THE IMPACT OF BANKS SIZE ON BANKS SYSTEMIC RISK – EVIDENCE FROM MENA

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Abstract :

Purpose – This paper examines the: impact of banks size (BS) on Banks' Systemic Risk (BSR), with a specific emphasis on banking distress, in MENA over the period of 2008-2018 shedding light on vital regulatory measures to be undertaken by regulatory entities and imposed on banks for better risk containment in the banking sector.

Design/methodology/approach – The researchers use a population of MENA region's listed banks. A convenience sample of all available online data, where Bank Specific Variables (BSV) data are obtained from Eikon online database, and Country Specific Variables (CSV) data are obtained from the World Development Indicators (WDI) database at the World Bank and World Bank Doing Business database. Independent BSV: Banks Size (lnNI). Control BSV: Equity Ratio, Regulatory Ratio (CAR), Loans Ratio, Loan Loss Provision, Net Loans Growth, Total Assets Growth, Return on Equity (ROE), and Liquid Assets Ratio. Control CSV: GDP Per Capita, Inflation Rate, and Depth of Information Sharing.

Limitations/Results – Limitations: Depending on secondary data sources, and data availability restrictions, where the researchers are confined to the listed and unlisted banks financial statements, which in-turn limits the sample size considerably. Results: BS has a negative effect on BSR; reflecting that larger banks may have lower banks systemic risk due to the “bailout effect” having more stringent regulations imposed on them by the regulatory entities supporting bailout. Credit Risk has a positive impact on BSR; the higher the bank’s credit risk the higher its BSR, the lower its asset quality.

Research Importance – The consistent development of MENA’s financial sector in terms of both market and financial institutions size constitute a gap in the academic literature where MENA’s banks systemic risk is understudied. This in turn can help in the evaluation of policy reform proposals that followed the 2008 global financial crisis (GFC) as well as the ones that will follow the current global economic crisis.

***Keywords*:** Systemic Risk, Banks Size, Financial Distress, CAMEL

1. INTRODUCTION

Taking into consideration the current global economic conditions and changes, and the recurrent occurrence of financial crises, the banking sector’s role is constantly evolving (Huang, Zhou and Zhu, 2009; Reboredo and Ugolini, 2015; Silva, Kimura and Sobreiro, 2017; Zedda and Cannas, 2017; Varotto and Zhao, 2018). This is very prominent in MENA region where stock markets are still immature, hence the banks' role, size, and risk appetite are constantly evolving, reforming, and expanding under the adoption of financial reforms (Braham, de Peretti and Belkacem, 2020; Issa, Girardone and Snaith, 2020). Currently, MENA is playing a globally impactful role amidst the global economic crises, where banks are currently facing the crises head-on by bailing out firms with lenient credit terms (IMF, 2016; World Bank, 2020). It's also been implied that the higher a regions' BSR the higher its probability to act as a buffer for other more systemically vital regions such as China, EU, and US (Fang et al., 2019).

Nevertheless, the literature on systemic financial risk is continuously advancing and becoming more widespread, reflecting the subject's diversity and various angles involved in the research (T. C. Silva et al., 2017). Moreover, the existing literature is depicted by its high quality, illuminating the subject's growing importance as well as the huge economic and social burdens tangled in financial crises (W. Silva et al., 2017; Stolbov and Shchepeleva, 2024). Not to mention, the subject involves regulatory aspects, where the economy, investors, and depositors must be consciously protected from the ramifications of portfolios' management (Ghosh, 2020). Respectively, this research addresses banks' size and overall systemic risk exposure in MENA region will provide insightful new findings for regulatory entities. Also, by having a specific emphasis on banking distress, this paper's results will shed light on vital regulatory measures to be undertaken by regulatory entities and imposed on banks for better risk containment in the banking sector. In effect, this will ensure the soundness and health of the financial institutions, which in turn will reflect on the economy as a whole; as a healthy banking system drives a vigorous economy (Luciano and Wihlborg, 2018; Summer, 2013).

1.1 PROBLEM STATEMENT

As a final point, with the current economic crisis hitting the global economy hard, where a significant drop in economic activity is prevalent worldwide, a huge burden falls on the banking sector with firms facing a decreased ability in repaying their loans, bombarding the syndicated loan markets (Iosifidi and Kokas, 2015), which in turn increases the banks' systemic risk exposure. Therefore, a well-rounded understanding of MENA's banks systemic risk (Ahmed and Huo, 2018; Tsuji, 2020) can help in the evaluation of policy reform proposals that followed the global financial crisis (GFC). Especially, with the presence of empirical evidence that Mergers were and are still used to resolve individual banking distress in the region highlighting the vital role banks size play (Sahut and Mili, 2011).

Accordingly, this research's problems and hypothesis can be stated as follows:

- What is the effect of banks' size on the MENA's Banking Sectors' systematic risk?

- H1: There is a significant statistical relationship between the banks size (as lnNI) and the banks systemic risk (BSR)

2. THEORETOCAL BACKGROUND

According to many research studies and surveys systemic financial risk doesn't have a conclusive or an all-inclusive definition (Citterio, 2024; Stolbov and Shchepeleva, 2024; Summer, 2013). Systemic financial risk is related to the malfunction of an institution spreading extensively and disorganizing the supply of credit and capital to the economy of real assets as explained by (Acharya et al., 2017; T. C. Silva et al., 2017). In other words, systemic risk can be defined as the joint failure of financial institutions and capital markets that considerably shorten the supply of capital to the real market. Nevertheless, other researchers explain that systemic financial risk can trigger a "systemic event" involving the collapse of one major financial institution or more, affecting the whole economy, where credit risk is one of its main constituents (Adachi-Sato and Vithessonthi, 2017; Patro et al., 2013). Therefore, systemic financial risk is not by definition systemic financial failure, it can lead to it depending on the severity of the systemic event involved. Consistently, systemic financial risk is the transmission of financial distress across the financial system due to the collective interconnectedness of financial institutions within the system (Billio et al., 2012; De Nicolo and Kwast, 2002; Zedda and Cannas, 2020, 2017). Moreover, other studies define

systemic financial risk in terms of "systemic financial stress" where the various market players exposed to amplified ambiguity alter their futuristic forecasts concerning financial gains or losses, thus, impacting the financial economy as a whole (Abdymomunov, 2013; Ozili, 2018; Peterson and Arun, 2018).
Significantly, a most recent study on BSR by Citterio (2024) contributes to the existing body of knowledge by summarizing empirical studies on bank bankruptcy prediction published post-2000. With a particular surge in interest following the 2008-2009 global financial crisis, this work examines prior studies, focusing on defining financial distress, selecting failure prediction models, and identifying key predictor variables, and has three key findings respectively (Citterio, 2024). Firstly, the lack of a precise definition of default and variations in the severity of financial distress concepts can result in an arbitrary definition of failure. This has led to significant heterogeneity among models, diminishing comparability and increasing the risk of unstable and sample-specific outcomes. Additionally, the challenge of distinguishing between failed and non-failed companies could lead to misclassification, potentially rendering classical statistical techniques, which rely on dichotomous variables, inappropriate. Secondly, while statistical models remain dominant, there is a growing trend towards employing AI techniques in bank bankruptcy prediction. Despite varied predictive accuracies across techniques and no standout model, ensemble classifiers

show promise in outperforming individual approaches; further research is necessary to validate this observation. However, there has been a limited focus on non-accounting variables, which could provide valuable non-financial insights. The research underscores that bank distress is a multifaceted event influenced by various factors—bank-specific, economic, and structural—that evolve over time, emphasizing the complexity of prediction models (Citterio, 2024).

Another recent survey examines the development of research on systemic risk from 2007 to 2021, a period marked by three major global financial upheavals: the Global Financial Crisis (GFC), the European financial crisis, and the onset of the COVID-19 pandemic (Stolbov and Shchepeleva, 2024). The study employs a bibliometric analysis, revealing a diminishing role of advanced countries in the research field over time, while emerging markets, particularly China, gain prominence. Notably, journals like the Journal of Financial Stability and Journal of Banking and Finance emerge as leaders in publishing on systemic risk during this period. The analysis also identifies influential institutions and scholars, predominantly from the USA, suggesting that the research field reached maturity around 2013-2014. This bibliometric aspect offers valuable insights for researchers exploring systemic risk, aiding in the establishment of collaborative networks and the selection of suitable journals for publication. Meanwhile, the identification of factors encouraging the publication of systemic risk research enables the design of targeted measures to incentivize scholars, thereby strengthening the scientific basis for macroprudential policy initiatives (Stolbov and Shchepeleva, 2024).

Additionally, a well-rounded understanding of MENA's banks systemic risk can help in the evaluation of policy reform proposals that followed the global financial crisis (GFC), are in effect now, as well as the ones that followed the pandemic crisis (Ahmed and Huo, 2018; Tsuji, 2020). Especially, with the presence of empirical evidence that mergers were and are still used to resolve individual banking distress in the region (Sahut and Mili, 2011). Currently, MENA is playing a globally impactful role amidst the crisis, where banks are currently facing the crisis head-on by bailing out firms with lenient credit terms due to COVID outbreak (IMF, 2016; World Bank, 2020). It's been implied that the higher a regions' BSR the higher its probability to act as a buffer for other more systemically vital regions such as China, EU, and US (Fang et al., 2019).

Nevertheless, various recent studies establish a direct positive link between bank size and bank systemic risk, where a growth in size has higher financial systemic risk exposures, where large banks systemic risk increased confirming "too big to fail" effects hypothesis, which spurs them onto taking on more credit risk irrespective of the quality of assets and consequences (Acharya et al., 2018; Ciola, 2020; De Jonghe et al., 2015). Thus concluding that larger a banks size, the higher its impact on the overall financial economy, implying that tighter regulations must be imposed on larger banks (Lorenc and Zhang, 2020). On the other side, looking at it from a different angle a larger bank size can similarly be connected with lower banks systemic risk due to the "bailout effect" having more stringent regulations imposed on larger financial institutions by the regulatory entities supporting bailout especially post the GFC (Vu et al., 2020). Interestingly, Vu et al. (2020) also propose that lager banks have higher information sharing, hence, more transparent than smaller banks, implying that larger banks are monitored more closely by regulators and are put under more stringent regulations (Vu et al., 2020). While, Lorenc and Zhang (2020) conclude that in countries having low information transparency or high market concentration will lead to higher systemic risk exposures. Accordingly, improving transparency and information disclosure, both externally and internally, within the financial system can work as an alternative to confining large banks' activities. Whereas Arif (2020) suggests that BSR of small banks only increases post covered-bond issuance, hinting that regulatory imposed bonds' limits are to be connected with the institution's size, where a strict governing context is mandatory when it comes to banks undertaking securitization (Arif, 2020). Finally, Ciola (2020) also establishes a positive connection between banks size and banks systemic risk, where low borrowers' quality and quantity counterweighs the benefits of large banks pros of having higher transparency as well as higher diversification of risks; in effect increasing their systemic risk (Ciola, 2020). Nonetheless, from a market's perspective having a higher loan loss provisions (llp) ratio can be indicative of lower bank credit risk due to viewing such banks as active lenders (Bostandzic and Weiß, 2018; Lee et al., 2014; Peterson and Arun, 2018; Williams, 2016). However, other studies find that the higher the bad debts (llp) ratio, the higher banks' credit and systemic risk (De Jonghe et al., 2015; Kamani, 2018). Hence, a non-conclusive loan growth and risk relation, as well as bad debts optimal percentage, recommended further research to fill in these gaps and also to find the optimal mix between banks' size, risk, and revenue diversification and specialization (Williams, 2016; Williams and Prather, 2010).

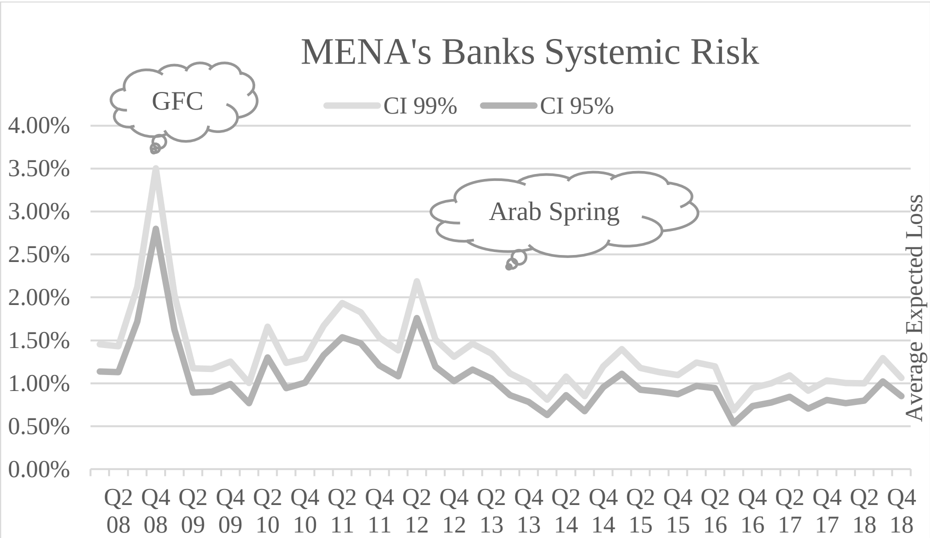
Consequently, based on the literature review the most used measures for banks size are usually defined in terms of a bank's total assets and/or total revenues (Acharya et al., 2018, 2017; Adachi-Sato and Vithessonthi, 2017; Arif, 2020; Bostandzic and Weiß, 2018; Cabrera et al., 2018; Cai et al., 2018; de Haan and Kakes, 2020; De Jonghe et al., 2015; Doan et al., 2018; Fina Kamani, 2019; Le, 2017; Lee et al., 2014; Mostak Ahamed, 2017; Peterson and Arun, 2018; Varotto and Zhao, 2018; Vu et al., 2020; Williams, 2016; Yang et al., 2020). Hereafter, the researchers use the natural logarithm of total revenue (LnTR) to control for size-induced difference of banks (Adachi-Sato and Vithessonthi, 2017; De Jonghe et al., 2015).

3. EMPIRICAL ANALYSIS

OVERVIEW

MENA region's BSR has been relatively consistent over the 11-year period of analysis. However, starting Q2 of 2008 it witnessed an upward hike reaching its highest peak at Q4 of 2008, with an average expected loss of 3.5% at a 99% confidence interval, which can be attributed to the Global Financial Crisis (GFC). The region also witnessed another peak at Q2 of 2012 due to the Arab Spring destabilizing impact on the region as a whole as reflected in figure 1.

Figure 1: MENA's Bank Systemic Risk Evolution (2008-2018)



3.1 Population and Study Sample

The population of the study is the MENA region's listed financial institutions. Notably the total number of MENA countries is 21, out of which only 15 have listed data on Eikon. The available Countries are Unites Arab Emirates, Bahrain, Egypt, Israel, Jordan, Kuwait, Lebanon, Morocco, Malta, Oman, Palestine, Qatar, Saudi Arabia, Syria, Tunisia. While the unavailable countries are Algeria, Dijibouti, Iraq, Iran, Libya, and Yemen. In addition, the total number of financial institutions in MENA region is 584, 44% of which are listed (publicly traded) on Eikon, making the total available sample of listed financial institutions 255. Thus, a convenience sample of the available MENA countries and their listed financial institutions is taken. Where the final sample includes 138 financial institution from Q1 2008 to Q4 2018; amounting to 4424 total observations as illustrated in table 1 below.

Table 1: Tabulation of Countries Stata iD

id_country	Freq.	Percent	Cum.
1 [BH – Bahrain]	406	9.18	9.18
2 [EG – Egypt]	412	9.31	18.49
3 [IL – Israel]	388	8.77	27.26
4 [JO – Jordan]	640	14.47	41.73
5 [KW – Kuwait]	309	6.98	48.71
6 [LB – Lebanon]	96	2.17	50.88
7 [MA – Morocco]	120	2.71	53.59
8 [MT – Malta]	12	0.27	53.87

9 [OM – Oman]	323	7.30	61.17
10 [PS – Palestine]	58	1.31	62.48
11 [QA – Qatar]	351	7.93	70.41
12 [SA – Saudi Arabia]	451	10.19	80.61
13 [SY – Syria]	58	1.31	81.92
14 [UAE]	800	18.08	100.00
Total	4424	100.00	

3.2 Data Collection

There are three main sources have been used to collect data. The three sources are as follows: Thomson Reuter's Eikon online database, World Bank's World Development Indicators (WDI) database, and World Bank's Doing Business database. Particularly, Bank Specific Variables (BSV) data are obtained from Eikon online database, and Country Specific Variables (CSV) data will be obtained from the world Bank's World Development Indicators (WDI) and Doing Business databases.

3.3 Variable Measurements

The study includes two main variables needed to be measured and tested empirically: banks systemic risk and banks size. Along with the following two sets of control variables: bank specific and country specific respectively. Control BSV: Equity Ratio, Capital to Assets Ratio, Capital Adequacy Ratio (CAR), Loans Growth, Bad Debt Charge to Assets (Credit risk), Loans to Assets, Liquid Assets Ratio, Return on Equity, and Total Assets Growth. Control CSV: GDP Per Capita, Inflation Rate, and Depth of Information Sharing. Table 2 shows a summary of the study's variables included in the research model as well as their measurements and impact on dependent variable (BSR).

Table 2: Summary of variables used, their measures results and expected impact

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		Dependent Variable	Measure	Dependent Variable Measures		
Bank Specific		Banks Systemic Risk (BSR)	Expected Shortfall (ES)	$ES\alpha = -E[R \mid R \leq -VaR\alpha]$		
Bank Specific		**Independent & Control Variables**	**Measure**	**Independent & Control Variable Measures**	**Res**	**Exp**
Bank Specific	Independent	Bank Size (BS)	Net Income (lnNI)	Natural Logarithm of Net Income	-	+/-
Bank Specific	Control	**CAMEL Rating System**				
Bank Specific	Control	Capital Adequacy	Equity Ratio (ER)*	Equity/Total Assets	+	-
Bank Specific	Control	Capital Adequacy	Regulatory Ratio (RR)*	(Tier1 Capital + Tier2 Capital)/Risk Weighted Assets	-	-
Bank Specific	Control	Asset Quality	Loans Ratio (LR)	Loans/Total Assets	-/+	+
Bank Specific	Control	Asset Quality	Loan loss Provision (LLP)*	Bad Debt Charge/Total Assets	+	+
Bank Specific	Control	Mngmt Efficiency	Net Loans Growth (NLG)	(Loans t+1 - Loans t)/ Loans t	-	+
Bank Specific	Control	Earnings Quality	Return On Equity (ROE)*	Revenue/Total Equity	+	+
Bank Specific	Control	Earnings Quality	Total Assets Growth (TAG)*	(Assets t+1 - Assets t)/Assets t	+	-
Bank Specific	Control	Liquidity Mngmt	Liquid Assets Ratio (LAR)*	Liquid Assets/Total Assets	-	-
Country Specific	Control	World Bank Indicators	GDP Per Capita (lnGDP)*	Natural Logarithm Gross Domestic Product	+	-
Country Specific	Control	World Bank Indicators	Inflation Rate (CPI)*	Consumer Price Index	0	+
Country Specific	Control	World Bank Indicators	Info Sharing (IS)*	Information Sharing Depth Annual Index	+	-

* Significant variables in the regression model

3.3.1 Dependent Variable Measure

In this study, the researchers calculate *Banks' Systemic Risk* using expected shortfall (ES) following Adrian and Brunnermeier (2016) which reflects banks average equity loss percentage in a given year conditional on the market experiencing one of its 5 percent lowest returns in that given year (at a 95% confidence interval) (Acharya, 2009; Acharya et al., 2017; Adrian and Brunnermeier, 2016; Kleinow et al., 2017). Significantly, the ES proceeds other measures because it's relatively easier to calculate, doesn't reject "extreme events," doesn't restrict a data shape distribution, and is proficient in forecasting banks with the poorest performance throughout the global financial crisis (GFC) from 2007 to 2009 (Acharya et al., 2017; Adrian and Brunnermeier, 2016, 2011). The ES of the market portfolio is calculated using the following formula:

$ES_{\alpha} = -E[R|R \leq -VaR_{\alpha}]$

R = banking sector's daily return,

VaR = value at risk,

α = extreme percentile

3.3.2 Independent Bank Specific Variable Measure

Ln Total Revenue: the researchers use the natural logarithm of total revenue (LnNI) to control for size-induced difference of banks; larger banks may have better cushion for riskier appetites and exposures due to overconfidence in its own size the "too big to fail" effects hypothesis (Acharya et al., 2018; Ciola, 2020; De Jonghe et al., 2015). Then again, looking at it from a different angle a larger bank size can similarly be connected with lower banks' risk due to the surveillance and restrictions of the governments or central banks "bailout effect" especially post the GFC (Vu et al., 2020).

3.3.3 Control Bank Specific Variables Measures

Equity Ratio: the researchers use the ratio of equity capital to total assets to account for leverage and profitability. Since banks' capital is considered as one of the important factors affecting banks' profitability, banks with higher capital are more capable of absorbing adverse blows and tend to have a lower insolvency risk. Higher capital also acts as an incentive for shareholders to monitor management activities, hence decreasing management's likelihood of taking on extreme risks (Cabrera et al., 2018; De Jonghe et al., 2015; Williams, 2016).

Capital Adequacy Ratio RR: the researchers use this ratio to account for the banks' stability and efficiency (Alber, 2015; Bostandzic and Weiß, 2018; Peterson and Arun, 2018; Williams, 2016).

Loan Loss Provisions Ratio LLP: the researchers calculate the loan loss provisions ratio as loan loss provisions to total assets and uses it to control for credit risk of individual banks. LLP ratio measures the loan quality of banks, which can act as reflection of a bank's assets quality assessment (Bostandzic and Weiß, 2018; Peterson and Arun, 2018; Williams, 2016).

Loans Growth: the researchers use this ratio to account for banks' riskiness. The higher the loans growth rate the higher the BSR, if the LLP is high, and vice versa (Peterson and Arun, 2018; Williams, 2016).

Loan Ratio: the researchers use the ratio of total loans to total assets to control for individual banks' asset composition. This ratio seizes the changes in the banks' asset portfolios, thus, the higher the Loan ratio, the higher the likelihood of a bank to be more geared towards more profitability as a result of having a significantly larger portion of interest-bearing assets (Bostandzic and Weiß, 2018; Lee et al., 2014; Peterson and Arun, 2018; Williams, 2016).

Return on Equity (ROE): the researchers use this ratios as a proxy for banks' profitability, where higher ratio indicates higher BSR (Alber, 2015; De Jonghe et al., 2015; Kamani, 2018).

Liquid Assets Ratio (LAR): the researchers use liquid assets to total assets (liquid assets ratio) as a measure of banks' liquidity, where a higher ratio is indicative of lower BSR (Varotto and Zhao, 2018; Williams, 2016).

Total Assets Growth (TAG): the researchers use annual total assets growth rate as a vital indicative of profitability, where higher ratio indicates lower BSR (De Jonghe et al., 2015; Lee et al., 2014; Mostak Ahamed, 2017; Varotto and Zhao, 2018).

3.3.4 Control Country Specific Variables Measures

Information Sharing Depth: Information Sharing Depth (IS) Index is collected from the World Bank Doing Business database. The higher the index the more transparent the information-sharing environment is, the lower risk effect of NII on BSR (Jonghe, O.D., Diepstraten, M., and Schepens, G., 2015).

GDP per Capita: the researchers use this macroeconomic indicator to account for country-to-country comparisons in terms of performance, development, and productivity. A high GDP per capita is indicative of a more developed country (De Jonghe et al., 2015; Doan et al., 2018; Kreis and Leisen, 2016).

Consumer price Index (CPI): the researchers use this index as a measure of an economy's inflation rate. The higher the index the more economically unstable a country is (De Jonghe et al., 2015; Kamani, 2018).

3.4 Research Model

To test the validity of the research hypothesis, multiple regression analysis is applied using STATA (version 14.2) package. This study consists of one empirical model to test the hypotheses of the study; the relationship between the noninterest income (NII) and the banks systemic risk (BSR) as seen in figure 2. The following multiple regression model is established to examine the first hypothesis (H1) that examines the impact of noninterest income (NII) on banks systemic risk (BSR). Therefore, the first regression model is established as follows:

$$BSR_{it} = \beta 0 + \beta_1 BS_{it} + \beta 2\ RR_{it} + \beta 3\ ER_{it} + \beta 4\ LR_{it} + \beta 5\ LLP_{it} + \beta 6\ NLG_{it} + \beta 7\ TAG_{it} + \beta 8\ ROE_{it} + \beta 9\ LAR_{it} + \beta 10\ LnGDP_{it} + \beta 11\ CPI_{it} + \beta 12\ IS_{it} + \boldsymbol{\varepsilon}_{it}$$

Figure 2: Research Model's Theoretical Framework

Bank specific	**Independent Variables**	Bank Size (BS)	Ln Total Revenue (lnTR)	→	**Dependent Variable** **Banks Systemic Risk**
	Control Variables	***CAMEL Rating System***		→	Expected Shortfall ESα =−E[R|R≤−VaRα]
		Capital Adequacy	Equity Ratio (ER)	→	
			Regulatory Ratio (RR)	→	
		Asset Quality	Loans Ratio (LR)	→	
			Loan loss Provision (LLP)	→	
		Mngmt Efficiency	Net Loans Growth (NLG)	→	
		Earnings Quality	Return On Equity (ROE)	→	
			Total Assets Growth (TAG)	→	
		Liquidity Mngmt	Liquid Assets Ratio (LAR)	→	
Country Specific		World Bank Indicators	GDP Per Capita (lnGDP)	→	
			Inflation Rate (CPI)	→	
			Information Sharing Depth (IS)	→	

3.5 Data analysis and Hypothesis Testing

This section focuses on analyzing the data collected, testing the validity of hypotheses and discussing the main findings of the study. STATA package (version 14.2) is employed to run panel data analysis to test the research hypotheses. This section implies treating missing values and outliers, descriptive statistics of the variables used in the study, correlation matrix, OLS assumptions and results of the regression analysis for the empirical model used in this study (Williams and Prather, 2010).

3.5.1 Treating missing values and outliers

There are no missing values in the data collection. Above and beyond, the researchers treat outliers by using the winsor2 command in STATA14 package at a 5% cutoff level, as the presence of the outliers leads to biased results.

3.5.2 Descriptive statistics

According to this section, descriptive statistics of each variable included in the study models aim to describe the characteristics of the data. This study comprises 138 financial institutions covering a period from Q1 2008 to Q4 2018, where the final number of observations is 4424. Table 3 presents the descriptive statistics of mean, standard deviation, minimum and maximum for the main variables.

Table 3: Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
BSR	4424	.033	.014	.015	.06
LnNI	4424	11.315	1.578	8.533	13.552
RR	4424	.177	.037	.132	.247
ER	4424	.172	.055	.101	.279
LR	4424	.652	.106	.468	.799
LLP	4424	.005	.004	0	.012
NLG	4424	.014	.037	-.02	.105
TAG	4424	.016	.036	-.013	.103
ROE	4424	.078	.045	.014	.155
LAR	4424	.087	.052	.028	.189
lnGDP	4424	9.735	.989	8.125	10.792
CPI	4424	109.218	8.416	97.606	124.558
IS	4424	6.301	1.947	4	9

Table 3 suggests that the mean of the BSR is 0.033, with a standard deviation of 0.014. The minimum is 0.015, while the maximum is 0.06 conveying low dispersion. On average, MENA's banks systemic risk in this sample of financial institutions is 3.3%, meaning that their average equity loss percentage in a given year conditional on the market experiencing one of its 5 percent lowest returns in that given year (at a 95% confidence interval) is 3.3% much lower than that of EU & US financial institutions (De Jonghe, 2010; De Jonghe et al., 2015).

Furthermore, the mean of lnNI is 11.315, with a standard deviation of 1.578; the minimum is 8.533, and the maximum is 13.552 where the natural log smoothes over the variations between values. Thus, the average of banks size in terms of Net Income the among sample is USD $82,043 (Adachi-Sato and Vithessonthi, 2017; De Jonghe et al., 2015; Williams, 2016). The low variance between the minimum and maximum values is due to taking the natural logarithm of total revenue (net income).

Concerning to the bank level control variables, the mean of the RR is 0.177, with a standard deviation 0.037, the minimum is 0.132 and the maximum is 0.247. The mean of the ER is 0.172, with a standard deviation 0.055, the minimum is 0.101 and the maximum is 0.279. The mean of LR is 0.652, with a standard deviation 0.106, the minimum and the maximum are 0.468 and 0.799 respectively. The mean of LLP is 0.005, with a standard deviation 0.004, the minimum and the maximum are 0 and 0.012 respectively. The mean of the NLG is 0.014, with a standard deviation 0.037, the minimum is -0.02 and the maximum is 0.105. The average loan growth among the sample is 1.4%. there is a variance between the minimum and maximum values of loans growth rate which refers differences in study sample's loan growth policies business orientation or strategy. The mean of TAG is 0.016, with a standard deviation 0. 036, the minimum and the maximum are -0.013 and 0.103 respectively. The average assets growth, mostly coatomers' deposits, among the sample is 1.6%, in line with the loans growth rate as well as the variance between the minimum and maximum values of assets growth rate which refers to in tandem growth policies business orientation or strategy for loans and assets. The mean of ROE is 0.078, with a standard deviation 0.045, the minimum and the maximum are 0.014 and 0.155 respectively. The mean of LAR is 0.087, with a standard deviation 0.052, the minimum and the maximum are 0.028 and 0.189 respectively.

Regarding to the country level control variables, the mean of lnGDP is 9.735, with a standard deviation of 0.989, the minimum is 8.125 and the maximum is 10.792. On average, MENA's GDP in this sample period is around USD $16,899, with a minimum $3,378 and maximum of $48,630. Furthermore, the mean of CPI is 109.218, with a standard deviation of 8.416; the minimum is 97.606, and the maximum is 124.558. Hence, the average inflation rate in MENA among sample is 9%. While IS has a mean of 6.301, with a standard deviation of 1.947; the minimum is 4, and the maximum is 9. Thus, the average of information disclosure in MENA is moderate.

3.5.3 Correlation Analysis

The Pearson's correlations are used to investigate if there is a correlation between variables. The result of the correlation analysis shows the strength and direction of the correlation between two variables and shows whether this correlation is significant. In addition, it tests for multicollinearity among independent variables. Where Multicollinearity may be a problem if the correlation among the explanatory variables is more than 90%. Table 4 shows the following correlations between the study variables respectively.

Table 4: Pearson's Correlation Matrix

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(1) BSR	1.000												
(2) LnNI	-0.165	1.000											
(3) FR	0.038	-0.112	1.000										
(4) ER	0.098	-0.006	0.417	1.000									
(5) LR	0.064	0.246	0.052	0.247	1.000								
(6) LLP	0.110	-0.101	0.089	0.092	0.077	1.000							
(7) NLG	0.070	0.021	-0.032	-0.001	0.095	-0.062	1.000						
(8) TAG	0.066	0.019	-0.025	-0.005	0.048	-0.059	0.349	1.000					
(9) ROE	-0.032	0.455	-0.018	-0.307	-0.037	-0.161	0.025	0.025	1.000				
(10) LAR	-0.125	-0.106	-0.098	-0.153	-0.290	-0.076	-0.046	-0.006	-0.105	1.000			
(11) lnGDP	0.091	0.362	0.027	0.300	0.527	0.098	0.048	0.037	-0.156	-0.181	1.000		
(12) CPI	-0.233	0.055	-0.043	-0.201	-0.255	-0.025	-0.036	-0.040	0.127	0.074	-0.312	1.000	
(13) IS	0.074	0.143	-0.089	0.023	-0.069	-0.043	0.016	0.001	0.005	0.103	0.163	0.112	1.000

Table 4 description: to start with, there is a negative correlation between BS (lnNI) and BSR, this means the increase in banks size reduces banks systemic risk, but this correlation is insignificant. Secondly, there is a positive correlation between RR and BSR, this means the higher the capital adequacy ratio is the higher the banks systemic risk, this correlation is significant at level 5%. Thirdly, there is a positive correlation between ER and BSR, this means an increase in equity ratio corresponds with an increase in banks systemic risk, this correlation is significant at level 10%. Fourthly, there is a positive correlation between LR and BSR, this means an increase in loans ratio matches with an increase in banks systemic risk, this correlation is significant at level 10%. Fifthly, there is a positive correlation between LLP and BSR, this means an increase in credit risk corresponds with an increase in banks systemic risk, but this correlation is insignificant. Sixthly, there is a positive correlation between NLG and BSR, this means an increase in loans (risky ones) corresponds with an increase in banks systemic risk, but this correlation is insignificant. Seventhly, there is a positive correlation between TAG and BSR, this means an increase banks assets correspond with an increase in banks systemic risk, this correlation is significant at level 10%. Eighthly, there is a negative correlation between ROE and BSR, this means the higher the ROE ratio is the lower the banks systemic risk, this correlation is significant at level 5%. Ninthly, there is a negative correlation between LAR and BSR, this means the higher the banks liquidity the lower the banks systemic risk, but this correlation is insignificant. Tenthly, there is a positive correlation between lnGDP and BSR, this means the higher a country's GDP is the higher the banks systemic risk, this correlation is significant at level 10%. Eleventhly, there is a negative correlation between CPI and BSR, this means the higher the country's inflation factor the lower the banks systemic risk, but this correlation is insignificant. Finally, there is a positive correlation between IS and BSR, this means the higher a country's information transparency is the higher the banks systemic risk, this correlation is significant at level 10%.

3.5.4 OLS assumptions

To test the study's hypotheses, the researchers depend on Ordinary Least Squares (OLS), where a set of assumptions must be verified prior to its usage, otherwise the regression results can be biased and misleading. The four main assumptions of OLS regression are as follows (Greene, 2012; Sekaran and Bougie, 2016): normality, multicollinearity, autocorrelation, and homoscedasticity. To begin with, the normality assumption assumes that the unobserved error is normally distributed. However, this assumption can be disregarded with large samples having many observations such as the case in this study.

Secondly, the multicollinearity assumption states that a high correlation or exact linear relationship between the independent variables should not exist. It is usually measured via the Variance Inflation Factor (VIF) which specifies the extent an independent variable is clarified by other independent (control) variables in the study's models. Hence, a multicollinearity problem exists between variables if the variance is high where the value of the VIF is greater than 10.

Thirdly, the non-autocorrelation assumption states that the errors are independent across the tested timeframe, no serial correlation, and can be detected using the Durbin Watson test. Stereotypically, the residual values are independent of each other when Durbin Watson's value is within the range of 1.5–2.5. However, according to the Durbin Watson significance tables the range is subjective to the sample size (138) and number of regressors (13). Therefore, the applicable range for this study is 1.27–1.84, thus an autocorrelation problem exists when the Durbin Watson's value is outside this appropriate range (Savin and White, 1977).

Fourthly, the homoscedasticity assumption sates that the error has the same variance irrespective of the independent variables' values. This means that errors are equally distributed; constant across observations to ensure validity, unbiasedness, and reliability of the model. However, if the error variances are nonconstant and variances change for each different observation (unequal spread), thus, a heteroskedasticity problem has existed. This assumption can be tested via The Breusch-Pagan/Cook-

Weisberg test to verify constant variance between residuals. The null hypothesis of this test assumes that the residuals are homoscedastic, whereas the alternative hypothesis is that the residuals are heteroscedastic. A null hypothesis is accepted if the probability calculated by the Breusch-Pagan/Cook-Weisberg test is greater than 5%, while the alternative hypothesis is accepted if the probability of the Breusch-Pagan /Cook-Weisberg test is less than 5%. Accordingly, table 5 shows the results of applying these assumptions on the proposed model.

Table 5: OLS assumptions

	Multicollinearity	**Autocorrelation**	**Homoskedasticity**
Model	Mean VIF	Durbin Watson (DW)	Breusch-Pagan/Cook-Weisberg
	1.812	1.357477	Prob > chi2 = 0.0000

Interpretation of Table 5: In this **Model** the multicollinearity assumption is verified as VIF is less than 10 (1.812), the autocorrelation assumption is verified with a value within the range of 1.27–1.84 (1.357477), and homoscedasticity assumption also is not verified because Breusch-Pagan/Cook-Weisberg probability less than 5% (0.0000). Therefore, the OLS regression provides good results for this model after the treatment of the heteroskedasticity problem using robust command in STATA. Therefore, the OLS regression provides good results for this model after the treatment of the heteroskedasticity problem using robust command in STATA. Hence, the results of this models will not be biased when using the OLS method because the researchers fix the autocorrelation problem in then using robust command in STATA.

3.6 Regression Analysis

The hypothesis (H1) states that there is a significant relationship between banks size in terms of natural log of net income (lnNI) and banks systemic risk (BSR). The study's model is used to test this hypothesis which includes lnNI as an independent variable and BSR as a dependent variable in addition to eight bank specific and three country specific control variables. Table 6 presents OLS regression analysis to test the study's empirical model.

Table 6: OLS regression results of the research model

BSR	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
LnNI	-.003	0	-13.46	0	-.003	-.002	***
RR	-.013	.007	-1.99	.047	-.026	0	**
ER	.017	.005	3.48	.001	.007	.026	***
LR	0	.002	-0.19	.849	-.005	.004	
LLP	.35	.057	6.12	0	.238	.462	***
NLG	-.013	.01	-1.27	.203	-.032	.007	
TAG	.043	.01	4.24	0	.023	.063	***
ROE	.049	.007	7.54	0	.036	.062	***
LAR	-.03	.004	-7.37	0	-.039	-.022	***
lnGDP	.001	0	4.00	0	.001	.002	***
CPI	0	0	-13.13	0	0	0	***
IS	.001	0	9.23	0	.001	.001	***
Constant	.078	.004	18.74	0	.07	.086	***

Mean dependent var	0.033	SD dependent var	0.014
R-squared	0.142	Number of obs	4424
F-test	61.466	Prob > F	0.000
Chi-Square	221.26	Prob > Chi-Square	0.000
Akaike crit. (AIC)	-25666.238	Bayesian crit. (BIC)	-25583.105

*** p<.01, ** p<.05, * p<.1*

Interpretation of Table 6: since the probability of F-test is lower than 0.05 (0.000), then the overall model is significant and shows that there is an effect of the independent variables on the dependent variable. Notably, the value of R square is 0.142 which indicates that the independent variable (lnNI) and control variables explain about 14.2% of the changes in BSR. Moreover, the coefficient of the main independent variable (lnNI) is negatively related with BSR (-0.003) and statistically significant at 1%, proving that banks size has a significant impact on banks systemic risk. Thus, the Study's hypothesis (H1) is accepted. As for the control variables, only six bank specific variables have a significant impact on BSR: RR, ER, LLP, TAG, ROE and LAR at a significance level of 5%, 1%, 1%, 1%, 1%, 1% respectively. While all three country specific variables have a significant impact on BSR: lnGDP, CPI, and IS; at a significance level of 1%. Notably, only RR and LAR out of the six bank specific control variables impact BSR negatively. Finally only CPI out of the three country specific control variables has zero impact on BSR, while the other two have a positive impact.

3.7 Study's Limitations

There are four main limitations in this study, firstly is depending on secondary data sources. Secondly, is the data availably restrictions, where the research is confined to the listed and/or published banks financial statements, which in-turn may limit the sample size considerably. Thirdly, treating missing values and balancing out the data reduces the sample size considerably and is rectified using a large sample. Fourthly, the chosen study period is bounded from 2008 till 2018, pre pandemic and war crises, due to data accessibility restrictions as the Eikon database's subscription was terminated by Cairo University's Faculty of Commerce in 2019. This also worked in the researchers' favor we were able to avoid these turbulent times where north African countries experienced severe currency devaluations, which in turn hugely impacts both independent and dependent variables values in terms of size and share price drops and could have distorted this research's results. To conclude, future research can accommodate this pandemic/war infested period and compare it with this study's findings.

4. FINDINGS

The researchers find that the independent variable, banks size (BS), has a significant negative effect on MENA's bank systemic risk (BSR) reflecting that larger banks may have constrained risk appetites with lower banks systemic risk due to the "bailout effect" having more stringent regulations imposed on them by the regulatory entities supporting bailout (Vu et al., 2020). While loan loss provision (LLP) has a significant positive impact on BSR as it controls for credit risk of individual banks, measuring the loan quality of banks, thus the higher the ratio the lower the bank's assets quality and the higher its BSR (Bostandzic and Weiß, 2018; Peterson and Arun, 2018; Williams, 2016). Furthermore, liquid assets ratio (LAR) has a significant negative impact on BSR as higher liquidity the higher the buffer in case of shocks, which in turn lowers the BSR (Varotto and Zhao, 2018; Williams, 2016). On the other hand, total assets growth (TAG) has a significant positive impact on BSR reflecting that assets growth in terms of profitability, or in this case low earnings quality, indicates a growth that aims to offset their losses from a deteriorating loan portfolio (Doan et al., 2018). Thus, providing insightful findings for policymakers and regulators by ensuring diversification activities enhance bank profitability, particularly for "lower asset quality" banks, eventually reducing instability in the banking sector (Mostak Ahamed, 2017). Furthermore, return on equity (ROE) has a positive impact on BSR as another proxy for banks' profitability, where higher ratio indicates higher BSR (Alber, 2015; De Jonghe et al., 2015; Kamani, 2018). In contrast, the regulatory ratio (RR), aka capital adequacy ratio (CAR), has a significant negative effect on MENA's bank systemic risk (BSR), since banks' capital is considered as one of the important factors affecting banks' profitability, banks with higher capital are more capable of absorbing adverse blows and tend to have a lower insolvency risk. Higher capital also acts as an incentive for shareholders to monitor management activities, hence decreasing management's likelihood of taking on extreme risks (Alber, 2015; Bostandzic and Weiß, 2018; Peterson and Arun, 2018; Williams, 2016). On the contrary, the equity ratio (ER) has a significant positive impact on BSR. Since equity capital to total assets accounts for leverage, it indicates that the financial institution is highly leveraged in risky assets or undertakes riskier ventures thus increases its ER to buffer out any defaults or financial distress (Cabrera et al., 2018; De Jonghe et al., 2015; Williams, 2016).

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