	Tunis	4	6
13	Morrocco	0	5
14	Mauritania	0	4
15	Algeria	1	4
16	Turkey	3	20
17	Pakistan	4	17
18	Syria	1	9
	Total	19	172

Public sector banks are controlled and authorized by the Government. Private sector banks are owned and controlled by private individuals and entities.

Although it is widely believed that corruption affects mostly the public banks through political corruption we believe that high levels of countrywide corruption can also affect the private banks through political pressure, bribery, fraud and similar corruptive practices. Hence our sample which is made up mainly by the private banks will provide us additional information on the impact of corruption on private banks which is mainly missed in the earlier literature.

Furthermore, a limited amount of research has been undertaken on corruption and credit risk of banks in MENAP region. This research fills this gap. Also, the countries listed in this region have a wide range of CPI levels, from 3.10 to 8.28 which makes it statistically suitable to conduct this research.

3.2 The Model

The model used for this research is summarized in Table 3, and explained below.

3.2.1 Dependent Variable

The dependent variable in our model is the NPLs (non-performing loans to total loans), such that a high NPLs points to an increased credit risk and probability of bank insolvency. In the literature, NPLs is the most widely employed measure of banks' credit risk (e.g. Das and Ghosh, 2007; Fiordelisi *et al*., 2011; Goel and Hasan, 2011; Koju et al, 2018).

3.2.2 The Independent Variables

The primary goal of this research is to determine the impact of corruption on credit risk of commercial banks in 18 MENAP countries. The independent variables used in this research are corruption, the macroeconomic indicators (GDP growth, gross capital formation) and the bank-specific determinants (bank size, inefficiency, profitability). Macroeconomic indicators and bank specific determinants are used as control variables. The independent variables are defined as below.

Table 3: Dependent variable and Expected Signs on the Coefficients of the Regression

Variable Name	Definition	Expected Sign
Dependent Variable:		
Non-performing loans ratio (NPLs)	It is the non-performing loans to total loans such that a high NPLs points to an increased credit risk and probability of bank insolvency. In the literature, NPLs is the most widely employed measure of banks' credit risk (e.g. Das and Ghosh, 2007; Fiordelisi et al., 2011; Goel and Hasan, 2011; Koju et al, 2018).	
Independent Variables:		
Countrywide Corruption (CORR)	We utilize the Corruption Perception Index (CPI) to survey the country's corruption, Between 1995 and 2011, the CPI was scaled from zero (extremely corrupt) to ten (i.e., very clean). However, the CPI ratings are currently graded from zero to 100. In line with Park (2012), we described the CPI as follows: CORR= 10 – CPI in 2011; CORR= 10- CPI/10 from 2012 to 2018. High CORR indicating high degree of corruption.	+ (Mohamad et al., 2020; Son et al., 2020) - (Levine et al. 2000) and (Lui, 1985)
Bank's Inefficiency (CTI)	The cost-to- income ratio (CTI) is an indicator of the banks' inefficiency. To get the ratio, divide the operating costs by operating income.	+ (Berger and DeYoung ,1997) - (Abid et al., 2014)
Bank's Profitability (ROAE)	The return on average equity (ROAE) is a financial ratio that measures the profitability of a bank. This financial metric is equal to net income after tax divided by the average shareholders' equity for a specific period of time.	- (Godlewski, 2005)
Bank Size (SIZE)	We measure bank size as the natural logarithm of total assets. A logarithmic transformation gives us a symmetric distribution more suitable for regression analysis. Bank size is generally used to capture potential economies or diseconomies of scale in the banking sector.	+ Louzis et al. (2012) - (de Lis et al., 2001)
Loan Growth (LG)	LG denotes loan growth in a bank. We measure loan growth as the percentage change in the amount of bank's total customer loans from the year t – 1 to year t.	- (Clair, 1992) + (Berger and Udell, 2004)
Growth in Gross Domestic Product (GDP growth)	GDP growth is the rate of growth in gross domestic product expressed as a percentage. It is utilized to control for macroeconomic factors those are expected to influence bank credit risk.	- Tan & Anchor (2017)
Gross Capital Formation or Investment (GCF)	The ratio proxies for business financing. A high GCF represents high demand for funding by businesses.	- (de Lis et al. 2001)

Corruption(CORR):

In this research, we used the Corruption Perception Index (CPI) as a proxy for the level of corruption in the sample countries, which has been broadly utilized in the past research like Weill (2011), Geol and Hasan (2011), Park (2012), Bougatef (2015 / 2016), and Toader et al. (2018). The CPI index is developed by the Transparency International in 1995. It is compiled annually by Transparency International and it currently ranks 180 countries from zero (highly corrupt) to 100 (very clean).

Between 1995 and 2011, the CPI index was scaled from zero to ten, however the scale has been changed from 0(extremely corrupt) to 100 (very clean) from 2012 onwards. Therefore, we converted 0-100 scale into the 0 to 10 scale in order to unify the scale for our research period of 2011 to 2018. Furthermore we reversed the scale from 0 to 10 where 0 represents the very clean and 10 represents the extremely corruption in order to harmonized the direction of this indicator with the rest of the explanatory variables. In his research Park (2012) applied the same method to unify the scale and reverse it in the same way we explained above. Hence in our research we describe the corruption with CPI index as follows:

CORR = 10 - CPI for year 2011;

CORR= 10 - CPI/10 for years 2012 to 2018,

With a high CORR indicating a high degree of corruption and low CORR indicate that the country is clean. As shown in Table 1, our sample countries have a wide range of CPIs ranging from 3.10 to 8.28.

Inefficiency:

The cost-to-income ratio (CTI) is used as an indicator to measure banks' inefficiency. The effect of this factor on NPLs is not straightforward. Credit risk can be associated with efficiency on many levels, all of which Berger and DeYoung have thoroughly reviewed (1997). They develop theoretical approaches that vary in the causal relationships. First, the researchers argue that, under the hypothesis of bad management , poor performance in banks' cost management suggests that these financial institutions are also possibly to handle their credit portfolio poorly, resulting in greater percentage of NPLs. In contrast, the skimping hypothesis suggests that low costs in banks lead to a higher rate of credit risk, as this implies an insufficient allocation of bank resources to loan assessment (Abid et al., 2014).

Profitability:

We use the return on average equity (ROAE) as an indicator for banks' profitability. The relationship between ROAE and credit risk can identify in two ways. First, the "bad management hypothesis" justifies the negative relationship ROAE and NPLs since poor profitability reflects poor managerial performance. Several studies have highlighted that banks with high profits are less pressured to participate in risky lending behaviors and usually follow strict loan assessment methods (Godlewski, 2005). Therefore, banks' ROAE is anticipated to have a bad impact on credit risk. In contrast, Rajan (1994) clarified the positive relationship between ROAE and NPLs by stating that bank management is likely to inflate current profits by undertaking negative net present value through using more liberal lending policies at the expense of future bad loans.

Size:

We use the logarithm of a bank's total assets as an indicator of their size (SIZE). The effect of this factor on credit risk is also not straightforward. The moral hazard hypothesis suggests that the reliance of large banks on state intervention during difficult times motivates banks to take excessive risk and adopt lenient assessment methods. The government has a reputation for shielding major financial institutions and their creditors from collapse. As a result, Large banks are more willing to accept risks by lending to riskier borrowers (Stern and Feldman, 2004). In addition, Louzis et al. (2012) discovered data supporting the Too Big To Fail concept. Moreover, Boyd and Gertler (1994) claimed that the US government's Too Big To Fail strategy strengthened big banks' propensity to hold on riskier portfolios in the 1980s.

Loan Growth:

LG represents loan growth in a bank. LG may have an adverse impact on NPLs if this growth is during the period of economic boom (Clair, 1992). Bhattarai (2015) used a survey of 26 Nepalese Commercial banks to examine the effect of bank-specific indicators on NPLs from 2002 to 2012. The findings showed that the loan growth has a substantial and adverse effect on NPLs as loan portfolios deteriorate. Several studies have shown that an expansion of the loan portfolio may lead to capacity constraints, rendering Commercial banks unable to effectively assess their loan applications and monitor them (Berger and Udell, 2004).

GDP Growth:

GDP growth is the rate of growth in gross domestic product expressed as a percentage. Following the studies of Carvallo et al. (2015), and Tan & Anchor (2017), the GDP growth rate is utilized to control for macroeconomic factors that are expected to influence bank credit risk. It is estimated that economic growth improves borrowers’ capacity to repay, whereas economic slowdowns negatively affect people’s financial capacity (Salas and Saurina, 2002). Therefore, GDP growth is likely to have a negative impact on credit risk.

Gross Capital Formation:

GCF is gross capital formation or investment. The ratio proxies for business financing. A high GCF represents high demand for funding by businesses. When there is increased demand for bank credit, commercial banks can be more selective and can cherry pick the best credit applicants without lowering their credit standards. Therefore, we would expect to see an adverse association between GCF and bank credit risk, i.e. their level of NPLs. (de Lis *et al*., 2001).

We excluded explanatory variables where other explanatory variables somehow captured their effect. For example, the inclusion of a real GDP growth rate made the effects of the inflation rate and unemployment rate insignificant. Thus, those variables are excluded from the model. This scenario is also adopted for the case of interest rate; however, as its impact did not appear to be significant, this variable is also ruled out from the model. Table 4 shows summary statistics and data providers for the factors used in the model.

Table 4: Summary Statistics and Data Sources for Sample Banks

Variable	NPLs	CPI	COC	CTI	GCF	GDP GROWTH	LG	ROAE	SIZE
Mean	7.42	5.80	1.39	48.84	60.04	3.50	6.77	11.88	6.86
Median	5.33	5.90	1.21	46.38	61.00	3.51	6.02	11.66	6.79
Maximum	71.81	7.70	4.29	183.64	113.00	9.33	162.29	50.13	8.35
Minimum	0.05	2.90	0.32	16.79	1.00	-3.48	-45.61	-49.28	5.08
Std. Dev.	7.37	1.30	0.67	18.14	30.09	1.97	17.43	8.75	0.63
Skewness	3.09	-0.84	0.37	2.01	-0.11	0.04	1.86	-0.54	-0.10
Kurtosis	17.64	2.82	3.10	12.56	2.03	3.63	17.13	11.74	2.59
Jarque-Bera	9790.45	109.46	22.00	4169.54	38.22	15.50	8278.28	3005.69	8.17
Probability	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02
Observations	1286	1498	1498	1349	1288	1475	1174	1350	1358
Source	Bankscope	TI	World Bank	Bankscope	WDI	WDI	Bankscope	Bankscope	Bankscope

Note: * NPLs: Non Performing Loans; CPI: Corruption Perception Index; COC: Control of Corruption; LG: Loan Growth; ROAE: Return on Average Equity; CTI: Cost to Income; SIZE: Size of the Bank; GDPgrowh: Growth in Gross Domestic Product; GCF: Gross Capital Formation.

3.3 The Methodology

3.3.1 Quantile Regression (QR) Method

As shown above, in Table 4, for the sample commercial banks the average of NPLs ratio is 7.42 while the kurtosis is 17.64, implying that the distribution of the dependent variable departs from the normal distribution. This characteristic is also verified through the application of the Jarque–Bera normality test. The result (the statistic is 9790.45 with P-value of 0.00) rejects the null hypothesis of normality and, therefore, it confirms the non-normality of NPLs. Furthermore, the means of the values of the NPLs for quantiles 0.25, 0.50, 0.75 and 0.95 are 1.91, 5.33, 7.89 and 24.50 respectively. Since the dependent variable has a non-normal distribution, we decided to used the quantile method which is robust to outliers and fat-tailed distributions (Powell, 2016).

Traditional regression techniques such as OLS, Fixed-effect, random-effect, and GMM have been practiced widely in statistics. However these methods depend on rigid assumptions such as the linearity of the coefficients, normality of the error distribution, constant variance of the errors, and no association between consecutive errors. A regression model's predictions, statistical significance, and empirical observations may be skewed or inaccurate if any of these assumptions are broken.

The QR model is a feasible alternative to traditional regression models. It determines the conditional median, or other quantiles of the dependent variable, while the system of OLS estimates the conditional mean of the dependent variable throughout values of the response variable. Instead of analyzing only the mean of the response variable, looking at the conditional distribution of the response variable for different quantiles of the explanatory variables can lead to very different inferences. The QR approach does not necessitate that the predictor variable be normally distributed, nor does it necessitate the other strict assumptions that conventional approaches entail. Where the linear regression conditions are not met, QR is used.

QR is recommended to obtain a complete regression picture (Koenker 2005). QR is a widely used method for determining conditional percentile approaches that have been used in a variety of observational studies; see Koenker and Bassett (1978), Koenker and Machado (1999), and He and Zhu (2003). The QR approach has recently gained popularity in a variety of fields such as science, finance, economy, and medicine (Koenker, 2017; Qin, 2012; Wang et al., 2018). This method offers detailed examination of the relationships among factors over a wide range.

In contrast to the typical regression methods, QR does not need observations to assume a particular distribution and can predict various results at different quantiles of the dependent variable. Furthermore, QR is thought to be more resilient to outliers due to the lower sensitivity of its estimation results to outliers and multimodality (Liu et al., 2013). QR can handle diversity for data gathered from different sources, places, and periods without making much assumptions (Qin, 2012; Qin et al., 2010; Qin and Reyes, 2011).

The application of QR in the context of panel data goes back to research by Koenker and Xiao (2004), who presented a general approach for estimating QR models for longitudinal data. This research can be regarded as the basis for the following studies in different areas. In recent years, Powell (2016) presented QR for panel observations with no additive individual effects in recent years, retaining the nondetachable disturbance term that has been widely correlated with quantile prediction and serves as the basis for this analysis.

Many researchers have practiced QR in different views of the banking and finance field, covering financial risk and regulations (Klomp and de Haan, 2012), insolvency expectation (Li and Miu, 2010), and loan risk (Schechtman and Gaglianone, 2012). Also, Cihak and Hesse (2007) examined the importance of cooperative banks in financial stability. They test the robustness of their results by using a robust estimation technique and QR. Moreover, Dima and Spulbăr (2014) employed a two-stages QR to examine the financial relationship formed by the banks' stability, competitiveness, and productivity in the banking system, as well as the growth of equity markets. Recently, Chowdhury and Masih (2017) applied dynamic GMM, QR, and wavelet coherence approaches to explore the bank-specific characteristics and macroeconomic and government variables of the Islamic banks' profitability in the GCC region. Furthermore, Lv and Xu (2017) employed a dataset of 62 countries, over a period of 1998-2011, and used the QR methodology to test the connection between response variable (tourism demand) and corruption as explanatory variable through different quantiles of the conditional distribution of the response variable.

Most recently, Karadima and Louri (2020) applied QR to annual dynamic panel data to identify the association between bank concentration and NPLs in 19 European Union countries. This study showed that, after the global financial crises, bank consolidation and concentration in European Union countries helped to reduce the NPLs of banks.

Following the earlier research in credit risk modeling our research uses QR to provide evidence on the correlation between banks' credit risk and a variety of determinants, including corruption, while controlling the heterogeneity at different Commercial banks. There follows an explanation of the selected method, the merit of the model, and the reason behind the application of this method to achieve the research objective. Quantiles are defined as cut points in a probability distribution that split the spectrum into adjacent intervals of equal probabilities. If p is a positive integer between 0 and 1, Thus, for a random variable y, the 100p percentile of the distribution, signified by Q(p), can be described as follows:

$$p = P\big(y \leq Q(p)\big) = F\big(Q(p)\big) = \int_{-\infty}^{Q(p)} f(y)dy \tag{1}$$

where f(y) stands for the continuous random variable's probability density function. Q(p) can be described using Formula 1 as follows:

$$Q(p) = F^{-1}(p) = Inf\{y: F(y) \geq p\}. 0 \leq p \leq 1 \tag{2}$$

where F^{-1} (inverse cumulative distribution function) is the quantile function; it gives the value of the quantile(z) at either the probability of the random vector is equal to or less than the given p-value or the cumulative probability of the random variable is equal to the given probability value and *Inf* symbolizes the greatest lower bound.

As with the sample mean, which yields the least residual sum of squares, the sample median for a stochastic variable *y* minimize the sum of absolute deviations. Subsequently, the overall *Q(p)* is considered an feasible solution for minimizing the weighted mean with values > or = *Q(p)* and samples with values < or = *Q(p)*, as follows:

$$\min[\textstyle\sum_{i\in\{i:y_i\leq Q(p)\}} p|y_i - Q(p)| + \sum_{i\in\{i:y_i>Q(p)\}}(1-p)|y_i - Q(p)|\,] \tag{3}$$

if y is a linear equation of the factors, as follows:

$$y = \beta X' + \varepsilon \quad (4)$$

where y represents the dependent factor, β is the vector of unidentified coefficients of the explanatory variables X, and ε is unsystematic error. As a result, the optimization problems can be extended to solve the prediction for βs:

$$\widehat{\beta}\,(p) = argmin_{\beta \in R^K}\,[\sum_{i \in \{i: y_i \leq \beta X'\}} p|y_i - \beta X'| + \sum_{i \in \{i: y_i > \beta X'\}} (1-p)|y_i - \beta X'|\,] \quad (5)$$

Thus, $\widehat{\beta}\,(p)$ can be viewed as the pth regression quantile for any quantile point (p) between 0 and 1, which decreases the sum of the weighted disturbance (Koenker and Bassett, 1978; Qin et al., 2010).

3.3.2 Panel QR Model

As the panel data framework recognizes, the QR model can work better both for computation and for dealing with the heterogeneity problem. Presume we have the model formulation shown below:

$$y_{it} = \beta_p X'_{it} + \alpha_i + \varepsilon_{it} \quad (6)$$

where y_{it} denotes the NPL rate as a dependent variable; X_{it} is a vector of such independent variables as; Corruption Perception Index (CPI), the return on average equity (ROAE), the ratio of cost to income (CTI), the bank size (SIZE), the loan growth in a bank (LG), the real growth rate of GDP (GDP GROWTH), and the gross capital formation (GCF); β_p stands for the coefficient at the p quintile; the time-invariant individual FE is denoted by α_i; and ε_{it} is the error term.

Chapter 4

EMPIRICAL RESULTS

To ensure that our results will not suffer from multicollinearity we first examined the correlation between our variables. When the explanatory variables in a regression equation are correlated, multicollinearity occurs. As Table 5 shows, in our model the correlation is weak between all variables, except “ROAE” and “CTI”. The coefficient of - 0.59 indicates moderate correlation between variables “ROAE” and “CTI”. Therefore, The correlation matrix presented in Table 5 shows that our model is free from multicollinearity.

Table 5: The Correlation Matrix of Variables

Correlation	NPL	CPI	CTI	GDP growth	GCF	LG	ROAE	SIZE
NPL	1							
CPI	0.25	1						
CTI	0.29	0.32	1					
GDP growth	-0.09	-0.11	0.05	1				
GCF	-0.02	0.14	0.07	0.37	1			
LG	-0.14	-0.06	0.02	0.16	0.07	1		
ROAE	-0.23	0.06	-0.59	0.13	0.00	0.02	1	
SIZE	-0.38	-0.30	-0.39	0.05	-0.04	-0.03	0.22	1

Note: * NPLs: Non performing loans; CPI: Corruption perception Index; ; CTI: Cost to income; GDPgrowth: Gross domestic product growth rate; GCF: Gross capital formation; LG: Loan growth; ROAE: Return on average equity; SIZE: Size of the bank.

In this research, we utilize the estimation process proposed by Powell (2016) because of its consistency and normal asymptotic distribution of coefficients. Powell (2016) allows no additive fixed effects, something that the other panel quantile with additive fixed effects methods such as Lamarche (2010); Canay, (2011), and Kato et al. (2012) cannot do. The method's process is based on the estimation of the unobserved FE ($\widehat{\alpha_{it}} = E_T[\, y_{it} - \hat{\beta}_p X'_{it}], \hat{\beta}_p = \sqrt{nT} - consistent\ estimator\ of\ \beta_p$) in the first step and conducting the standard QR through $\hat{y}_{it} = y_{it} - \hat{\alpha}_i$ on the vector of independent factors and obtaining the estimator at the percentile, as seen in formula (5).

4.1 Model Estimation Results

Based on the general model stated in Chapter 3, the specific model of this research can be expressed as:

$NPLs_{it} = \beta_p X'_{it} + \alpha_i + \varepsilon_{it}$

where i and t subscripts indicate country and year, respectively. Credit risk is measured with non-performing loans (NPLs) as a main dependent variable; X_{it} is a vector of such explanatory variables as; Corruption (CORR) as a main independent variable, the return on average equity (ROAE), the ratio of cost to income (CTI), the bank size (SIZE), the loan growth in a bank (LG), the gross domestic product real growth rate (GDP growth), and the gross capital formation (GCF); β_p stands for the coefficient at the p quintile; the time-invariant individual FE is denoted by α_i; and ε_{it} is the error term.

This research illustrates that the regression coefficients of some variables act differently across the conditional distribution of credit risk (quantiles). Commercial banks with higher credit risk (upper quantiles) appear to treat certain banking characteristics differently from commercial banks with lower credit risk (lower quantiles). All of our analyses show that parameters vary statistically across quantiles, illustrating the power of our methodology. Table 6 presents the approximate coefficients of credit risk determinants for quantiles Q.25, Q.50, Q.75, and Q.95.

Most importantly, our findings show that corruption has a substantial and positive influence on bank credit quality. This finding is similar to previous findings by Goel and Hasan (2011), Park (2012), Bougatef (2016), and Toader et al. (2018). Moreover, our findings provide additional information that corruption has a stronger impact on the credit risk of commercial banks in the upper quantiles than in the lower ones. This is because the corruption coefficient is estimated to be around 0.202 for quantile .25, increases to 0.717 for quantile .75, and then reaches its maximum value of 1.260 in the .95 quantile. This shows that not only does corruption make the credit risk of all commercial banks much worse, but also that its impact is stronger on the commercial banks with higher credit risk. According to our results, for every unit raise in the CPI, the NPL ratio for banks in the lowest credit risk category increases by 0.202 percentage point. Whereas the same change in the CPI index increases the NPLs ratio of banks in the highest credit risk category by 1.260 of a percentage point.

Table 6: Quantile Regression Coefficients at Different Quantiles

Variable	Quantile Coefficient				Fixed effect
	0.25	0.5	0.75	0.95	FE
CPI	0.202***	0.191***	0.717***	1.260***	0.171
	(0.004)	(0.004)	(0.187)	(0.063)	(0.404)
ROAE	-0.032***	-0.056***	-0.129***	-0.278***	-0.160***
	(0.001)	(0.001)	(0.023)	(0.006)	(0.025)
CTI	0.043***	0.047***	0.002	0.039***	0.018
	(0.001)	(0.001)	(0.019)	(0.002)	(0.015)
SIZE	-1.294***	-2.524***	-4.848***	-7.904***	-11.23***
	(0.010)	(0.014)	(0.454)	(0.117)	(1.551)
LG	-0.037***	-0.040***	-0.031***	-0.007**	-0.023**
	(0.001)	(0.001)	(0.001)	(0.002)	(0.007)
GDP growth	-0.002	-0.108***	-0.050	0.204***	-0.048
	(0.006)	(0.001)	(0.063)	(0.028)	(0.086)
GCF	-0.003***	-0.001***	-0.002	-0.043***	-0.001
	(0.001)	(0.001)	(0.002)	(0.001)	(0.004)

*, **, and *** parameters are relevant at α =10%, 5%, and 1%, sequentially. The NPLs rate are reported at the 25th, 50th, 75th, and 95th quartiles. Numbers in parenthesis for each column denotes the robust standard errors.

Similar to Makri *et al*. (2014) and Sheefeni (2015), our estimation outcomes also show that bank profitability, i.e. ROAE is absolutely crucial and has a negative relationship with credit risk. The estimated coefficients of ROAE appears to increases across quantiles Q.25 = −0.032, Q.50 = −0.056, Q.75 = −0.129, and Q.95 = −0.278. This indicates that the impact of profitability to reduce the rate of NPLs is actually higher in the upper quantiles where the high credit risk banks are classified.

The results of the regression also show that the higher the banks' CTI ratio, the higher NPLs. This outcome supports the results of Podpiera and Weill (2008) and Louzis *et al*. (2012). Our analytical findings confirm the bad management concept, where it suggests that commercial banks with bad cost management are likely to have bad loan portfolio management.

Regarding to bank size (SIZE) our findings reveal that SIZE significantly and adversely affects bank NPLs. The estimated coefficients are Q.25= -1.294, Q.50=-2.524, Q.75= -4.848 and Q.95 = -7.904 indicates that the impact of the SIZE has a progressively greater influence on reducing the rate of NPLs, the greater is the underlying rate of NPL of the quantile. Advantages of the larger size banks relative to the smaller banks are explained by a number of studies. As stated by Salas and Saurina (2002), big banks are likely to be more diversified. Similarly, Rajan and Dhal (2003), big banks have sophisticated technology and professional human resources to control their credit risk. In the same vein, Zribi and Boujelbène (2011), bigger commercial banks are more probably to have more expertise in risk management and they are more diversified, which may enable them to deal efficiently with non-payers.

Our estimation results on the association concerning banks' LG and their NPLs are also consistent with previous research outcomes (Koju *et al*., 2018; Shingjergji, 2013) showing that lower banks' LG result in higher credit risk. Overall, the empirical outcomes suggest that commercial banks will have a greater chance to diversify their portfolio of loan and reduce their credit risk if they increase their loan growth. Further, Koju *et al*. (2018) argued that during loan growth periods, the possibility of bad loans may be avoided by applying strict controls and maintaining high credit standards. Findings also show that there is relatively little difference between the estimated coefficients in different quantiles.

Another interesting finding relates to the impact of economic growth on bank credit risk. Our results show an inverse association between the rate of GDPgrowth and credit risk in all the quantiles except 0.95 quantile. This suggests that economic growth affects high credit risk and low credit risk banks differently. The negative estimated coefficients are also supported the outcomes of Salas and Saurina (2002) and Thiagarajan et al. (2011) that GDPgrowth can significantly improve borrowers' ability to repay loans. In other words, an increase in GDPgrowth rate can decrease credit risk by improving borrowers' financial ability to pay off debts. In contrast, high GDPgrowth result in high NPLs at the 0.95 quantile, indicating that economic growth worsens NPLs of high credit risk banks. This may be attributed to banks' loosening lending conditions at the highest quantile. This finding follows those of Fofack (2005) and Beck et al (2013). Despite the fact that Beck et al. (2013) reiterated the desirable association between GDPgrowth and credit risk, they also stated that lagged GDPgrowth has an undesirable effect. Moreover, Fofack (2005) established that a substantial increase in credit risk would produce uncontrolled credit risk growth.

Finally, our empirical results support the theory of pro-cyclicality between gross fixed capital formation and NPLs. This theory suggests that higher gross fixed capital formation leads to greater economic activity and lower credit risk. The conventional wisdom is that rapid economic growth is motivated by investment. Similar to Festić *et al*. (2011), our findings indicate a negative correlation between GCF and NPLs of banks across all quantiles.

4.2 Robustness Tests

We perform two robustness tests to check the robustness of our results. First, we perform the same analysis using an alternative regression method and second, we use an alternative corruption indicator.

4.2.1 Alternative Regression Method

We use the FE regression to investigate the association between corruption and banks' credit risk. For comparison, the FE regression results are presented in the last column of Table 6. Overall, we observe that the outcomes of the FE method do not differ significantly in either substance or sign from the results of the QR technique. For example, the estimated coefficient of corruption is significantly positive in the QR method, where it is positive but not significant according to the FE method. This is because the FE estimator, by concentrating only on the mean of the distributions, does not allow the impact of corruption on banks' credit risk to differ across quantiles. In contrast, the estimated coefficients of the corruption variable is different in each quantile. Moreover, the higher the quantile the larger the size of the estimated coefficient is.

Furthermore, both FE and QR methods have similar estimations with respect to ROAE, SIZE and LG variables. However, FE methodology did not find CTI, GDP growth rate and GCF variables significantly related to credit risk of banks. When we check the QR , the estimation results of these variables vary between the quantiles showing that the impact of these variables changes depending on the riskiness of the banks, however FE methodology does not allow the impact of these variables on banks' credit risk to differ across quantiles. Hence in the FE estimation results, the estimated coefficients of these variables are insignificant.

4.2.2 Alternative Corruption Indicator

For an alternative indicator of corruption, we use the control of corruption (COC) indicator published by the World Bank to capture corruption on a scale of −2.5 to +2.5, where the higher the score, the less the corruption indicated. In order to make it consistent with the rest of the variables, this index is transformed into a scale from 0 to 5 using the formula ((5-(COC+2.5))/(COC+2.5)) where the higher the value is higher the corruption indicated.

As shown in Table 7, there is no significant change in the findings. COC is positively and significantly related to credit risk. Furthermore, the magnitude of the estimated coefficients are higher in higher risk categories (Q .25= 1.102, Q.50= 1.474, Q.75= 2.578, Q.95=4.711) indicating that an increase in the level of corruption (COC) will increase the NPL rate of banks in higher risk categories more than the lower risk categories. Taken together, our results show that commercial banks in higher credit risk categories are likely to be impacted more severely by corruption than the banks in lower credit risk categories.

Table 7 : 2nd Robustness Analysis (Different Measure of Corruption COC Index)

Variable	Quantile Coefficient				Fixed effect
	0.25	0.5	0.75	0.95	FE
COC	1.102***	1.474***	2.578***	4.711***	4.549***
	(0.055)	(0.126)	(0.039)	(0.009)	(0.987)
ROAE	-0.058***	-0.075***	-0.215***	-0.242***	-0.160***
	(0.003)	(0.009)	(0.001)	(0.001)	(0.025)
CTI	0.025***	0.049***	0.010***	-0.014***	0.013
	(0.001)	(0.011)	(0.001)	(0.001)	(0.015)
SIZE	-1.087***	-2.274***	-3.628***	-7.930***	-9.970***
	(0.093)	(0.055)	(0.017)	(0.015)	(1.541)
LG	-0.031***	-0.021***	-0.049***	-0.098***	-0.019*
	(0.002)	(0.004)	(0.001)	(0.001)	(0.007)
GDP growth	-0.033**	-0.136***	0.249***	0.460***	0.031
	(0.012)	(0.035)	(0.006)	(0.001)	(0.085)
GCF	-0.002	0.002	-0.001***	-0.058***	-0.004
	(0.001)	(0.002)	(0.001)	(0.001)	(0.004)

*, **, and *** parameters are relevant at α =10%, 5%, and 1%, sequentially. The NPLs rate are reported at the 25th, 50th, 75th, and 95th quartiles. Numbers in parenthesis for each column denotes the robust standard errors.

Chapter 5

CONCLUSION

This research explores the impact of countrywide corruption on the credit risk of commercial banks with different levels of credit risk. We use QR methodology and employ both macroeconomic and bank-specific data from a sample of 191 commercial banks to test the impact of country-wide corruption on the credit risk of commercial banks operating in 18 MENAP countries. This is the first research to employ QR methodology to investigate the association between corruption and banks' credit risk. Using this methodology provided us additional information on how corruption and other control variables affect banks at different credit risk levels.

Our findings show that corruption has a positive and statistically significant relationship with commercial banks' credit risk. Furthermore, our results illustrate that the regression coefficients of some independent variables behave differently across different credit risk levels, or quantiles. For example, the estimated coefficients show that corruption has a stronger impact on banks that have higher level of credit risk than the banks that have lower levels of credit risk. In other words, banks with high credit risk appear to be more vulnerable against corruption than banks with low credit risk.

Considering that the 90% of the sample banks used in this research owned by the private sector, these findings suggest that private banks are as vulnerable to corruption as the public banks when the countrywide corruption is high. Therefore, the idea that banks' credit risk could be insulated through private ownership may not be correct when countries suffer from a widespread high levels of corruption.

On the basis of these findings we can argue that lower levels of countrywide corruption will result in lower levels of NPLs in commercial banks, in particular, high credit risk banks with benefit more than others. Therefore we can argue that lower levels of countrywide corruption will promote healthier banking sectors. However, it is beyond the scope of this research to study how corruption could be reduced or eliminated.

On the basis of our findings we can suggest that countries with high corruption levels should consider to tighten their banking regulations and supervise their high credit risk banks closely to reduce the credit risk in their banking sectors. For example, regulators may impose higher provisioning for banks with high credit risk. In addition, having frequent on-sight inspections to examine credit portfolios of high credit risk banks will help to limit the credit risk exposure of these banks to the corruptive practices in the country.

Furthermore, in order to prevent banks from making decisions under the political pressure transparency should be increased in the credit departments of banks through sharing credit applications and credit approval decisions with other divisions in the bank and outside bodies such as the Central Bank, and bank supervisors.

Our findings show that corruption does not affect all banks at the same level. Hence, further research is recommended to understand the interventions that will serve to control this behavior. Moreover, it is important to understand the channels that countrywide corruption affects private banks' credit decisions. How the governance of commercial banks could be improved in highly corruptive environments should also be investigated in further research. This research is conducted in MENAP region, similar research in other regions, with different levels of income and public sector corruption are also recommended.

REFERENCES

Abd Karim, M. Z., Chan, S. G., & Hassan, S. (2010). Bank efficiency and non-performing loans: Evidence from Malaysia and Singapore. *Prague Economic Papers*, *2*(1).

Abid, L., Ouertani, M.N. and Zouari-Ghorbel, S. (2014), “Macroeconomic and bank-specific determinants of household’s non-performing loans in Tunisia: A dynamic panel data”, *Procedia Economics and Finance*, Vol. 13, pp. 58–68.

Agarwal, S., Qian, W., Seru, A. and Zhang, J. (2015), “Disguised corruption: Evidence from consumer credit in China”, working paper presented at the Asia Bureau of Finance and Economics Research, available at http://abfer.org/docs/2015/program-1/disguised-corruption-evidence-from-consumer-credit-in-china.pdf (accessed 20 February 2019).

Ahlin, C., & Bose, P. (2007). Bribery, inefficiency, and bureaucratic delay. *Journal of Development Economics*, *84*(1), 465-486.

Ahmad, F. (2013). Corruption and information sharing as determinants of non-performing loans. *Business Systems Research Journal*, *4*(1), 87-98.

Aidt, T. S. (2003). Economic analysis of corruption: a survey. *The Economic Journal*, *113*(491), F632-F652.

Akins, B., Dou, Y., & Ng, J. (2017). Corruption in bank lending: The role of timely loan loss recognition. *Journal of Accounting and Economics*, *63*(2-3), 454-478.

Al Rahahleh, N., Ishaq Bhatti, M., & Najuna Misman, F. (2019). Developments in risk management in Islamic finance: A review. *Journal of Risk and Financial Management*, *12*(1), 37.

Alandejani, M., & Asutay, M. (2017). Nonperforming loans in the GCC banking sectors: Does the Islamic finance matter?. *Research in International Business and Finance*, *42*, 832-854.

Ali, M. S. B., Fhima, F., & Nouira, R. (2020). How does corruption undermine banking stability? A threshold nonlinear framework. *Journal of Behavioral and Experimental Finance*, *27*, 100365.

Al-Jarrah, I. M. (2012). Evaluating the riskiness of the banking sector of Jordan. *European Journal of Economics, Finance and Administrative Sciences*, *48*(48), 86-95.

Altıntaş, M. A. (2012). *Kredi kayıplarının makroekonomik değişkenlere dayalı olarak tahmini ve stres testleri: Türk bankacılık sektörü için ekonometrik bir yaklaşım*. Türkiye Bankalar Birliği.

Amador, J. S., Gómez-González, J. E., & Pabón, A. M. (2013). Loan growth and bank risk: new evidence. *Financial Markets and Portfolio Management*, *27*(4), 365-379.

Anastasiou, D., Bragoudakis, Z. and Malandrakis, I. (2019), “Non-performing loans, governance indicators and systematicliquidity risk: evidence from Greece”, working paper no. 260, Bank of Greece.

Andriani, V., & Wiryono, S. K. (2015). Bank-specific determinants of credit risk: Empirical evidence from Indonesian banking industry. *International Journal of Technical Research and Applications*, *21*, 1-4.

Angbazo, L. (1997). Commercial bank net interest margins, default risk, interest-rate risk, and off-balance sheet banking. *Journal of Banking & Finance*, *21*(1), 55-87.

Ariffin, N.M., Archer, S. and Karim, R.A.A. (2009), “Risks in Islamic banks: Evidence from empirical research”, *Journal of Banking Regulation*, Vol. 10 No. 2, pp. 153–163.

Asiedu, E. (2003). Foreign direct investment to Africa: The role of government policy, governance and political instability. *Department of Economics, University of Kansas*.

Atakelt, H.A., Veni, P. (2015). Credit Risk Management Tools Practiced in Ethiopian Commercial Banks. *International Journal of Social Science and Interdisciplinary Research, 4*(5).

Atkins, B., Dou, Y., & NG, J. T. Y. (2015). Corruption in bank lending: The role of timely loan loss provisioning.

Bahoo, S., (2020), "Coruption in banks: A bibliometric review and agenda", *Financial Research Letters,* Vol. 35, 101499.

Bardhan, S., Sharma, R., & Mukherjee, V. (2019). Threshold effect of bank-specific determinants of non-performing assets: An application in Indian banking. *Journal of Emerging Market Finance*, *18*(1_suppl), S1-S34.

Barth, J. R., Caprio Jr, G., & Levine, R. (2004). Bank regulation and supervision: what works best?. *Journal of Financial intermediation*, *13*(2), 205-248.

Barth, J. R., Dopico, L. G., Nolle, D. E., & Wilcox, J. A. (2002). Bank safety and soundness and the structure of bank supervision: a cross-country analysis. *International Review of Finance*, *3*(3-4), 163-188.

Barth, J. R., Lin, C., Lin, P., & Song, F. M. (2009). Corruption in bank lending to firms: cross-country micro evidence on the beneficial role of competition and information sharing. *Journal of Financial Economics, 91*(3), 361-388.

Basle Committee on Banking Supervision, & Bank for International Settlements. (2000). *Principles for the management of credit risk*. Bank for International Settlements.

Bayley, D. H. (1966). The effects of corruption in a developing nation. *Western political quarterly*, *19*(4), 719-732.

Beck, R., Jakubik, P. and Piloiu, A. (2013), "Non-performing loans: What matters in addition to the economic cycle?", working paper no. 1515, European Central Bank, February, 3-20.

Beck, R., Jakubik, P., & Piloiu, A. (2015). Key determinants of non-performing loans: new evidence from a global sample. *Open Economies Review*, *26*(3), 525-550.

Bekaert, G., C. Harve, and C. Lundblad (2001): "Does financial liberalization spur growth?", NBER Working Paper 8245.

Bencivenga, V. R., & Smith, B. D. (1991). Financial intermediation and endogenous growth. *The review of economic studies*, *58*(2), 195-209.

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

Berger, A.N. and Udell, G.F. (2004), “The institutional memory hypothesis and the procyclicality of bank lending behavior”, *Journal of Financial Intermediation,* Vol. 13 No. 4, pp. 458–495.

Bessis, J. (2011). *Risk management in banking*. John Wiley & Sons.

Bhattarai, S. (2015). Determinants of non-performing loan in Nepalese commercial banks. *Economic Journal of Development Issues*, 22-38.

Bhatti, M. I., Al Rahahleh, N., & Qadri, H. M. U. D. (2019). Recent Development in Islamic Finance and financial products. *The Growth of Islamic Finance and Banking*, 32-49.

Blavy, R., & Souto, M. (2009). Estimating default frequencies and macrofinancial linkages in the Mexican banking sector. *IMF Working Papers*, 1-32.

Bloem, A. M., & Freeman, R. (2005, June). The treatment of nonperforming loans. In *Issue Paper Prepared for the July 2005 Meeting of the Advisory Expert Group on National Accounts, Fondo Monetario Internacional*.

Boudriga, A., Taktak, N.B. and Jelloli, S. (2010), “Bank Specific, Business and Institutional Environment Determinants of Banks Nonperforming Loans: Evidence from MENA Countries”, working paper 547, Economic Research Forum, pp. 1–28.

Bougatef, K. (2015). The impact of corruption on the soundness of Islamic banks. *Borsa Istanbul Review, 15*(4), 283-295.

Bougatef, K. (2016), "How corruption affects loan portfolio quality in emerging markets?", *Journal of Financial Crime*, Vol. 23 No. 4, pp. 769–785.

Boyd, J. H., & Gertler, M. (1994). The role of large banks in the recent US banking crisis. *Federal Reserve Bank of Minneapolis Quarterly Review, 18*(1), 2-21.

Canay, I.A. (2011), "A simple approach to quantile regression for panel data", *The Econometrics Journal*, Vol. 14 No. 3, pp. 368–386.

Carvallo, O., Kasman, A., & Kontbay-Busun, S. (2015). The Latin American bank capital buffers and business cycle: Are they pro-cyclical?. *Journal of International Financial Markets, Institutions and Money*, *36*, 148-160.

Castro, V. (2013). Macroeconomic determinants of the credit risk in the banking system: The case of the GIPSI. *Economic Modelling*, *31*, 672-683.

Cebenoyan, A. S., & Strahan, P. E. (2004). Risk management, capital structure and lending at banks. *Journal of banking & finance*, *28*(1), 19-43.

Chaibi, H., & Ftiti, Z. (2015). Credit risk determinants: Evidence from a cross-country study. *Research in international business and finance*, *33*, 1-16.

Charumilind, C., Kali, R., & Wiwattanakantang, Y. (2006). Connected lending: Thailand before the financial crisis. *The Journal of Business*, *79*(1), 181-218.

Chen, M., Jeon, B.N., Wang, R. and Wu, J. (2015), "Curruption and bank risk-taking: Evidence from emerging economies", *Emerging Markets Review*, Vol.24, pp.122-148.

Chen, Y., Liu, M., & Su, J. (2013). Greasing the wheels of bank lending: Evidence from private firms in China. *Journal of Banking & Finance*, *37*(7), 2533-2545.

Chowdhury, M. A. F., Haque, M. M., Alhabshi, S. O., & Masih, A. M. M. (2016). Socioeconomic development and its effect on performance of Islamic banks: dynamic panel approaches. In *Macroprudential Regulation and Policy for the Islamic Financial Industry* (pp. 229-243). Springer, Cham.

Cihak, M., & Hesse, H. (2007). *Cooperative banks and financial stability* (No. 2007/002). International Monetary Fund.

Clair, R.T. (1992), "Loan growth and loan quality: Some preliminary evidence from Texas banks", *Economic Review, Federal Reserve Bank of Dallas, 1992*(Third Quarter), pp. 9–22.

Cooray, A., Dzhumahev, R. and Schneider, F. (2017), "How does corruption affect public debt? An empirical analysis", *World Development*, Vol. 90, pp. 115–127.

Crouhy, M.; Galai, D.; Mark, R. 2007. Risk Management. McGraw-Hill, New York

Das, A. and Ghosh, S. (2007), "Determinants of credit risk in Indian state-owned banks: An empirical investigation", *Economic Issues,* Vol. 12 No. 2, pp. 48–66.

De Lis, F.S., Martínez Pagés, J. and Saurina, J. (2001), "Credit growth, problem loans and credit risk provisioning in Spain", *BIS papers,* Vol. 1, pp. 331–353.

Dike, V. E. (2005). Corruption in Nigeria: A new paradigm for effective control. *Africa economic analysis*, *24*(08), 1-22.

Dima, B., Dincă, M. S., & Spulbăr, C. (2014). Financial nexus: Efficiency and soundness in banking and capital markets. *Journal of International Money and Finance*, *47*, 100-124.

Djalilov, K., and Piesse, J., (2019), "*Bank regulation and efficiency: Evidence from transition countries", International Review of Economics and Finance*, Vol. 64, pp.308-322.

Dreher, A., & Gassebner, M. (2013). Greasing the wheels? The impact of regulations and corruption on firm entry. *Public Choice*, *155*(3-4), 413-432.

Ehrlich, I., & Lui, F. T. (1999). Bureaucratic corruption and endogenous economic growth. *Journal of Political Economy*, *107*(S6), S270-S293.

Elkamel, H. (2019), “The effect of corruption, seigniorage and borrowing on inflation”, *PSU Research Review*, Vol. 3 No. 1, pp. 1–15.

El-Maude, J.G., Abdul-Rehman, A. and Ibrahim, M. (2017), “Determinants of Non-Performing Loans in Nigeria’s Deposit Money Bank”, *Archives of Business Research*, Vol. 5 No. 1, pp. 74–88.

European Banking Authority (2013). Risk Assessment of the European Banking System, 46 p.

Festić, M., Kavkler, A., & Repina, S. (2011). The macroeconomic sources of systematicrisk in the banking sectors of five new EU member states. *Journal of Banking & Finance, 35*(2), 310-322.

Fiordelisi, F., Marques-Ibanez, D. and Molyneux, P. (2011), “Efficiency and risk in European banking”, *Journal of Banking & Finance*, Vol. 35 No. 5, pp. 1315–1326.

Fofack, H.L. (2005), “Nonperforming loans in Sub-Saharan Africa: Causal analysis and macroeconomic implications”, Policy Research Working Paper No. WPS 3769, World Bank, Washington, DC.

Foos, D., Norden, L., & Weber, M. (2010). Loan growth and riskiness of banks. *Journal of Banking & Finance, 34*(12), 2929-2940.

Frisch, D. (1996). The effects of corruption on development. The courier ACP-EU, 158: 68–70. Global competitiveness report, 2007–08. In *World Economic Forum*.

Gallo, J. G., Apilado, V. P., & Kolari, J. W. (1996). Commercial bank mutual fund activities: Implications for bank risk and profitability. *Journal of Banking & Finance*, *20*(10), 1775-1791.

Galvao, A.F., Lamarche, C. and Lima, L.R. (2013), "Estimation of censored quantile regression for panel data with fixed effects", *Journal of the American Statistical Association*, Vol. 108 No. 503, pp. 1075–1089.

Gaulia, A., & Mačerinskienė, I. (2006). Adaptation of bank's X risk management model to the new basel capital accord using algorithm based on paired comparison. *Vadyba [Vilniaus universitetas]*, (2), 48-57.

Godlewski, C.J. (2005), "Bank capital and credit risk taking in emerging market economies", *Journal of Banking Regulation*, Vol. 6 No. 2, pp. 128–145.

Goel, R. K., & Hasan, I. (2011). Economy-wide corruption and bad loans in banking: international evidence. *Applied Financial Economics*, *21*(7), 455-461.

Hakimi, A. and Hamdi, H. (2017), "Does corruption limit FDI and economic growth? Evidence from MENA countries", *International Journal of Emerging Markets*, Vol. 12 No. 3, pp. 550–571.

He, X., & Zhu, L. X. (2003). A lack-of-fit test for quantile regression. *Journal of the American Statistical Association, 98*(464), 1013-1022.

Hilbers, P. L. C., Leone, A. M., Gill, M. S., & Evens, O. (2000). *Macroprudential Indicators of Financial System Soundness* (No. 192). International Monetary Fund.

Houston, J.F., Jiang, L., Lin, C. and Ma, Y. (2014), “Political connections and the cost of bank loans”, *Journal of Accounting Research*, Vol. 52 No. 1, pp. 193–243.

Huntington, S. P. (1979). Political and economic-change in Southern Europe and Latin-America. *Europa Archiv, 34*(8), 231-242.

Idris, I. T., & Nayan, S. (2016). The moderating role of loan monitoring on the relationship between macroeconomic variables and non-performing loans in association of Southeast Asian nations countries. *International Journal of Economics and Financial Issues, 6*(2).

İslamoğlu, M. (2015). The effect of macroeconomic variables on non-performing loan ratio of publicly traded banks in Turkey. *Transactions on Business and Economics*, *12*, 10-20.

Jackson, P., & Perraudin, W. (1999). The nature of credit risk. *Financial Stability Review*.

Jensen, M. C., & Meckling, W. H. (1976). Theory of the firm: Managerial behavior, agency costs and ownership structure. *Journal of financial economics*, *3*(4), 305-360.

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

Karadima, M. and Louri, H. (2020), Non-performing Loans in the Euro Area: Does Market Power Matter? Working Paper, No: 271, Bank of Greece.

Kato,K. Galvao Jr, A.F., and Montes-Rojas, G.V.,(2012), "Asymptotics for panel quantile regression models with individual effects", *Journal of Econometrics*, Vol. 170, No.1, pp.76-91.

Kaufmann, D (1997) Economic Corruption. Published in Foreign Policy Summer 1997 pp.114-131.

Khan, M. A., Siddique, A., & Sarwar, Z. (2020). Determinants of non-performing loans in the banking sector in developing state. *Asian Journal of Accounting Research*.

Khwaja, A. I., & Mian, A. (2005). Do lenders favor politically connected firms? Rent provision in an emerging financial market. *The Quarterly Journal of Economics*, *120*(4), 1371-1411.

Klein, N. (2013). *Non-performing loans in CESEE: Determinants and impact on macroeconomic performance*. International Monetary Fund.

Klitgaard, R. (1991). Gifts and bribes. *Strategy and Choice*, 419-435.

Klomp, J., & De Haan, J. (2012). Banking risk and regulation: Does one size fit all?. *Journal of Banking & Finance*, *36*(12), 3197-3212.

Koenker, R. (2005). *Quantile Regression*. New York: Cambridge University Press.

Koenker, R. (2017), "Quantile regression: 40 years on", *Annual Review of Economics*, Vol. 9, pp. 155–176.

Koenker, R. and Bassett Jr., G. (1978), "Regression quantiles", *Econometrica*, Vol. 46 No. 1, pp. 33–50.

Koenker, R. and Xiao, Z. (2004), "Unit root quantile autoregression inference", *Journal of the American Statistical Association*, Vol. 99 No. 467, pp. 775–787.

Koenker, R. and Xiao, Z. (2004), "Unit root quantile autoregression inference", *Journal of the American Statistical Association*, Vol. 99 No. 467, pp. 775–787.

Koenker, R., & Machado, J. A. (1999). Goodness of fit and related inference processes for quantile regression. *Journal of the american statistical association*, *94*(448), 1296-1310.

Köhler, M. (2012). Which banks are more risky? The impact of loan growth and business model on bank risk-taking.

Koju, L., Koju, R. and Wang, S. (2018), "Does banking management affect credit risk? Evidence from the Indian banking system", *International Journal of Financial Studies*, Vol. 6 No. 3, pp. 1–11.

Krueger, A. O. (1974). The political economy of the rent-seeking society. *The American economic review*, *64*(3), 291-303.

Kwan, S., & Eisenbeis, R. A. (1997). Bank risk, capitalization, and operating efficiency. *Journal of financial services research*, *12*(2), 117-131.

La Porta, R., Lopez-de-Silanes, F., Shleifer, A. and Vishny, R.W. (1997), "Legal determinants of external finance", *Journal of Finance,* Vol. 52 No. 3, pp. 1131–1150.

Lamarche, C. (2010), "Robust penalized quantile regression estimation for panel data", *Journal of Ecoometrics,* Vol.157, No.2, pp.396-408.

Laryea, E., Ntow-Gyamfi, M., & Alu, A. A. (2016). Nonperforming loans and bank profitability: evidence from an emerging market. *African Journal of Economic and Management Studies*.

Lee, B.S. and Li, M.Y.L. (2012), "Diversification and risk-adjusted performance: A quantile regression approach", *Journal of Banking & Finance*, Vol. 36 No. 7, pp. 2157–2173.

Leff, N. H. (1964). Economic development through bureaucratic corruption. *American behavioral scientist*, *8*(3), 8-14.

Levin, M., & Satarov, G. (2000). Corruption and institutions in Russia. *European journal of political economy*, *16*(1), 113-132.

Levine, R. (2001). International financial liberalization and economic growth. *Review of international Economics*, *9*(4), 688-702.

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

Li, M. Y. L., & Miu, P. (2010). A hybrid bankruptcy prediction model with dynamic loadings on accounting-ratio-based and market-based information: A binary quantile regression approach. *Journal of Empirical Finance*, *17*(4), 818-833.

Liu, P., Li, H. and Guo, H. (2020) The impact of corruption on firms' access to bank loans: evidence from China, *Economic Research- Ekonomska Istrazivanja,* 33:1, 1963-1984.

Liu, T., Hammoudeh, S. and Thompson, M.A. (2013), "A momentum threshold model of stock prices and country risk ratings: Evidence from BRICS countries", *Journal of International Financial Markets, Institutions and Money*, Vol. 27, pp. 99–112.

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

Lui, F. T. (1985). An equilibrium queuing model of bribery. *Journal of political economy*, *93*(4), 760-781.

Luu, H.N., Nguyen, N.M., Ho, H.H. and Nam, V.H. (2019), "The effect of corruption on FDI and its modes of entry", *Journal of Financial Economic Policy*, Vol. 11 No. 2, pp. 232–250.

Lv, Z. and Xu, T. (2017) "A panel data quantile regression analysis of the impact of corruption on tourism", *Current Issues in Tourism,* Vol. 20, No.6, pp 603-616.

Makri, V., Tsagkanos, A. and Bellas, A. (2014), “Determinants of non-performing loans: The case of Eurozone”, *Panoeconomicus*, Vol. 61 No. 2, pp. 193–206.

Manz, F. (2019). Determinants of non-performing loans: What do we know? A systematic review and avenues for future research. *Management Review Quarterly*, *69*(4), 351-389.

Messai, Ahlem Selma, and Fathi Jouini. "Micro and macro determinants of non-performing loans." *International journal of economics and financial issues* 3.4 (2013): 852.

Mishkin, F. S. (2001). *Financial policies and the prevention of financial crises in emerging market economics* (Vol. 8087). World Bank Publications.

Misman, F. N., Bhatti, I., Lou, W., Samsudin, S., & Abd Rahman, N. H. (2015). Islamic banks credit risk: a panel study. *Procedia Economics and Finance*, *31*, 75-82.

Mohamad, A., & Jenkins, H. (2020). Corruption and banks’ non-performing loans: empirical evidence from MENA countries. *Macroeconomics and Finance in Emerging Market Economies*, 1-14.

Mongid, A. (2007, December). The political openness of banking system, political governance, law enforcement and cost of banking crisis: Indonesia in the international perspective. In *32nd Annual Conference of the Federation of ASEAN Economist Association FAEA, Bangkok* (pp. 7-8).

Murharsito, M., Fauziah, F.E., Kristijadi, E. and Iramani, R. (2017), "Provincial corruption and local development bank performance", *Economic Journal of Emerging Markets*, Vol. 9 No. 1, pp. 66–73.

Murshed, M. and Saadat, S.Y. (2018), "An empirical investigation of non-performing loans and governance: a South Asian perspective", *World Review of Business Research*, Vol. 8 No. 1, pp. 188–206.

Nkusu, M. (2011). Nonperforming loans and macrofinancial vulnerabilities in advanced economies. *IMF Working Papers*, 1-27.

Norton, J. J., & Olive, C. D. (1996). Globalization of financial risks and international supervision of banks and securities firms: lessons from the Barings debacle. *The International Lawyer*, 301-344.

Olken, B.A., and Pande, R. (2012), "Corruption in Developing Countries", *The Annual Review of Economics, Vol* 4, no.1, pp. 479-509.

Ozcan, I. S. İ. K., & Bolat, S. (2016). Determinants of non-performing loans of deposit banks in Turkey. *Journal of Business Economics and Finance, 5*(4), 341-350.

Park, J. (2012). Corruption, soundness of the banking sector, and economic growth: A cross-country study. *Journal of international money and Finance, 31*(5), 907-929.

Peristiani, S. (1996). Evaluating the postmerger X-efficiency and scale efficiency of US banks. *Federal Reserve Bank of New York, working paper*.

Podpiera, J. and Weill, L. (2008), "Bad luck or bad management? Emerging banking market experience", *Journal of Financial Stability*, Vol. 4 No. 2, pp. 135–148.

Powell, D. (2016), "Quantile treatment effects in the presence of covariates", RAND labor and population working paper, 1–53.

Qi, S., & Ongena, S. (2019). Will money talk? Firm bribery and credit access. *Financial Management*, *48*(1), 117-157.

Qian, J., & Strahan, P. E. (2007). How laws and institutions shape financial contracts: The case of bank loans. *The Journal of Finance*, *62*(6), 2803-2834.

Qin, X. (2012), "Quantile effects of casual factors on crash distributions", *Transportation Research Record: Journal of the Transportation Research Board*, Vol. 2279 No. 1, pp. 40–46.

Qin, X. and Reyes, P.E. (2011). Conditional quantile analysis for crash count data. *Journal of Transportation Engineering*, Vol. 137 No. 9, pp. 601–607.

Qin, X., Ng, M. and Reyes, P.E. (2010), "Identifying crash-prone locations with quantile regression", *Accident Analysis and Prevention*, Vol. 42 No. 6, pp. 1531–1537.

Quagliariello, M. (2009). Macroeconomic uncertainty and banks' lending decisions: The case of Italy. *Applied Economics*, *41*(3), 323-336.

Radivojević, N., Cvijanović, D., Sekulic, D., Pavlovic, D., Jovic, S., & Maksimović, G. (2019). Econometric model of non-performing loans determinants. *Physica A: Statistical Mechanics and its Applications*, *520*, 481-488.

Rahman, A. A., & Shahimi, S. (2010). Credit Risk and Financing Structure of Malaysian Islamic Banks. *Journal of Economic Cooperation & Development*, *31*(3).

Rajan, R. and 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*, Vol. 24 No 3, pp. 81–121.

Rajan, R. G. (1994). Why bank credit policies fluctuate: A theory and some evidence. *the Quarterly Journal of economics*, *109*(2), 399-441.

Rajha, K. S. (2016). Determinants of non-performing loans: Evidence from the Jordanian banking sector. *Journal of Finance and Bank Management*, *4*(1), 125-136.

Reinhart, C. M., & Rogoff, K. S. (2011). From financial crash to debt crisis. *American Economic Review*, *101*(5), 1676-1706.

Rodríguez-Moreno, M., & Peña, J. I. (2013). Systematicrisk measures: The simpler the better?. *Journal of Banking & Finance, 37*(6), 1817-1831.

Roman, A., & Bilan, I. (2015). An empirical analysis of the macroeconomic determinants of non-performing loans in EU28 banking sector. *Revista Economică*, *67*(2), 108-127.

Salas, V., & Saurina, J. (2002). Credit risk in two institutional regimes: Spanish commercial and savings banks. *Journal of Financial Services Research*, *22*(3), 203-224.

Şan, T. (2018), "Non-Performing loans increase in the Albanian Banking sector during the Last Global Economic Crisis - An Analysis Based on the Client Groups", *European Journal of Marketing and Economics,* Vol. 1 No. 3, pp. 123–130.

Schechtman, R., & Gaglianone, W. P. (2012). Macro stress testing of credit risk focused on the tails. *Journal of Financial Stability*, *8*(3), 174-192.

Sequeira, S. (2012). Advances in measuring corruption in the field. *New advances in experimental research on corruption*.

Sheefeni, J.P.S. (2015), "Evaluating the impact of bank specific determinants of non-performing loans in Namibia", *Journal of Emerging Issues in Economics, Finance and Banking*, Vol. 4 No. 2, pp. 1525–1541.

Shi, L., Allan, N., Evans, J., & Yun, Y. (2018). Significance of controllable and uncontrollable drivers in credit defaults. *Economic Papers: A journal of applied economics and policy*, *37*(1), 30-41.

Shingjergji, A. (2013), “The impact of bank specific variables on the non-performing loans ratio in the Albanian banking system”, *Research Journal of Finance and Accounting*, Vol. 4 No. 7, pp. 148–152.

Škarica, B. (2014). Determinants of non-performing loans in Central and Eastern European countries. *Financial theory and practice*, *38*(1), 37-59.

Son, T. H., Liem, N. T., & Khuong, N. V. (2020). Corruption, nonperforming loans, and economic growth: International evidence. *Cogent Business & Management*, *7*(1), 1735691.

Stern, G. and Feldman, R. (2004), *Too big to fail: The hazards of bank bailouts*, Brookings Institution, Washington, DC.

Stiglitz, J. E., & Weiss, A. (1981). Credit rationing in markets with imperfect information. *The American economic review*, *71*(3), 393-410.

Syed, A., & Tripathi, R. (2020). Nonperforming Loans in BRICS Nations: Determinants and Macroeconomic Impact. *Available at SSRN 3528097*.

Tan, Y., & Anchor, J. (2017). The impacts of risk-taking behaviour and competition on technical efficiency: evidence from the Chinese banking industry. *Research in International Business and Finance*, *41*, 90-104.

Thalassinos, E. I., & Thalassinos, Y. (2018). Financial Crises and e-Commerce: How Are They Related. *Available at SSRN 3330169*.

Thiagarajan, S., Ayyappan, S. and Ramachandran, A. (2011), “Credit risk determinants of public and private sector banks in India”, *European Journal of Economics, Finance and Administrative Sciences*, Vol. 34, pp. 147–154.

Toader, T., Onofrei, M., Popescu, A. I., & Andrieș, A. M. (2018). Corruption and banking stability: Evidence from emerging economies. *Emerging Markets Finance and Trade*, *54*(3), 591-617.

Transparency International (2019) Corruption Perception Index, 2011-2018. https://www.transparency.org/en/cpi

Vishny, R. W., & Shleifer, A. (1993). *Corruption*. National Bureau of Economic Research.

Wang, L., Zhou, Y., Song, R. and Sherwood, B. (2018), “Quantile-optimal treatment regimes”, *Journal of the American Statistical Association*, Vol. 113 No. 523, pp. 1243–1254.

Weill, L. (2011), "How corruption affects bank lending in Russia", *Economic Systems*, Vol. 35 No. 2, pp. 230–243.

Williams, J., & Gardener, E. (2003). The efficiency of European regional banking. *Regional Studies*, *37*(4), 321-330.

Williamson, O. E. (1963). Managerial discretion and business behavior. *The American Economic Review*, *53*(5), 1032-1057.

World Bank (2019) World Bank Development Indicators, https://databank.worldbank.org/source/world-development-indicators

World Bank, 2000. World Business Environment Survey. Washington, D.C.: The World Bank.

Zribi, N. and Boujelbène, Y. (2011), "The factors influencing bank credit risk: The case of Tunisia", *Journal of Accounting and Taxation*, Vol. 3 No. 4, pp. 70–78.