Research article

Banks' credit risk, systematic determinants and specific factors: recent evidence from emerging markets

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A R T I C L E   I N F O

A B S T R A C T

Non-performing loans (NPLs, henceforth) represent the main challenge that jeopardizes the steadiness of the banking sector. The purpose of this study is to explore the main determinants of banks' non-performing loans in emerging markets. To better understand the hidden aspects of these determinants, the current research employs a panel approach and dynamic data estimates through Generalized Methods of Moments (GMM) using data of 53 banks listed in five Middle East and North African (MENA) emerging markets between 2000 and 2019. This study documents that GDP growth, unemployment, bank capitalization, bank performance, bank operating inefficiency, bank ownership concentration, inflation, sovereign debt and bank size are the main determinants of NPLs, whereas, loan growth, bank diversification and interbank competition were found to have an insignificant impact on NPLs. This analysis is motivated by the recent economic changes surrounding the financial systems in emerging countries with the aim to provide new evidence and insights. The results show that non-performing loans can be explained mainly by macroeconomic variables and bank-specific factors with interesting differences in their quantitative impacts. This study has substantial theoretical and practical contributions. It shows strong evidence on the leading indicators of future problematic loans. The identification of these factors would help regulators address appropriate interventions, design ample credit policies and adopt adjusted prudential regulations. Further, it empowers the regulatory authorities with an in-depth understanding of credit risk determinants, allowing them to place emphasis on risk management systems and procedures that minimize borrowers' default in order to avert future financial instability. Our findings underscore the necessity of closely monitoring bank-specific factors along with reinforcing country level mechanisms to reduce banks' credit risk.

1. Introduction

Considered as the backbone of the economy and the primary contributor to its survival and growth, the banking sector plays a vital role in the economic stability of any country. It is the sinew that keeps the economy working as it grants credits and allows businesses and households to save, invest and increase their spending, which ultimately support the economic growth (Naili and Lahrichi, 2020). This sector, nevertheless, faces numerous kinds of risks that, not only destabilize its financial well-being, but jeopardize the stability of the whole country. In particular, one of the risks that erodes banks' profitability and marks the onset of a crisis is bank credit risk (Berger and Deyoung, 1997). Central bankers agreed that the distress of the financial sector during financial crises was predominantly due to banks' credit risk, mostly conveyed by the level of banks' non-performing loans.[1] By definition, a loan is considered non-performing when its payment is past due by at least 90 days (IMF, 2005, p 8), mirroring the banks' assets quality and serving as a signpost of their well-being (Cucinelli et al., 2018; Partovi and Matousek, 2019; Reinhart and Rogoff, 2011; Salas and Saurina, 2002; Tarchouna et al., 2017).

In view of the lessons learned from the past financial downturns, the accumulation of non-performing loans is regarded as a red flag and a potential sign of deeper troubles. Their consequences are not only harmful for the creditors, but for the whole economy. It was documented by various scholars that the level of NPLs is significantly associated with the banking sector vulnerability and crisis occurrence (Calomiris et al., 2007; Desmet, 2000; Laeven and Valencia, 2008; Reinhart and Rogoff, 2011; Salas and Saurina, 2002; Samad, 2012). For instance, a research

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[1] Central bankers agreed that banks' NPLs were the reason behind the onset of several financial crises including the slump of the US financial system in the 1980s, the Asian crisis during the 1990s and 2000s, the US subprime crisis and, more recently, the loans debacle of the European credit crisis.

piloted by Salas and Saurina (2002) documents that large levels of NPLs harm the liquidity and profitability of credit institutions. Besides, Reinhart and Rogoff (2011) argued that a NPLs ratio reflects an alarming indicator that mark the beginning of a financial slump. Other scholars categorized NPLs as "financial pollution" due to the scars it leaves on banks' balance sheets (Barseghyan, 2010; Makri et al., 2014; Zeng, 2012).

The issue of NPLs came to dominate the economic debate especially in the aftermath of the financial crises. For instance, the crisis of the sub-prime left profound scars on the United States affecting both, developed and emerging countries due to global integrated financial systems (Shahin and El-achkar, 2018). Billions of NPLs were recorded, making the strongest economies look fragile (Jabbouri and Naili, 2019a). With regards to the recent European crisis, various countries recorded a huge pile of NPLs as well. EU banks recorded approximately €1 trillion worth of NPLs by 2013, which distressed the economy (ECB, 2017). In 2016, Greece and Cyprus held alone an NPLs ratio of 46% and 45%, respectively. The European Central Bank and the European Banking Authority spare no efforts to reduce the level of NPLs. In this sense, a special taskforce has been created, fully dedicated to tackle NPLs issue.[2] Aside from the economic conditions, the ECB provides strong evidence that the immense volume of NPLs is a result of banks' internal drivers including, among others, improper credit screening and insufficient internal governance (ECB, 2017). As a result, the level of NPLs has been reduced considerably, from €958 billions in December 2014 to €688 billions in 2018. Yet, the remaining stock still poses a considerable issue and requires further efforts (ECB, 2017). Asset quality has been as well the concern of economic policymakers in emerging countries. Emerging markets have been buffeted by a number of economic shocks including non-performing loans (Farooq and Jabbouri, 2015a). A recent and comprehensive review of literature showed that despite the significant number of studies that explored the determinants banks' credit risk, the issue of NPLs remains unsolved (Naili and Lahrichi, 2020). In addition to that, given the importance of banks' credit risk and the little attention given to emerging markets in terms of research[3], this paper aims to extend knowledge on the main determinants of banks' NPLs in a sample of MENA emerging markets. To meet this objective, the present paper aims to answer the following questions:

1. What are the macroeconomic determinants of banks' credit risk in emerging markets?
2. What are the bank-specific determinants of banks' credit risk in emerging markets?
3. What are the industry-specific determinants of banks' credit risk in emerging markets?

To answer these questions, a sample of 53 banks listed in five emerging markets was employed, with the hope of providing new and significant insights on the aforementioned relationships. The scarcity of empirical studies in emerging markets and the importance of banks' credit risk in the survival and growth of economies, make this research an appealing substance of research.

The rest of this research is arranged as follows. Section 2 introduces the review of literature and hypotheses development. Sections 3 presents data collection and variables measurement. Section 4 illustrates the

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[2] A comprehensive strategy set by the European Central Bank to tackle of the NPL issue, since 2015. Several reports have been published in this sense: the NPL guidance on 2017, the Addendum to the NPL guidance on 2018 and the ECB press release on supervisory expectations for NPL stock in July 2018. These reports are a result of comprehensive research on the main drivers of NPLs in the EU countries. All reports are published on the ECB website.

[3] It was reported that over the past 33 years, only 7% of conducted research on the determinants of banks' NPLs focused on emerging markets (Naili and Lahrichi, 2020).

empirical procedure and Section 5 discusses the results. Section 6 exhibits the robustness test. Finally, Section 7 concludes.

2. Review of literature and hypothesis development

There is an extensive body of research that shed lights on the determinants of credit risk. There are three kinds of studies regarding these determinants. There are research that explore the macroeconomic determinants (Louzis et al., 2012; Nkusu, 2011; Radivojevic and Jovovic, 2017; Salas and Saurina, 2002; Vouldis and Louzis, 2017), the ones that investigate the bank-specific variables (Beaton et al., 2016; Iannotta et al., 2007; Jabbouri and Naili, 2019a; Messai and Jouini, 2013) and the studies that explore the banking-industry specific variables (Natsir et al., 2019; Schaeck et al., 2009).

2.1. Bank-specific factors

The unique features of the banking system along with the different policy choices of each bank are expected to have an impact on the emergence and evolution of NPLs. There is ample evidence that examines the relationship between bank internal factors and their credit risk.

2.1.1. Bank size

There is an abundant amount of literature that addresses the association between bank size and the level of NPLs. Yet, no clear-cut evidence was found in the literature regarding this relationship.

On one hand, scholars document that larger banks are more likely to incur lower loan losses (Alhassan et al., 2014; Louzis et al., 2012; Salas and Saurina, 2002; Solttila and Vihriälä, 1994). This negative link was explained by the fact that larger banks are more able to conduct proper loan screening given their sophisticated risk management techniques (Salas and Saurina, 2002). In the same context, larger banks are in a better position to devote adequate resources to loan analysis and assessments which prevent them from granting loans to low-quality borrowers (Louzis et al., 2012).

On the other hand, literature shed lights on the "too big to fail" hypothesis, implying that larger banks consider themselves indispensable and thus, engage in riskier lending practices. These banks usually suppose that they will be bailed out by the government in case of financial breakdowns (Louzis et al., 2012; Stern and Feldman, 2004). On a sample of 15 European countries, Haq and Heaney (2012) tested and confirmed the aforementioned hypothesis. The authors report that large-sized banks, whose role in the nation's financial system is vital, usually take excessive risk as they do not shoulder the burden of their lending decisions. Given the contrasting evidence, it is worthwhile to investigate this relationship further through the following hypothesis:

H1. Bank size has an impact on banks' credit risk, conveyed by the level of NPLs.

2.1.2. Bank capitalization

The literature presented evidence that capital adequacy ratio (CAR, henceforth) has a strong effect on loan loss rates (Sinkey and Greenawalt, 1991). This impinged capital is usually used as a buffer against excessive risks.

A strand of literature presents evidence that banks holding a large capital as a proportion of their risk-weighted assets experience lower loan losses (Shrieves and Dahl, 1992). The rationale behind this negative link is that banks with high capital adequacy are more likely to engage in thoughtful lending to sustain the capital set aside (Shrieves and Dahl, 1992). This relationship was further explained by the moral hazard hypothesis, insinuating that thinly capitalized banks will more likely take excessive risk given the limited loss they may incur in a potential breakdown (Berger and Deyoung, 1997; Keeton and Morris, 1987).

In rebuttal, other scholars documents a negative link regarding the CAR-NPLs relationship (Ghosh, 2017; Koehn and Santomero, 1980;

Rime, 2001). On a sample of US commercial banks spanning the period between 1992 and 2016 Ghosh (2017) documents that loan losses usually coincide with high capital adequacy. This latter leads banks to involve in riskier lending with insufficient risk evaluation and assessments (Ghosh, 2017). To confirm or reject the previous empirical evidence, we formulate the following hypothesis:

H2. Capital adequacy ratio (CAR) has an impact on banks' credit risk, conveyed by the level of NPLs.

2.1.3. Bank Performance

There is an important number of literature that tackles the link between NPLs and banks' performance (Garcí a-Marco and Dolores Robles-Fernández, 2008; Louzis et al., 2012; Rajan, 1994). Researchers have investigated the impact of the lagged profitability on banks' bad loans. For instance, Louzis et al. (2012) formulated the bad management hypothesis, explaining the negative link between banks' profitability and NPLs. He documents that low profitable banks incur higher loan losses due to their poor management skills and inefficient lending strategies. In this line of research, a study analyzed 50 US banks between 1984 and 2013, corroborates the prior findings and suggests that, on the other hand, profitable banks are less likely to take higher risks which improves their credit quality (Ghosh, 2015; Makri et al., 2014).

Rajan (1994) contends that banks may boost up-front fees to escalate their current earnings through concealing the level of their NPLs, which results in heavy future loan losses.[4] Further, a study conducted on a sample of Spanish banks spanning the period between 1993 and 2000, provides evidence that a positive relationship exists between lagged profitability and NPLs. The authors argue that poorly performing banks are more likely to engage in thoughtful lending through the adoption of conservative credit policy in order to limit further losses (Garcí a-Marco and Dolores Robles-Fernández, 2008).

These conflicting arguments make the question of whether bank's profitability impacts the level of NPLs, a heatedly debated issue that requires a deeper analysis:

H3. Bank profitability has an impact on banks' credit risk, conveyed by the level of NPLs.

2.1.4. Loan growth

Prior literature suggests that loan growth has a significant impact on banks' NPLs (Boudriga et al., 2010; Foos et al., 2010; Keeton and Morris, 1987). In fact, loan growth was one of the main reasons triggering the recent financial crisis (Naili and Lahrichi, 2020). One of the earliest studies examining the link between credit growth and NPLs, contends that rapid loan growth leads to higher loan losses (Keeton and Morris, 1987). The authors argue that when banks increase their lending, loan screening and credit standards deteriorate. A study conducted on a sample of 16 countries between 1997 and 2009 presents compelling results, arguing that banks will more likely ease their credits standards in order to achieve a targeted loan growth which, in turn, results in heavy future losses (Foos et al., 2010). The positive association between loan growth and NPLs was as well supported by Salas and Saurina (2002) and Alhassan et al. (2014).

Other studies contradict prior findings and report a negative relationship between loan growth and NPLs. For instance, Boudriga et al. (2010) found that banks who aim at increasing their lending, are more likely to perform proper loan and screening in order to cope with defaulters. Furthermore, a negative link between NPLs and credit risk was further reported in study conducted in the MENA region between 2003 and 2016. Thus, it comes as no surprise that loan growth is a significant determinant of NPLs, but with inconclusive points of view in the literature about its impact on credit risk.

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[4] This can be achieved through the extension of credits' terms, renewal of borrowers' credit lines and weakening covenants.

H4. Loan growth has an impact on banks' credit risk, conveyed by the level of NPLs.

2.1.5. Bank inefficiency

A large body of literature attempted to address the link between bank inefficiency and bank credit risk, yet the results are vague. Berger and Deyoung (1997) investigated a sample of US bank spanning the period between 1985-1994 and formulated three main hypotheses. The bad management hypothesis suggests that due to the poor managerial skills of banks' managers, low-cost efficient banks incur high levels of NPLs, through inadequate collateral evaluation, poor credit scoring and low borrower monitoring. This hypothesis was further validated by Podpiera and Weill (2008) who investigated Czech banks between 1994 and 2005. The link between bank inefficiency and NPLs was further explained by the bad luck hypothesis, indicating that unpredicted events such as an economic slowdown lead to an increase in NPLs. During these economic crises, managerial efforts are doubled resulting in extra operating costs, which in turn, impacts banks' cost efficiency (Berger and Deyoung, 1997).

On the other hand, the skimping hypothesis provides opposing views and supports a negative link between bank inefficiency and NPLs. This latter insinuates that cost-efficient banks who devote insufficient resources to credit underwriting and loan quality to the costs devoted to underwriting and clients' evaluation (Louzis et al., 2012; Rossi et al., 2009).

H5. Bank inefficiency has an impact on banks' credit risk, conveyed by the level of NPLs.

2.1.6. Ownership concentration

The importance of ownership concentration within financial institutions amplifies given the nature of financial institutions and the unique characteristics of banks. As a matter of fact, banks operate in a highly regulated environment, distinguished by special corporate governance mechanisms and information opacity (Barth et al., 2004; Berger and Deyoung, 1997; Macey and O'Hara, 2003; Jabbouri and AlMustafa, 2021; Prowse, 1997).

There is ample evidence on the role of concentrated ownership in reducing the level of banks' NPLs. For instance, Iannotta et al. (2007) conducted a study on a sample of 181 banks from 15 European countries between 1999 and 2004 and concluded that ownership concentration is positively associated with NPLs. Other researchers confirm prior findings, arguing that concentrated ownership leads to a significant decrease in banks' non-performing loans (Shehzad et al., 2010). They concluded that ownership concentration contributes to lowering the level of NPLs by enhancing the supervisory control and investors' protection within banks, improving the monitoring of management and the capital adequacy ratio, which is considered as a buffer against excessive risk-taking (Leech and Leahy, 1991; Shehzad et al., 2010). In parallel to the above arguments, it is documented that the absence of monitoring within widely dispersed banks increases agency problems and encourages managerial self-serving behaviors, which upsurges the level of NPLs.

In rebuttal, an opposing strand of literature documents a positive relationship between ownership concentration and banks' NPLs (Berle and Means, 1933; Haw et al., 2010; Louzis et al., 2012). Due to the potential conflicts of interests between controlling and minority shareholders, agency problems intensify in concentrated banks, which leads to higher loan losses. Furthermore, controlling shareholders are tempted to take part in expropriating and tunneling activities and transferring the firm resources to serve their own agendas, which exacerbates agency problems and increases the level of bad loans (Barclay and Holderness, 1989; Stulz, 1988). These studies conclude that large shareholders have the power to influence bank risk-taking, by coercing bank managers to undertake risky investments and conduct unthoughtful lending, which burgeons the level of NPLs.

Given this theoretical and empirical contention, it is worthwhile to investigate the impact of concentrated ownership on banks' NPLs.

H6. Ownership concentration has an impact on banks' credit risk, conveyed by the level of NPLs.

2.1.7. Diversification

Researchers have documented that banks' diversification has a significant impact on banks' risk taking. Louzis et al. (2012) claim that diversification has a negative impact on the level of banks' NPLs. The authors explain their finding by the "dark side" of diversification. This latter claims that banks who expand into new businesses are more likely to incur higher loan losses due to the increased risk (Louzis et al., 2012; Stiroh, 2004). Another study analyzed a sample of Chinese banks and confirmed the prior findings and claims that diversification increases the probability of banks' collapses particularly during deregulation periods (Boyd and Graham, 1986; Zhou, 2014). Given the scarcity of research tackling the relationship between diversification and NPL, future research could yield valuable insights. We, thus, hypothesize that:

H7. Banks' diversification has a negative impact on banks' credit risk, conveyed by the level of NPLs.

2.2. Macroeconomic factors

2.2.1. GDP growth

There is ample empirical evidence that links the macroeconomic environment to credit quality. It has been reported that under the expansionary phase of economic growth, individuals and firms face sufficient stream of revenues to repay their financial obligations (Louzis et al., 2012). During challenged times, firms and households are more likely to default on their loans due to the decrease in asset values that serve as collaterals, which lead to the increase of NPLs. Several empirical studies confirm that the level of NPLs decreased during economic booms and the opposite happens during economic slowdowns (Jabbouri and Naili, 2019a; Nkusu, 2011; Salas and Saurina, 2002). Based on these arguments, we expect inverse relationship between GDP growth and banks' credit risk. We hypothesize that:

H8. GDP growth has a positive impact on banks' credit risk, conveyed by the level of NPLs.

2.2.2. Inflation

Prior literature provides sufficient evidence on the casual relationship between inflation and NPLs (Ghosh, 2015; Naili and Lahrichi, 2020; Nkusu, 2011). However, the literature remains ambiguous about the direction of this relationship. Rinaldi and Sanchis-Arellano (2006) documents that higher inflation aggravates bank credit risk. They claim in a study conducted on a sample of European countries, that high inflation rates erode the real value of borrowers' revenue which then restricts their capacity to reimburse their debts. Other studies confirm prior findings, reporting that under inflationary conditions, borrowers' probability to default upsurges, especially in case of variable interest rates loans (Amuakwa-Mensah et al., 2017; Klein, 2013). In emerging markets, inflation is one of the biggest concerns of central bankers as wages are in most cases sticky, which increase the level of NPLs and make firms and households more challenged to repay their debts.

Conversely, other pieces of literature support opposing views. Nkusu (2011) They document that inflation decreases the value of outstanding debts which, in turn, improves the repayment capacity of borrowers. In the same line, Khemraj and Pasha (2009) examined banks in Guyana and argued that labor wages are more likely to adjust to the increase of prices, which ensures borrowers' sustainability of repayments. These findings were confirmed as well in an empirical study conducted on a sample of Indian banks, reporting that inflation has a negative relationship with NPLs (Gulati et al., 2019). Given the contracting evidence, it is important to investigate this relationship further. We formulate the following hypothesis:

H9. Inflation has an impact on banks' credit risk, conveyed by the level of NPLs.

2.2.3. Public debt

Prior literature provides compelling evidence about the relationship between public debt or the so-called sovereign debt and the level of NPLs – a relationship that, at first sight, does not appear evident. In fact, prior empirical research points that public debt plays a significant role in triggering financial crises (Laeven and Valencia, 2013). In this sense, 290 banking crises and 209 sovereign default episodes were investigated in 70 countries (Reinhart and Rogoff, 2011). The authors of this study report that a significant relationship was detected between banking downturns and public debt crises. Yet, the relationship is still ambiguous. A school of thought argues that public debt cuts the public spending which leads to a downswing in households income and social expenditure (Reinhart and Rogoff, 2011). A high public debt impacts the creditworthiness of banks as well by putting a sovereign ceiling on their solvency. As a result, banks face higher difficulties to raise market financing and borrowers become more challenged to refinance their debts (Reinhart and Rogoff, 2011). The sovereign debt hypothesis was formulated to stipulate that higher public debt leads to higher NPLs (Louzis et al., 2012). Several authors tested this hypothesis reporting that an increase in fiscal deficit leads to a deterioration of loan quality (Ghosh, 2015; Makri et al., 2014). These findings are in accordance with the role of public debt as an important determinant of NPLs. Accordingly, we formulate the following hypothesis:

H10. Public debt has an impact on banks' credit risk, conveyed by the level of NPLs.

2.2.4. Unemployment

Unemployment is a key macroeconomic determinant of banks' credit risk. It has been hypothesized that as the country's unemployment rate increases, banks' loan quality deteriorates (Salas and Saurina, 2002). In this line of research, studies stipulate that borrowers with low income face higher chances of unemployment, which in turn, limits their reimbursement capacity (Ghosh, 2015). In addition to that, individuals with low-income levels are considered as risky clients. This lead banks to charge them higher interest rates due to the uncertainty of their employment status, which worsen their repayment ability (Lawrence, 1995). To empirically test previous findings, we formulate the following hypothesis:

H11. Unemployment has a negative impact on banks' credit risk, conveyed by the level of NPLs.

2.3. Industry-specific factors

2.3.1. Interbank competition/concentration

Another impact determinant of credit risk is bank competition. This latter has gained keen interest especially after the global financial crisis, providing countless lessons to bank regulators on how banks' competition and concentration can, either, harm or coarsen the financial sector (Naili and Lahrichi, 2020).

Keeley (1990) demonstrated a direct association between interbank competition and the number of banks' collapses in the US during the 1980s. In this sense and in line with the competition-fragility paradigm, the author developed the "franchise value hypothesis" to explain this relationship. This latter asserts that banks risk exposure increases as interbank competition increases. In the same vein, Hellmann et al. (2000) argued that interbank competition influences banks' franchise value as it reduces their profitability. This will more likely induce banks to engage in riskier lending. The positive relationship between competition/concentration and credit risk was further explained by the

adverse-selection problems. On the other hand, in a concentrated inter-bank market where large banks monopolize, low quality borrowers cannot easily access to credits, which decreases the probability of default (Boudriga et al., 2009). Other scholars confirm the aforementioned findings such as Wang (2018), Turk Ariss (2010) and De Haan and Poghosyan (2012).

Contrariwise, other scholars criticized the above hypothesis, contending that the financial system stability can be enhanced by interbank competition (Jiménez and Saurina, 2005; Ozili, 2019). The authors assert that competition drives banks to lower their lending rates, reducing the profitability of defaults (Boyd and Nicolo, 2005). In the same line, competition would press bank managers to minimize their credit risk through careful lending decisions and adequate borrowers screening in order to gain advantageous risk management perception from their bank regulators and investors (Jiménez and Saurina, 2005; Ozili, 2019). The opposing views regarding the impact of interbank competition/concentration on banks' NPLs, make this relationship of a particular interest. New evidence on this association would offer bank regulators, managers, and academicians new enriching insights.

H12. Interbank competition/concentration has an impact on banks' credit risk, conveyed by the level of NPLs.

3. Methodology

3.1. Sample and data sources

The sample used in this research consists of 53 banks in the following MENA non-GCC countries: Morocco, Tunisia, Egypt, Jordan and Turkey. The time period covers between 2000 and 2019. The sample covers conventional banks and excludes saving and investment banks as they have different business models. The aggregate data used in this research is annual given that data for the majority of variables is available on a yearly basis. The data is obtained from two major sources: Bank Scope and Thomson Reuters database. The data on non-performing loans were extracted from the Thomson Reuters database and verified in the official

annual report of each bank. For data unavailability, the ratio of NPLs to total gross loans is employed instead of the sectorial NPLs' ratio. The bank-specific data as well as the ownership structure data were extracted from the Thomson Reuters Database. The macroeconomic data was extracted from the World Bank official database. Our final sample comprises 1060 bank-year observations from 53 banks spanning the period between 2000 and 2019.

3.2. Variable definition

The variables used in this research are divided into three major categories: bank-specific, macroeconomic and industry-specific factors.

3.2.1. Dependent variable

Our dependent variable is the bank's credit risk which is conveyed by the ratio of non-performing loans (NPL) calculated as the level of the bank total level of NPLs over the total gross loans (Louzis et al., 2012; Salas and Saurina, 2002; Vouldis and Louzis, 2017; Zhang et al., 2016) (see Table 1).

3.2.2. Independent variables

3.2.2.1. Bank-specific variables.

- Bank size (SIZE): Natural logarithm of a bank total assets is used to estimate bank size (Khemraj and Pasha, 2009; Mensah and Adjei, 2014).

- Capital adequacy ratio (CAR): This ratio refers to the level of capital a bank should set aside as a proportion of its risky assets. The capital adequacy ratio is measured as total capital to total risk-weighted assets (Naili and Lahrichi, 2020; Salas and Saurina, 2002).

- Bank Performance (ROE): Profitability is estimated using ROE of previous year. ROE is computed as the ratio of net income to total equity (Louzis et al., 2012; Us, 2017).

Table 1. Description of the determinants of NPLs, their proxies, symbols and a representative sample of their use in the literature.

Determinant	Proxy	Symbol	Sample of the literature
Credit risk	Ratio of non-performing loans (NPLs) to total gross loans	NPL	(Ghosh, 2017; Louzis et al., 2012; Salas and Saurina, 2002; Shehzad et al., 2010; Zhang et al., 2016)
Bank-specific variables			
Bank size	Natural log of total assets	SIZE	(Albaity et al., 2019; Zhang et al., 2016)
Bank capitalization	$\frac{\text{Tier 1 Capital} + \text{Tier 2 Capital}}{\text{Risk Weighted assets}}$	CAR	(Ghosh, 2017; Rime, 2001; Shrieves and Dahl, 1992)
Bank performance	$ROE = \frac{\text{Net income}}{\text{Total equity}}$	ROE	(Louzis et al., 2012; Makri et al., 2014; Jabbouri and El Attar, 2018b; Benrquia and Jabbouri, 2021)
Loan growth	Percentage growth of total loans between two consecutive years	GROWTH	(Peric and Konjusak, 2017; Salas and Saurina, 2002; Vithessonthi, 2016)
Bank inefficiency	$\frac{\text{Operating expenses}}{\text{Operating income}}$	INEFF	(Espinoza and Prasad, 2010; Koju et al., 2018; Louzis et al., 2012; Ozili, 2019; Shehzad et al., 2010)
Ownership concentration	$\frac{\text{Total shares held by stake insiders}}{\text{Total shares outstanding}}$	OC	(Berle and Means, 1933)
Bank diversification	$\frac{\text{Noninterest income}}{\text{Total income}}$	DIV	(Ghosh, 2017; Koju et al., 2018; Louzis et al., 2012; Stiroh, 2004)
Macroeconomic variables			
GDP Growth	Annual percentage growth rate of GDP	GDP	(Beck et al., 2015; Ghosh, 2017; Kadanda and Raj, 2018; Salas and Saurina, 2002; Vouldis and Louzis, 2017)
Inflation	Annual average inflation rate	INF	(Ghosh, 2017; Nkusu, 2011; Peric and Konjusak, 2017)
Public debt	Gross government debt as % of GDP	DEBT	(Louzis et al., 2012; Makri et al., 2014)
Unemployment	Percentage (%) of unemployment in year t	UNEM	(Lawrence, 1995; Louzis et al., 2012; Rinaldi and Sanchis-Arellano, 2006)
Industry-related variables			
Concentration	Concentration ratio: the share of the three largest banks' total assets	CR3	(Boudriga et al., 2009; Leech and Leahy, 1991; Natsir et al., 2019; Farooq and Jabbouri, 2015b; Srairi, 2013)

- Loan growth (GROWTH): The current year's gross loans as a percentage of the previous year's is used to proxy for loan growth (Shehzad et al., 2010).

- Bank inefficiency (INEFF): The ratio of operating expense to operating profit ratio is employed to measure bank's inefficiency (Shehzad et al., 2010).

- Ownership concentration (OC): Bank's ownership concentration, is measured by the fraction of the closely-held shares (Berle and Means, 1933; Jabbouri and Naili, 2019b; Jabbouri et al., 2019). The fraction of closely held shares is measured as the total number of shares held by stake insiders over the total number of shares outstanding. According to the World Scope, the stake insiders includes "shares held by officers, directors and their immediate families, shares held by shareholders who hold more than 5% of the total outstanding shares" (Worldscope, 2007).

- Diversification (DIV): Bank diversification will be proxied by the ratio of noninterest income to total income (Naili and Lahrichi, 2020).

3.2.2.2. Macroeconomic variables.

- GDP growth (GDP): GDP growth is defined as the yearly change in the natural logarithm of real GDP in each country (Louzis et al., 2012; Naili and Lahrichi, 2020).

- Inflation (INF): The annual inflation rate in a country is used to capture this variable (Nkusu, 2011).

- Public debt (DEBT): Public debt is proxied by the gross government debt as percentage of GDP (Amuakwa-Mensah et al., 2017; Makri et al., 2014).

- Unemployment (UNEM): Unemployment is measured by the unemployment rate in a country (Ćurak et al., 2013; Ghosh, 2015).

3.2.2.3. Industry-specific variables

- Concentration (CR3): The banking sector related variables comprise mainly interbank competition and concentration. According to the literature, these factors can be proxied by different measures including Lerner Index, the Boone indicator or using the concentration ratio. Due to data availability, we will capture this variable using the share of the three largest banks' total assets (Boudriga et al., 2010; Srairi, 2013).

3.3. Descriptive statistics

Table 2 shows the descriptive statistics for all banks for the study period, 2000–2019.[5] The mean NPL ratio is 8.9, which is high compared to the world's average estimated at 5.03 during the same period (World Bank, 2019). Banks had an average loan growth of 13.95, and an inefficiency of 48.18, a relatively high capital adequacy ratio of 11.46 and an overall positive profitability during the period analyzed. Regarding the macroeconomic indicators used in our study, the statistics indicate an average economic growth of 4.10, an inflation of 8.29, a relatively high public debt of 72.14 and an unemployment ratio close to 12 percent. Concerning the banking sector related variables, the average demonstrates that the banking sector in the selected countries has a considerably high concentration of 59.77.

Table 2. Descriptive statistics for the whole sample period 2000–2019.

	Mean	Min	Max
Credit risk	8.90	0.18	54.37
Bank-specific variables			
Bank size	15.20	9.19	20.97
Bank capitalization	11.46	-6.03	77.86
Bank performance	11.96	-363	187.42
Loan growth	13.95	-214.43	340.20
Bank inefficiency	48.18	0.300	269.50
Ownership concentration	72.97	14.44	100.00
Bank diversification	31.93	-61.25	149
Macroeconomic-determinants			
GDP growth	4.10	-20.40	11.11
Inflation	8.29	-8.728	54.91
Public debt	72.14	27.50	138.32
Unemployment	11.96	6.495	22.78
Industry-specific determinants			
Concentration	59.77	35.38	87.84

Value are expressed in percentage except for SIZE which captures bank size as the logarithm of a bank's total assets.

To have an in depth understanding of the determinants used in the sample, descriptive statistics of each factor year wise and country wise are provided in Table 3. Panel A exhibits the descriptive statistics of our variables country-wise. Among the countries included in our study, Egypt has the highest level of NPLs. As a matter of fact, during the recent years and aside from the Arab revolutions, Egypt faced numerous political and economic struggles. The country faced a remarkable depreciation in the Egyptian pound against the US dollar, which defied the banking sector. In addition to that, a slump in real estate prices was witnessed during recent years, which impaired the performance of the overall banking sector given that these loans amounts to 30% of total banking loans assets (BMI, 2017). In the same context, Egypt, Morocco, and Jordan have a mean NPL ratio of 8.30, 11.06 and 8.52, respectively, which is higher than the region's mean, demonstrating the immense threat of credit risk in these countries. On the other hand, Turkey has the lowest NPL ratio of 4.5 and a rapid economic growth during the recent years as the mean GDP ratio stands at 16.30, which might explain the low level of impaired loans compared to the other sampled countries. The banks' profitability and loans' growth in the selected countries remain positive. Besides, the sampled banks demonstrate an adequate level of capital adequacy, which is usually used as a buffer against risks. A high concentration ratio of 79.36 is witnessed in Tunisia, while Jordan has recorded the lowest concentration ratio of 41.69. Concerning the diversification of the banking sector of the selected countries, the descriptive statistics show a relatively small diversification ratio in almost all countries except for Tunisia which has a mean banks' diversification of 60. In addition to that, Panel B shows that the ratio of NPLs is increasing from 6.41 in 2000 to 9.03 in 2019. A remarkable increase in NPLs is witnessed as well between the period 2007–2010, from 6.69 to 9.52, respectively. This increase can be explained by the dire consequences of the global financial crisis. As the crisis emerged in the US, the global banking sector has been affected including the non-GCC countries. However, compared to European countries, the impact is less pronounced in our sample, given that the selected countries were less integrated in the global financial markets as they focus mainly on traditional lending. The level of non-performing loans continued its upward trend to reach 9.03 in 2019, which casts attention to NPLs as red flags. Figure 1 exhibits the evolution of NPLs during the period of the study.[6]

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[5] The descriptive statistics were obtained using the command xt*sum* and *describe* in STATA.

[6] To measure the reliability of our dataset, the *alpha* command in STATA was used. An alpha higher than 0.7 indicates that all variables are reliable and thus, confirms the reliability of our data.

Table 3. Descriptive statistics country and year-wise.

Country	N	NPL	SIZE	CAR	ROE	GROWTH	OC	DIV	INEFF	GDP	INF	DEBT	UNEMP	CR3
Panel A: Descriptive statistics of dependent variables and independent variables country-wise														
Morocco	8	8.30	16.87	8.56	9.34	8.84	63.78	29.01	50.08	4.14	1.90	64.52	10.23	64.06
Egypt	11	11.06	16.67	9.19	11.84	16.35	84.29	23.11	44.76	4.47	11.74	97.79	10.80	59.02
Tunisia	8	7.12	10.67	8.53	8.96	9.70	65.14	60.57	55.87	1.75	4.03	56.11	14.71	79.36
Jordan	13	8.52	14.19	12.87	10.78	12.08	70.09	30.99	48.36	4.45	3.59	88.13	14.20	41.69
Turkey	13	4.80	17.19	15.53	16.61	19.32	77.43	23.92	4.90	16.30	13.68	47.11	9.97	50.20
Mean	-	8.90	15.20	11.46	11.96	13.95	72.97	31.93	48.18	4.10	8.29	72.14	11.96	59.77
Median	-	6.50	15.61	10.59	11.59	9.80	75.26	28.00	47.00	4.29	5.79	70.20	11.90	59.96
Std.	-	6.36	2.70	5.62	21.89	25.70	18.32	21.66	21.11	3.57	8.29	24.47	2.667	15.50

Year	NPL	SIZE	CAR	ROE	GROWTH	OC	DIV	INEFF	GDP	INF	DEBT	UNEMP	CR3
Panel B: Descriptive statistics of dependent variables and independent variables year-wise													
2000	6.41	14.29	11.05	11.41	16.07	69.84	25.44	48.47	5.25	15.24	78.20	10.88	66.17
2001	7.19	14.42	10.40	7.11	15.57	70.39	21.20	52.79	2.45	16.69	83.15	11.88	69.31
2002	6.99	14.51	10.90	12.43	6.88	69.93	30.60	48.11	5.01	14.65	82.71	12.51	68.64
2003	7.89	14.60	11.34	15.53	18.97	70.43	38.46	47.45	4.66	7.28	91.97	12.42	67.26
2004	8.18	14.72	12.54	11.39	13.44	72.00	38.43	48.91	6.83	5.15	90.44	14.37	67.89
2005	7.15	14.82	11.10	14.28	33.30	69.45	4.34	42.89	6.16	5.84	8.45	12.34	64.88
2006	6.89	14.93	11.75	14.58	21.62	69.68	33.39	48.67	7.08	8.31	81.90	11.56	60.20
2007	6.69	15.08	12.24	12.75	21.66	70.33	30.34	43.93	6.25	7.31	73.17	10.56	59.70
2008	6.67	15.17	11.75	12.22	11.78	70.37	31.36	46.84	5.00	9.22	68.55	10.57	58.74
2009	7.74	15.24	12.13	10.62	9.41	71.09	29.15	44.55	2.22	4.22	55.45	11.45	58.41
2010	9.52	15.32	12.21	9.66	9.46	72.81	33.08	45.92	3.99	5.47	56.96	10.85	57.61
2011	9.55	15.37	12.81	9.01	16.33	75.08	31.22	50.38	4.23	5.43	58.78	11.12	58.37
2012	8.67	15.47	12.07	6.77	8.79	77.01	32.98	48.99	3.34	6.18	69.56	11.71	57.64
2013	7.74	15.53	11.67	11.80	9.11	75.73	32.26	48.86	4.34	6.61	62.40	11.98	56.42
2014	7.93	15.59	11.41	5.71	12.34	74.73	33.63	49.39	3.44	6.86	64.54	11.68	56.31
2015	8.09	15.68	10.80	12.23	12.68	75.02	31.96	51.06	3.84	6.84	66.06	12.27	53.35
2016	8.37	15.74	10.59	15.46	16.07	75.00	33.63	48.58	2.51	5.55	68.41	12.70	54.27
2017	8.46	15.82	10.69	14.84	13.59	76.22	30.21	49.08	4.08	8.66	66.04	12.43	54.73
2018	8.83	15.84	10.61	14.71	6.50	75.30	29.52	50.69	3.06	10.60	70.98	12.24	52.32
2019	9.03	15.89	11.29	13.47	3.77	76.32	26.16	49.94	1.90	11.00	69.30	12.77	44.75

Besides, before addressing the empirical procedure and running the descriptive statistics for our sample, correlation analysis should be introduced. In this sense, to assess the correlation and multicollinearity among our variables, the Pearson's pair-wise correlation matrix and variance inflation factor (VIF) were produced.[7] The pair-wise correlation matrix is exhibited in Table 5, demonstrating a relatively small pairwise correlation among all the explanatory variables.

To further assess whether the sample suffers from multicollinearity, the variance inflation factor (VIF) was produced. According to Table 6, the VIF values of all the explanatory variables are relatively very small and are within the permissible range as none of the values exceed 3. Therefore, the absence of multicollinearity in our dataset can be concluded, which is consistent with the precedent analysis based on the correlation matrix (see Tables 7 and 8).

Besides, to test the reliability of our variables, the Cronbach's α was used. This latter is one of the most common methods for assessing scale score reliability in a data sample. The test indicates that all variables are reliable given that the estimated αs were all equal or greater than 0.7 (see Table 4).

4. Empirical procedure

In the current research, a panel data analysis will be conducted. We will examine the impact of macroeconomic, bank-specific and industry-specific variables on the level of NPLs (Eq. 1). The regression investigating the impact of macroeconomic, bank-specific and industry-specific variables on the level of NPLs takes the following form:

$$NPL_{it} = \alpha_i + \underbrace{\sum_{j=1}^{J} \beta_j \mathbf{BANK}_{it}^j}_{J-Bank-specific} + \sum_{K=J+1}^{J+K}$$

$$\times \underbrace{\beta_k \mathbf{MACRO}_t^k}_{K-Macroeconomic} + \underbrace{\sum_{n=J+K+1}^{J+K+N} \beta_n \mathbf{INDUSTRY}_t^n}_{N-Industry-specific} + \mu_i + \varepsilon_{it} \qquad (1)$$

Where:

- NPL_{it} denotes the model's dependent variable,
- J denotes the number of bank-specific variables (J = 7 in our study),
- K denotes the number of macroeconomic variables (K = 4 in our study),
- N denotes the number of industry-specific variables (N = 1 in our study)
- $(BANK^j_{it})$ denotes a vector of bank-specific variables,
- $(MACRO^k_t)$ represents the vector of macroeconomic variables,
- $(INDUSTRY^n_t)$ denotes the industry-specific variables,
- β are the coefficients of vectors,
- α_i is the constant term,

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[7] The variance inflation factor (VIF) quantifies the severity of multicollinearity in an ordinary least squares regression. The Variance Inflation Factor is defined as: VIF $(\beta_k) = 1/(1-R^2_k)$, where R^2_k is the coefficient of multiple determination, R^2-value obtained by regressing the kth predictor on the remaining predictors. The VIF can be interpreted as the ratio of the actual variance of the estimated coefficient, β_k, to what it would have been if there was no multicollinearity and $R^2_k = 0$.
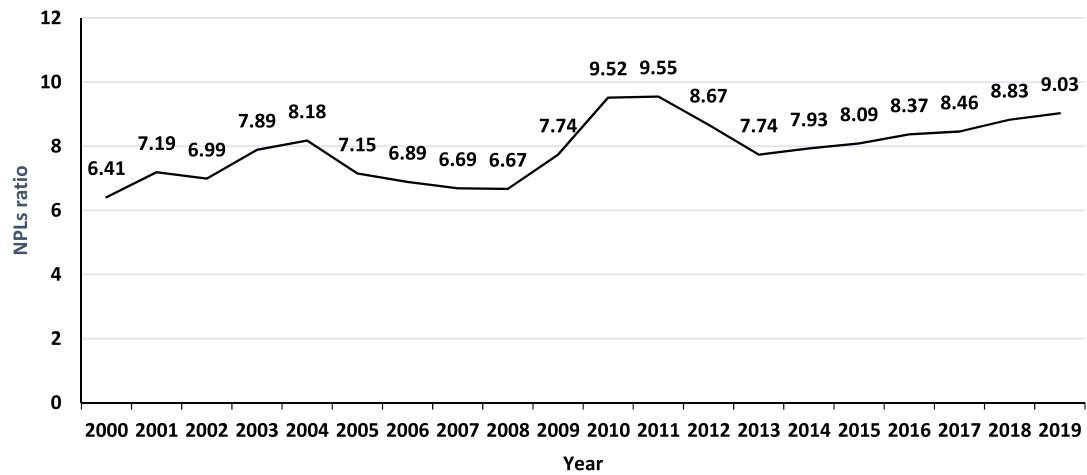
Figure 1. The evolution of NPLs ratio year wise for the sampled countries.

Table 4. Reliability statistics.

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	Number of items
0.859	0.860	12
Cronbach's Alpha per Item		
Variable	**Observations**	**Alpha**
Bank size	1060	0.714
Bank Capitalization	1060	0.825
Bank performance	1060	0.717
Loan growth	1060	0.814
Bank inefficiency	1060	0.824
Ownership Concentration	1060	0.862
Bank diversification	1060	0.702
GDP growth	1060	0.701
Inflation	1060	0.722
Public debt	1060	0.815
Unemployment	1060	0.701
Concentration	1060	0.700

Table 6. Variance inflation factor (VIF).

Variable	VIF
Bank size	1.73
Bank capitalization	1.26
Bank performance	1.31
Loan growth	1.07
Bank inefficiency	1.36
Ownership concentration	1.14
Bank diversification	1.49
GDP growth	1.14
Inflation	1.18
Public debt	1.97
Unemployment	1.78
Concentration	2.13
Mean	1.46

Table 5. Pearson's pair-wise correlation matrix.

	1	2	3	4	5	6	7	8	9	10	11	12	13
Credit risk	1												
Bank size	0.0021	1											
Bank capitalization	-0.1793	0.0491	1										
Bank performance	-0.3672	0.0941	0.1775	1									
Loan growth	-0.0115	0.0246	-0.0398	0.1004	1								
Bank inefficiency	0.2658	0.0744	0.1051	0.0012	0.0340	1							
Ownership Concentration	0.0996	-0.1833	-0.2264	-0.4661	-0.0252	-0.0285	1						
GDP growth	-0.0403	0.1321	0.1271	0.0647	0.1948	-0.0448	-0.0266	1					
Inflation	0.2034	0.1746	0.1378	0.0590	0.0862	0.2271	-0.1039	-0.0146	1				
Public debt	0.0732	0.0528	-0.1149	-0.0168	0.1106	0.0925	0.0070	0.1174	0.0255	1			
Unemployment	0.0732	-0.1393	-0.1501	-0.0395	-0.0127	-0.1726	0.1082	-0.1536	-0.2686	0.1916	1		
Bank diversification	0.0103	-0.1535	-0.2592	-0.1020	-0.0083	-0.1662	0.2153	-0.0932	-0.2359	-0.0897	0.3612	1	
Concentration	0.1251	0.1546	0.0890	-0.0263	0.0590	-0.0564	-0.0139	0.1845	-0.0551	0.2505	0.1678	-0.2152	1

The numbers 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13 refers to Credit risk, Bank size, Bank capitalization, Bank performance, Loan growth, Bank inefficiency, Ownership concentration, GDP growth, Inflation, Public debt, Unemployment, Bank diversification and Concentration, respectively.

- μ_i are the unobservable bank-specific effects,
- ε_{it} is the error term.

In order to investigate these regressions, this study will focus on two main approaches: fixed effects model (FE) and random effects model (RE).

4.1. The fixed effects model

$$NPL_{it} = \alpha_i + \beta_1 SIZE + \beta_2 CAR + \beta_3\ ROE + \beta_4\ GROWTH + \beta_5\ INEFF + \beta_6\ OC + \beta_7 DIV + \beta_8\ GDP + \beta_9\ INF + \beta_{10}\ DEBT + \beta_{11}\ UNEM + \beta_{12}\ CR3 + \mu_{it} \quad (1.1)$$

Where:

- i and t represent cross-section dimension and time indicator, respectively,
- α_i denotes the unknown intercept for each bank,
- μ_{it} is the error term.

4.2. The random effects model

$$NPL_{it} = \alpha + \beta_1 SIZE + \beta_2 CAR + \beta_3\ ROE + \beta_4\ GROWTH + \beta_5\ INEFF + \beta_6\ OC + \beta_7 DIV + \beta_8\ GDP + \beta_9\ INF + \beta_{10}\ DEBT + \beta_{11}\ UNEM + \beta_{12}\ CR3 + \mu_i + \varepsilon_{it} \quad (1.2)$$

Where:

- μ_i is the between-entity error,
- ε_{it} is the within-entity error.

The main reason behind the use of these two approaches, is to unhidden the differences and similarities across models. The analysis of the two different regressions will enhance the robustness of our results in case these latter are consistent in terms of significance and correlation. In addition to that, due to the time persistence of the credit risk structure and the importance to include lags of the dependent variable in the model, a dynamic approach would be advised.

4.3. Empirical results

This section presents the empirical results. To identify the main determinants of credit risk in our sampled countries, a panel data technique is employed. This empirical analysis is conducted using the fixed and random effects models[8]. These models allow for variable intercepts as well as heterogeneity across firms, which ensure the consistency and efficiency of estimates (see Tables 7 and 8).

Prior to documenting the empirical results, heteroscedasticity and serial correlation tests are of vital importance to confirm the validity and efficiency of the analysis.

In order to test for heteroscedasticity in our model, White General test is employed.[9] The results of the test indicate the presence of

heteroscedasticity in our model. To correct for heteroscedasticity, we employed the Eicker–Huber–White standard errors estimator that is, mainly known as Huber/White sandwich estimator[10]. Besides, a serial correlation test was conducted, referring to the Wooldridge test[11] (Jabbouri and El Attar, 2017). The test indicates that our model's estimates are robust to serial correlation.

In order to decide which model is the most suitable for our analysis, Hausman test is conducted. This common approach points if the parameters estimates differ in the two models, fixed and random, and if there is any correlation between the unit effects and the independent variables (Hausman, 2015). In our case, the Hausman test indicates that the random effect is most appropriate for the current analysis as the difference in coefficients is systematic and the error terms are correlated with the regressors.[12]

5. Discussion of the results

The results exhibited in the tables above are interesting and will shed a better light on the factors influencing NPLs. Despite the similarities between the two models, Hausman test indicates that the random effects model is the most appropriate for the current analysis. Thus, the empirical results of random effects will be considered. Indeed, the analysis reports an adjusted R-square value of 61.1 percent.

5.1. The impact of bank-specific determinants of banks' credit risk

The literature is inconclusive about the relationship between bank size and NPLs. Our current research found that, in MENA emerging markets, bank size is negatively associated with the level of NPLs, at a significance level of 1 percent. This result confirms prior findings, arguing that larger banks are in a better position to conduct proper loan screening and successfully cope with defaulters thanks to their sophisticated risk management mechanisms, lessening the level of NPLs (Alhassan et al., 2014; Hu et al., 2004; Louzis et al., 2012; Salas and Saurina, 2002; Solttila and Vihriälä, 1994). As a matter of fact, small-sized banks are more likely to devote limited resources to risk management procedures, which causes the upsurge of NPLs. Further, our results provide strong evidence in favor of the diversification hypothesis, postulating that larger banks tend to be more diversified compared to their smaller counterparts, which reduces their risk exposure and, thus, the level of bad loans (Louzis et al., 2012).

Regarding the CAR-NPLs relationship, our analysis documents striking results. We report a significant and negative relationship between banks' capital adequacy and the level of NPLs, significant at the 1 percent level. This result corroborates the results documented by; Sinkey and Greenawalt (1991), Barth et al. (2004) and Boudriga et al. (2009) and contradicts the finding of Ghosh (2017) and Rime (2001). In fact, our findings support the notion that undercapitalized banks usually raise their capital in response to additional risk exposure. This negative relationship can be explained by the fact that banks with high CARs, are more likely to avoid imprudent lending to sustain the capital set aside, usually used as a buffer against excessive risks (Salas and Saurina, 2002; Us, 2017). This research confirms the moral hazard

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[8] The fixed effect model is estimated using the command *areg, absorb ()* in STATA 14, while the random effect model is estimated using the STATA 14 command; *xtreg re* (Baker et al., 2017; Jabbouri and El Attar, 2018a; Jabbouri and Jabbouri, 2020; Jabbouri and Farooq, 2021).

[9] *whitetst* computes the White (1980) general test for heteroscedasticity in the error distribution by regressing the squared residuals on all distinct regressors, cross-products, and squares of regressors. The test statistic, a Lagrange multiplier measure, is distributed Chi-squared(p) under the null hypothesis of homoscedasticity (Greene, 2005). In order to test for heteroscedasticity, we employed the *estat imtest, white* command in STATA 14. The results of the test indicate that the p value is lower than 0.05, meaning that we reject the null hypothesis H_0, leading to the presence of heteroscedasticity.

[10] The command *vce(robust)* STATA 14 to correct for heteroscedasticity.

[11] We test the serial correlation using the Wooldridge's test through the command *xtserial* in STATA 14. The results of the test indicate that autocorrelation does not exist in the model as the p-value was greater than 0.05, indicating that we fail to reject the null hypothesis (H0: no first order autocorrelation).

[12] The Hausman test confirms the appropriateness of the random model. The command *Hausman* was employed in STATA 14 after storing the estimates of the two models using the commands *estimates store re* and *estimates store fe*. The result shows that Prob>chi2 = 0.0000, which means we reject the null hypothesis; stating that difference in coefficients is not systematic. The random effects model is more appropriate. In fact, the error terms are correlated with regressors which makes the random effect more appropriate for our sample.

Table 7. The impact of the macroeconomic, bank-specific and industry-specific determinants on banks' NPLs. The fixed effects results.

Variable	[1]	[2]	[3]	[4]	[5]
SIZE	-0.00103 (0.0028)	-0.0004 (0.0029)	-0.00512 (0.0032)	**-0.0098** (0.0041)	**-0.0085**(0.0042)
CAR	**- 0.0637*** (0.0355)	**-0.1155*** (0.0679)	**-0.0852*** (0.0428)	**-0.0736*** (0. 0435)	**0.0587***(0.0317)
ROE	**-0.0509*** (0.0091)	**-0.0809*** (0.01053)	**-0.0478*** (0.0090)	**-0.0451*** (0.0081)	**-0.0450*** (0.0105)
GROWTH	0.0015 (0.0068)	0.0030 (0.0084)	0.0037 (0.0069)	0.0045 (0.0069)	0.0054 (0.0068)
INEFF	**-0.0334*** (0.0107)	**-0.0334*** (0.0107)	**-0.0341*** (0.0105)	**-0.0350*** (0.0108)	**-0.0345*** (0.0105)
OC	**0.01321**(0.0066)	**0.0154 **(0.0074)	**0.0156 ** (0.0078)	**0.0189** (0.0095)	**0.0392** (0.0200)
GDP		**-0.1275** (0.064)	**-0.1744** (0.0741)	**-0.1862** (0.0729)	**-0.1853** (0.0726)
INF		0.0314 (0.0261)	0.0511 (0.0262)	0.0459 (0.03117)	0.0502 (0.0314)
DEBT			**0.0480*** (0.0140)	**0.0580**** (0.0147)	**0.0606*** (0.01462)
UNEM			**0.4146*** (0.0928)	**0.42538*** (0.0924)	**0.4013*** (0.09152)
CR3				0.0052 (0.0339)	0.0110 (0.03347)
DIV					-0.0246 (0.0241)
Constant	**-0.0501*** (0.0296)	**-0.0605*** (0.233)	**-0.1167*** (0.0586)	**-0.1845*** (0.0927)	**-0.1448*** (0.0766)
Observations	1060	1060	1060	1060	1060
Number of banks	53	53	53	53	53
Time effect	Yes	Yes	Yes	Yes	Yes
Country effect	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.545	0.547	0.563	0.582	0.591
F-stat	11.45	11.41	10.00	10.33	9.98
Prob $> F$	0.000	0.000	0.000	0.000	0.000

Notes: Table 7 presents the fixed effects results of the relationship between NPLs and explanatory variables. The standard errors are reported in parentheses. They represent robust standard errors corrected for potential heteroscedasticity and time-series autocorrelation within each bank using the robust cluster option in STATA. Dummies for time and country effects are used. The bold coefficients denote the statistically significant values. Asterisks indicate the significance at the 1 percent (*), 5 percent (**) and 10 percent (***) level.

Table 8. The impact of the macroeconomic, bank-specific and industry-specific determinants on banks' NPLs. The random effects results.

Variable	[1]	[2]	[3]	[4]	[5]
SIZE	**- 0.0169***(-0.0058)	**- 0.0181***(0.0062)	**- 0.017*** (0.0058)	**- 0.0140*** (0.005)	**- 0.0163*** (0.0056)
CAR	**-0.1246*** (0.0416)	**-0.1074*** (0.0356)	**-0.0954*** (0.0402)	**-0.0985*** (0.0407)	**-0.1241*** (0.0416)
ROE	**-0.0815*** (0.0101)	**-0.0506*** (0.0091)	**-0.0798*** (0.0103)	**-0.0808*** (0.0106)	**-0.0815*** (0.0100)
GROWTH	0.00215 (0.0076)	0.0025 (0.0069)	0.0018 (0.0085)	0.0030 (0.0081)	0.0021 (0.0084)
INEFF	**-0.05154*** (0.0108)	**-0.0334*** (0.0105)	**-0.0486*** (0.0110)	**-0.0514*** (0.0112)	**-0.0587*** (0.01139)
OC	**0.0587*** (0.0114)	**0.0541*** (0.0169)	**0.0492*** (0.0109)	**0.05280*** (0.0128)	**0.0515*** (0.0108)
GDP		**-0.7384***(0.1488)	**-0.6495***(0.1503)	**-0.6811*** (0.165)	**-0.5958*** (0.164)
INF		0.0314 (0.028)	**0.0487*** (0.0269)	**0.04324*** (0.0247)	**0.0466*** (0.0271)
DEBT			**0.0485*** (0.0151)	**0.0387*** (0.0127)	**0.0342*** (0.0114)
UNEM			**0.1972*** (0.0605)	**0.1863*** (0.0597)	**0.2085*** (0.0596)
CR3				0.0185 (0.0179)	0.0122 (0.0203)
DIV					-0.0066 (0.0110)
Constant	**-0.0453*** (0.0268)	**-0.06050*** (0.0304)	**-0.0452*** (0.0224)	**-0.0451***(0.0222)	**-0.0453*** (0.0226)
Observations	1060	1060	1060	1060	1060
Number of banks	53	53	53	53	53
Time effect	Yes	Yes	Yes	Yes	Yes
Country effect	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.576	0.562	0.576	0.577	0.611
Wald χ^2 statistic	269.22	268.21	263.98	267.01	286.02
Prob $>$ Chi2	0.000	0.000	0.000	0.000	0.000

Notes: Table 8 presents the random effects results of the relationship between NPLs and the explanatory variables. The standard errors are reported in parentheses. They represent robust standard errors corrected for potential heteroscedasticity and time-series autocorrelation within each bank using the robust cluster option in STATA. Dummies for time and country effects are used. The bold coefficients denote the statistically significant values. Asterisks indicate significance at the 1 percent (*), 5 percent (**) and 10 percent (***) level. Based on Hausman test, the results of the random effects model will be considered in the current study.

hypothesis, contending that thinly capitalized banks tend to engage in irresponsible lending with inadequate risk screening given the limited loss they may incur in a potential financial slump, which justifies a higher level of NPLs (Berger and Deyoung, 1997). In order to monitor banks' risk, major regulatory changes have been adopted by central

banks in MENA emerging markets during the last decade (BMI, 2017). The regulatory measures include the reinforcement of the level of banks' CAR, used as an instrument to control excessive risk taking. In this sense, MENA banks with a low level of CAR were requested to comply with the new Basel accords and adjust their balance sheet to

comply with the regulatory requirements, either by raising more capital or reducing risk-weighted assets (BMI, 2017).

In contrast to Garcí a-Marco and Dolores Robles-Fern á ndez, 2008 who have demonstrated that bank profitability is positively linked to NPLs, the current research reports a negative relationship between bank profitability and credit risk in the considered emerging markets, significant at the 1 percent level. Our analysis supports the bad management hypothesis, which suggests that low profitability denotes poor management skills with regards to lending strategies, and thus, a high the level of NPLs (Louzis et al., 2012). In fact, banks incurring a low profitability are more likely to increase their risk exposure and adopt a liberal credit policy to recover the preceding losses and maintain a decent current profitability, which may be achieved, at the expense of higher future NPLs. Since they are less pressed to generate more income compared to their counterparts, highly profitable banks are less likely to grant risky loans, which minimizes their credit risk (Ghosh, 2015; Louzis et al., 2012).

The current study documents a positive relationship between credit growth and NPLs. This finding associates rapid loans growth to riskier lending behaviors and supports the results documented by Salas and Saurina (2002), Foos et al. (2010) and Keeton and Morris (1987). This can be approached through different perspectives. First, as banks shift their supply, loan screening and analysis deteriorate, which inflates the level of NPLs. Put differently, a rapid credit growth could overwhelm the resources dedicated to loan screening and monitoring, leading to insufficient risk analysis and thus, a higher level of NPLs. Further, the current research supports the notion that in search to expand their credit portfolios, banks may be interested in increasing short-term profits through easing their credit standards, often, at the expense of heavy future bad loans (Solttila and Vihriâlà, 1994). Nevertheless, the impact of loan growth is less pronounced in the sampled MENA emerging markets. Our current state of knowledge on this suggests that, compared to the other macroeconomic variables, the slight and inconsequential increase (decrease) of loan growth in the sampled countries may explain the insignificance of this relationship.

The current analysis reports a negative relationship between bank inefficiency and NPLs, which is significant at the 1 percent level. This result supports the findings reported by Louzis et al. (2012) and Rossi et al. (2009). We provide a strong evidence in favor of the skimming hypothesis, while we present opposing evidence to the bad management and bad luck hypotheses. The finding of this research links the costs devoted to credit assessment and evaluation processes to the quality of banks' loan portfolios. This implies that banks devoting insufficient resources to conduct adequate loan analysis and underwriting are cost efficient in the short run, yet they will incur higher loan losses in the long run. On the other hand, banks dedicating necessary resources to loan assessment have better chances to minimize their NPLs (Rossi et al., 2009). In the aftermath of the global financial crisis, most MENA emerging countries adopted transformation programs, which aim at decreasing banks' credit risk by dedicating sufficient capital and resources to loans underwriting and monitoring (BMI, 2017).[13]

The literature exposes contracting arguments about the effect of ownership concentration on banks' credit risk. The finding of this research is in line with the school of thought that suggests a positive relationship between ownership concentration and NPLs (Berle and Means, 1933; Dong et al., 2014; Haw et al., 2010; Louzis et al., 2012). Our analysis supports the notion that ownership concentration increases agency problems which might results in an increased level of NPLs. In fact, the result of this finding confirms that agency problems intensify in the presence of strong ownership concentration due to potential conflicts

of interests between controlling and minority shareholders (Shleifer and Vishny, 1986). We contend that shareholders in concentrated banks have the power to influence bank risk-taking, by coercing bank managers to undertake risky investments with high expected returns, which in turn, increases the level of loan problems (Jensen and Meckling, 1976). The results of this research draw a particular attention to the severity of agency problems within concentrated banks in the MENA emerging markets. These banks are more likely to exhibit an increase level of credit risk and suffer from massive NPLs due to the unbalance of power between controlling and minority shareholders.

Furthermore, this research contends that banks' diversification is negatively linked to NPLs and confirms our initial hypothesis. This rejects the notion that banks entering new businesses in which they have little experience face excessive risks (Louzis et al., 2012; Stiroh, 2004). In contrast, we argue that when banks extend and diversify their activities, their focus on credits shifts and their loan lending might decrease, which may result in a decreased level of NPLs. Yet, the negative relationship between diversification and banks' credit risk is found to be insignificant, implying that diversification does not necessary impact banks' risk behaviors in the sampled MENA emerging countries. As a matter of fact, banks in the MENA region remain less diversified compared to their counterparts in developed countries. The noninterest income, which is the proxy for bank diversification, includes mainly income from investment banking, insurance brokerage commissions, venture capital, gains on non-hedging derivatives and income from trading and securitization. These activities are still underdeveloped in the sampled countries. In this sphere, the core activities of MENA banks are, predominantly, issuing loans and collecting the interest payments which may explain the insignificance of the diversification-credit risk relationship.

5.2. The impact of macroeconomic determinants of banks' credit risk

The analysis confirms our initial hypothesis and reports a negative relationship between GDP growth and banks' NPLs, significant at the 1 percent level. As expected, this result is in line with prior findings, arguing that the economic conditions impact significantly the level of banks' NPLs (Anastasiou et al., 2019; Beck et al., 2015; Carey, 1998; Ghosh, 2017; Jabbouri and Naili, 2019a; Nkusu, 2011; Salas and Saurina, 2002). Furthermore, GDP growth has always been used as the primary indicator that mirrors the status of the country's business cycle. In this sense, we argue that under good economic conditions, households and businesses are more likely to service their debts, which lessens the level of bad loans. In rebuttal, during economic abysses, creditors will struggle to honor their debt obligations, which weakens banks' credit quality.

In contrast to the findings of Khemraj and Pasha (2009), Nkusu (2011) and Gulati et al. (2019) who argue that inflation is negatively related to banks' credit risk, the current research contends that as inflation increases, the level of NPLs escalates, especially in case of floating rates loans. Given that inflation has an adverse impact of household's income, high inflation rates erode the real value of household's revenues, which limits their capacity to reimburse their debts. As a matter of fact, in MENA emerging countries, inflation is considered as one of the main concerns of financial regulators as wages are often sticky. That is said, households are more challenged to repay their debts under inflationary conditions, which worsens banks' loan quality.

Consistent with the previous findings of Reinhart and Rogoff (2011) and Louzis et al. (2012), public debt was found to be positively linked to NPLs, at a significance level of 1 percent. We argue that as public debt increases, the creditworthiness of banks becomes doubtful. This puts a sovereign ceiling on their solvency, making banks hard pressed to raise market financing, which makes refinancing loans a tedious task for borrowers. Further, our findings are in accordance with the sovereign debt hypothesis, stipulating that higher public debt leads to higher NPLs (Louzis et al., 2012). Indeed, in the MENA emerging countries, the social demands triggered by the Arab spring at the beginning of 2011 have

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[13] Modernized mechanism have been adopted as part of the regulatory frameworks initiated by central banks in MENA emerging countries, mainly Morocco, Jordan and Tunisia. These latter's purpose is to dedicate adequate resources to face the threat of credit risk through a rigorous credit assessment and loan evaluation (BMI, 2017).

pushed regulators and policy makers to increase their spending in order to finance the structural reforms aiming to tackle the social unrest.[14] As a result, banks' liquidity and credit growth were impacted, pushing banks to reduce their lending. In addition to that, as public debt upsurges, governments are more likely to raise taxes and reduce subsidies, which adversely impact households' income and purchasing power and, thus, their capacity to honor their debt obligations.

Another important finding of the study is the significant and positive relationship between unemployment and NPLs, at the 1 percent level. This result confirms our hypothesis, documenting that unemployment is one of the major determinants of NPLs in emerging countries. This finding is consistent with prior studies of Ghosh (2015), Nkusu (2011) and Salas and Saurina (2002). This outcome stipulates that when jobs are scarce, borrowers are less likely willing to repay their debts, which escalates the level of NPLs. In addition to that, due to the uncertainty of their employment status, individuals with low-income levels are charged ballooned interest rates which, impairs their capacity to service their loans.

5.3. The impact of industry-specific determinants of banks' credit risk

Contrary to the findings reported by Keeley (1990), Broecker (1990) and Hellmann et al. (2000) who contend that competition impacts banks' franchise value, which decreases their incentives to grant thoughtful loans; this study asserts that interbank competition leads to an enhanced loan quality portfolio. As a matter of fact, the finding of this research rejects the so-called "franchise value hypothesis" and supports the notion that interbank competition tends to lessen banks' charged interest rates which, therefore, reduces the number of defaulters. Also, we argue that banks' competition would press managers to ensure solid loan quality portfolios through adequate loan screening and monitoring in order to gain advantageous risk management perception from their bank regulators and investors (Jiménez and Saurina, 2005; Ozili, 2019).

5.4. The impact of GDP components on banks' credit risk

The current paper pursues innovation by analyzing the impact of GDP components on banks' credit risk. Given the significant impact of GDP on the evolution of banks' NPLs, it would be interesting to investigate the impact of its components. In this sense, the previous regressions will be re-conducted by a GDP breakdown of three main sectors: agricultural GDP growth (GDPagri), services (GDPservices) and industrial GDP growth (GDPindustry).

In order to decide which model is more suitable for this analysis, we conducted the Hausman test. The test indicates that the random effects model is the most suitable. Table 9 exhibits the results using the random effects model through four main models.

The regression exhibits striking results. All GDP components were found to be significant at the 1 percent level. Interestingly, agricultural GDP was found to have the greatest impact on banks' NPLs. This finding contends that an increase (decrease) in agricultural GDP is more likely to decrease (increase) the level of NPLs, compared to an increase (decrease) in the other GDP components. Put differently, fluctuations in the agricultural sector would have a prenominal impact on the quality of banks' loan portfolios. As a matter of fact, in the considered MENA emerging countries, the agricultural sector remains the backbone of the economy, employing a high percentage of its workforce and massively contributing to export revenues. Given that the sector is documented to be one of the main occupations of the majority of citizens in our sample of countries, its collapse would harm borrowers' capacity to service their debt obligations. Thus, these findings emphasize the necessity of closely monitoring and reinforcing country level mechanisms by providing an environment conducive to economic growth.

6. Robustness test

To deal with endogeneity and due to the time persistence of the credit risk structure, a Generalized Method of Moments (GMM) is applied as a robustness check. This latter allows the introduction of more instruments that can massively improve the model's efficiency (Roodman, 2009)[15]. In addition to that, in our dynamic model, we ensure to control for the three types of endogeneity, namely, unobserved heterogeneity, simultaneity and dynamic endogeneity. The estimated models take the following general forms:

$$\text{Static model}: y_{it} = (\dots) + \sum_{i=1}^{i} \beta_i X'_{it} + \eta_i + \varepsilon_{it} \qquad (a)$$

$$\text{Dynamic model}: y_{it} = \alpha + \sum_{j=1}^{J} \Upsilon_j y_{i,t-1} + \sum_{i=1}^{I} \beta X'_{it} + \eta_i + \varepsilon_{it} \qquad (b)$$

Where:

- The subscripts i and t represent the cross-sectional and the time dimensions of our data, respectively,
- α is the constant term,
- $y_{i,t-1}$ is the one-period lagged independent variable and Υ_j is the coefficient of persistence;
- X'_{it} is the $k \times 1$ for the dependent variables,
- β is a $k \times 1$, vector of coefficients,
- η_i are the firm fixed effect,
- ε_{it} is the error term.

The introduction of the lag of the dependent variable might influence the traditional models such as the pooled OLS, the fixed and random effects models due to the correlation between the lagged dependent variable $y_{i,t-1}$ and the bank-specific factors η_i. Sargan test of over-identifying restrictions is used to test for the overall validity of our instruments and to ensure the consistency of our model (Arellano and Bond, 1991; Arellano and Bover, 1995). Second, the Arellano-Bond autocorrelation tests were conducted to evaluate the assumption of serially uncorrelated errors, ε_{it}.

In Table 10, we present the estimated coefficients of the system GMM and difference GMM, the Sargan test and the autocorrelation tests; AR (1) and AR (2). The Sargan over-identification test indicates that all instruments are valid. The AR (1) test rejects the null hypothesis of no first-order serial correlation, yet it does not reject the null hypothesis that there is no second-order serial correlation. Hence, all requirements of the tests are met as suggested by p-values, which confirms the consistency of our dynamic model. The analysis of our dynamic model indicates that NPLs are time persistent. The results of the different estimation techniques are quite similar, and the coefficient estimates are fairly stable across models. The results of the GMM analysis are consistent with the previous findings in terms of significance and correlation between NPLs and the independent variables, which confirms the robustness of our findings to changes in empirical models.

7. Conclusion

Banks' credit risk, considered as a prominent threat to the stability of the banking sector, has been widely discussed among researchers and policymakers. Yet, research on MENA emerging economies continues to lag far behind many regions. In order to lessen this void in the literature,

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[14] During the Arab spring, public revenues have declined due to the economic conditions in major countries.

[15] The *xtabond2* command can be used to implement these estimators in STATA (Roodman, 2009). This command, compared to the previous *xtabond* command, implements the two estimators and makes available a finite sample correction to the two-step covariance matrix (Roodman, 2009). Besides, it makes two-step robust more efficient than one-step robust along with addressing the instruments proliferation problem. We used the *collapse* option to address these problems and ensure the validity of our instruments.

Table 9. Random effects results by a GDP Breakdown: GDPagriculture, GDPindustry and GDPservices.

Variable	[1]	[2]	[3]	[4]
SIZE	**-0.0122** (0.0061)	**-0.0118** (0.0120)	**-0.0123** (0.0060)	**-0.01234**** (0.0044)
CAR	**- 0.0925** (0.0414)	**- 0.0922** (0.0415)	**- 0.0515** (0.0231)	**-0.0891** (0.0423)
ROE	**-0.0788**** (0.0106)	**-0.0755**** (0.01037)	**-0.0751**** (0.01020)	**-0.0475**** (0.0158)
GROWTH	0.0033 (0.0083)	0.0008 (0.00819)	0.0014 (0.0080)	0.00651 (0.0067)
INEFF	**-0.0470**** (0.0112)	**-0.05043**** (0.0109)	**-0.05236**** (0.0107)	**-0.03206**** (0.0105)
OC	**0.0333**** (0.0112)	**0.0335**** (0.0110)	**0.03958***(0.0113)	**0.05847**** (0.0206)
GDPservices	**-0.3100**** (0.1036)	**-0.3023 *** (0.1035)	**-0.3031**** (0.1010)	**- 0.4368**** (0.1120)
GDPindustry	**-0.3201**** (0.0802)	**-0.3778**** (0.0551)	**-0.3500**** (0.0696)	**- 0.43387**** (0.0552)
GDPagriculture	**-0.4751**** (0.1609)	**-0.4413**** (0.1529)	**-0.5065**** (0.1741)	**- 0.6026**** (0.1295)
INF			0.01787 (0.02717)	0.03666 (0.0228)
DEBT			**0.0381***** (0.0132)	**0.0645**** (0.0165)
UNEM			**0.19580**** (0.0657)	**0.3207**** (0.0874)
CR3				0.0241 (0.03456)
DIV				- 0.0066 (0.0113)
Constant	**0.2328**** (0.01624)	**0.3731**** (0.0601)	**0.3044** (0.0880)	**0.2600*** (0.1103)
Observations	1060	1060	1060	1060
Number of banks	53	53	53	53
Time effect	Yes	Yes	Yes	Yes
Country effect	Yes	Yes	Yes	Yes
Adjusted R^2	0.545	0.557	0.558	0.562
Wald Chi2 statistic	270.12	287.00	289.00	279.67
Prob > Chi2	0.000	0.000	0.000	0.000

Notes: Table 9 presents the random effects results of the relationship between NPLs and the explanatory variables using GDP components. The standard errors are reported in parentheses. They represent robust standard errors corrected for potential heteroscedasticity and time-series autocorrelation within each bank using the robust cluster option in STATA. Dummies for time and country effects are used. The bold coefficients denote the statistically significant values. Asterisks indicate significance at the 1 percent (*), 5 percent (**) and 10 percent (***) level.

Table 10. Regression analyses using GMM estimation techniques.

Variable	One-step system GMM	Two-step system GMM	One-step difference GMM	Two-step difference GMM
Lag*NPL*	**0.8463**** (0.21157)	**0.84651**** (0.2344)	**0.84355**** (0.10544)	**0.82344**** (0.2086)
SIZE	**-0.00156 **(0.00094)	**-0.00051** (0.00188)	**-0.0067** (0.0028)	**-0.00622** (0.0031)
CAR	**-0.15616 *** (0.04071)	**-0.0250**(0. 0418)	**-0.0982**** (0.03049)	**-0.09821**** (0.0248)
ROE	**-0.08076**** (0.01016)	**-0.0505**** (0.00890)	**-0.0877**** (0.0194)	**-0.0912**** (0.0304)
GROWTH	-0.0063 (0 0082)	-0.00240 (0.00685)	-0.00221 (0.00245)	-0.00762 (0.0078)
INEFF	**0.0507**** (0.0109)	**0.03644**** (0.0104)	**0.09871** (0.0501)	**0.08110**** (0.03003)
OC	**0.0658 ***(0.0112)	**0.05011 ***(0.0172)	**0.0233**** (0.0080)	**0.0345**** (0.0120)
GDP	**-0.659*** (0.2245)	**-0.5393*** (0.1871)	**-0.320*** (0.1103)	**0.3011*** (0.1003)
INF	0.0553 (0.0271)	0.0288 (0.02778)	**0.0076* (0.0045)	0.0165 (0.0110)
DEBT	**0.0480**** (0.0140)	**0.0278***** (0.0127)	**0.0556**** (0.0206)	**0.0651** (0.0325)
UNEM	**0.2379** (0.0983)	**0.3591**** (0.1205)	**0.129***(0.0431)	**0.381**** (0.10533)
CR3	0.04801 (0.0139)	**0.00459* (0.0256)	0.00230 (0.0191)	0.00127 ((0.00104)
DIV	- 0.0066 (0.0109)	-0.0026 (0.0110)	-0.00233 (0.0022)	-0.00210 (0.0024)
Constant	**-0.1453 ** (0.0267)	**-0.1845** (0.0760)	**- 0.1102** (0.0551)	**-0.1100** (0.0552)
Number of observations	1060	1060	1060	1060
Number of banks	53	53	53	53
Time effect	Yes	Yes	Yes	Yes
Country effect	Yes	Yes	Yes	Yes
Sargan test *p*-value	0.233	0.354	0.312	0.401
Hansen test *p*-value	0.462	0.422	0.398	0.312
AR (1), *p*-value	z = -2.93 (0.003)	z = -2.28, (0.022)	z = -1.99 (0.004)	z = -1.98, (0.013)
AR (2), *p*-value	z = 0.05 (0.562)	z = 0.99, (0.321)	z = 0.05 (0.212)	z = 0.99, (0.265)

Notes: Table 10 illustrates the regressions' results using GMM estimation techniques; system and difference GMM. Dummies for time and country effects are used. The bold coefficients denote the statistically significant values, standard errors are reported between parentheses and, corrected for potential heteroscedasticity and time-series autocorrelation within each bank using the robust option. The one-step system GMM are estimated using the collapse option to address the instruments proliferation problem. The p-values of the Sargan test, the Hansen test are reported in brackets. The p-value of the Arellano-Bond serial correlation tests AR(1) and AR(2) are reported in brackets. Asterisks indicate significance at the 1 percent (*), 5 percent (**) and 10 percent (***) level.

this research aims to explore the main determinants of banks' NPLs in a sample of five MENA emerging markets between 2000 and 2019. Using a panel approach and a dynamic data estimation technique through system GMM, this research documents that GDP growth, unemployment, bank capitalization, bank profitability, bank operating inefficiency, bank ownership concentration, inflation, sovereign debt and bank size are the main determinants of NPLs, whereas, loan growth, bank diversification and interbank competition were found to have an insignificant impact on NPLs. More precisely, it appears that the systematic determinants i.e., macroeconomic ones, are preponderant compared to bank's specific factors. This implies that in terms of exposure to credit risk, banks are strongly dependent on the economic context and cannot offset or avoid the impact of the latter even through an effective management of bank specific factors. Thus, reinforcing country level regulations and mechanisms is of vital importance to control banks' credit risk.

The findings of this research have substantial implications. This research provides new evidence on the determinants of banks' credit risk in MENA emerging markets which will empowers regulators and policymakers with a comprehensive understating of credit risk in MENA emerging markets. In fact, the identification of these factors would help regulators address appropriate interventions, design appropriate credit policies and adopt adjusted prudential regulations. More specifically, economic and fiscal policies should be directed towards the creation of an environment conducive to economic growth with less unemployment and an effective management of public debt. Likewise, this study pursue innovation by exploring the effect of bank ownership concentration, as an important internal mechanism of corporate governance, on credit risk. Given that central banks acquired the role of forestalling bank panics, integrating ownership concentration as a fundamental determinant of NPLs is crucial to anticipate future financial calamities. In this sense, it is necessary for policymakers and bank regulators to develop adapted regulatory and supervisory frameworks and reforms for banks in the MENA region regarding the degree of ownership of the ultimate shareholders, as this region differs from other regions in term cultural and institutional environment. Furthermore, practitioners are likely to benefit from the results of this research as it sheds lights on the relationships between a wide range of variables, which will help address prejudices and improve collaboration between market participants. Prior studies have been largely silent on how industry-related factors can shape banks' credit risk. Hence, to have a holistic understating of NPLs' determinants, this paper adds more to the existing finance and banking literature by exploring industry-related variables and their impact on banks' risk taking. Finally, this research provides academicians and researchers with rich findings related to the key determinants of NPLs, as an extension of the existing literature, covering a large sample of bank and a more recent period. In the same vein, this study can be of significance to scholars as it offers important information and data related to banks' credit risk from another market, MENA region, in which research is infrequent.

Qualitative research on this topic using structure questionnaires and interviews could yield profound understanding of the main determinants of NPLs. Thus, future research can further examine the factors shaping banks' credit risk from the perspectives of banks' managers and regulators.

Declarations

Author contribution statement

Maryem Naili: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Wrote the paper.

Younes Lahrichi: Conceived and designed the experiments; Contributed reagents, materials, analysis tools or data; Analyzed and interpreted the data.

Data availability statement

Data will be made available on request.

Declaration of interests statement

The authors declare no conflict of interest.

Additional information

No additional information is available for this paper.

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